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ECOBRIDGE an expert system for spatial downscaling of land use/land cover change scenario outputs

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ABSTRACT

Present day mapping captures fine land cover/land use (LC/LU) details, but future/alterative LC/LU scenarios are typically constructed at coarser spatial resolution, hindering comparisons.

ECOBRIDGE (**Eco**logy and **B**iodive**r**sity **I**ntegrated **D**ownscale **Ge**neration) is an open, knowledge-based ArcGIS Pro workflow, to produce high-resolution LC/LU maps from coarser sources. ECOBRIDGE draws on specialist knowledge to parse a low-resolution baseline and scenario, a higher-resolution baseline and information defining LC/LU change, to generate high-resolution spatial data for the scenario.

These outputs are produced in the form of two datasets: as a raw pixel map and as an intelligent mapping layout which considers the structure of the landscape. The datasets created by ECOBRIDGE can contribute to more detailed analysis, bridging the gap between low-resolution datasets and more precise high-resolution information.

1. Introduction

The way that humans use and modify the earth's surface is one of the most fundamental drivers of our impact on the planet. Categorising these drivers has resulted in the interlinked concepts of Land Cover (LC) and Land Use (LU). These terms have often been used interchangeably, even if the consensus is that these are two very different concepts (Bununu et al., 2023). Generally, LC is defined (García-Álvarez et al., 2022) in terms of the natural, biological, and physical components that can be found on the surface of the Earth (for example, water, rock, sand, etc.) while LU relates to how societies employ the land in question (García-Álvarez et al., 2022). Alternatively, LC can be detected by Earth observation means, while LU identification needs social, economic, and even historical interpretation (Yang et al., 2014). However, these concepts are very tightly linked, since the activities that humans perform on the land (LU) are strongly determined by the natural materials which can be found on it (LC), with complex relationships existing between LC and LU (Meyfroidt et al., 2018). It is therefore appropriate to consider the two concepts in tandem.

Whilst changes in LU and LC have taken place throughout the history of humankind (Hassan et al., 2016), the pace of change is accelerating with 32 % of the global land surface affected over the past six decades (Winkler et al., 2021). Currently, Land Use and Land Cover Change (LULCC) is driving transformation in ecosystem biodiversity (Jung et al., 2020), soil composition and degradation, and species distribution (Dendoncker et al., 2006), flood risk (Zhu et al., 2019), air quality (Mccarty and Kaza, 2015), and other environmental phenomena. These changes are, in turn, driving economic, social and political transformations (Lambin et al., 2003). LULCC is also closely linked to climate change, since a changing environment affects what land covers are possible as well as the way land is used, and LULCC can also be a climate change driver or mitigator (e.g. via creation or restoration of carbon-sequestering land covers).

The relevance of LULCC for 21st century societies has highlighted the importance of developing techniques for detecting, analysing and forecasting these transformations. While LULCC monitoring and exploration has been boosted in recent years by the advancement and increased affordability of satellite technologies (Walsh et al., 2024) and Unmanned Aerial Vehicles (UAVs) (Kleinschroth et al., 2022), these new technological advancements do not provide trend detection or forecasting of future LULCC by themselves (Chen et al., 2019). Modelling complements these remote sensing technologies and allows us to detect

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drivers, explore dynamics, and analyse what-if LULCC scenarios (Verburg et al., 2006). Scenario approaches do not attempt to predict the future, but instead aim to explore multiple potential futures, to gain a better understanding of the range and uncertainties of the potential pathways and impacts of LULCC (Audsley et al., 2006; Moss et al., 2010). Scenarios help to prioritise further research and identify LULC policy options (Gaur and Singh, 2023), but vary widely in their aims, the systems to which they are applied and how they are constructed. For example, scenarios can be based on economic or non-economic factors (Overmars et al., 2007), may be spatially explicit or not (Ren et al., 2019), and can be statistical/empirical (Sun and Robinson, 2018) or based on rules (Verburg et al., 2004). There are many tools to create scenarios and to translate scenario narratives into quantifiable changes in LULC (Britz et al., 2011). Many scenario developers then produce spatially explicit realisations (i.e. maps) of LULCC, which allow the exploration of spatial variation in scenario outcomes and allow for scenario impacts on environmental and socioeconomic outcomes to be modelled via tools which require such spatial data as inputs (Finch et al., 2021). As a result, there are many existing LULC maps available, from a wide range of scenarios, generated by a wide range of methods (Friedl et al., 2022).

Traditionally, most methods and models that allow the production of spatially explicit LULCC scenarios produce outputs at low spatial resolutions, typically equivalent to 1 km × 1 km or coarser. This is generally because scenario generation models are computationally expensive, so running them at finer scales is costly in terms of time or computational power, and because reliable data on the drivers and constraints of LULCC at finer scales is often lacking (e.g. the ownership and management of individual land parcels). However, this places limitations on the use of these outputs for practical applications at the local level (Friedl et al., 2022). A lack of high-resolution output predictions can also lead to under or overestimation of model output (Woodman et al., 2023) and limits our ability to simulate many environmental processes that are highly dependent on fine-scale spatial context (Giuliani et al., 2022).

In recent years, the increase in computing capacity, new modelling approaches and higher-quality baseline LULC datasets, combined with a bigger demand for LULCC models and applications, have meant that downscaling methods for higher-resolution LULC scenario maps are being developed. These systems employ different strategies to generate fine resolution data from lower resolution information. Many use statistical or probabilistic methods: e.g. Hoskins et al. (2016), Giuliani et al. (2022). Other approaches have also been identified, including the use of integrated assessment models (West et al., 2014), but the main alternative approach to statistical downscaling strategies is the use of rule-based methods. Designers of rule-based methods have often combined expert knowledge with interpretations of spatial storylines, analysis of past LULCC, and high-resolution datasets (Rickebusch et al., 2011). This knowledge, the core of rule-based strategies, is often expressed as *transitions* (Le Page et al., 2016): change vectors governing how data will be transformed from low-level to high-level resolution.

ECOBRIDGE aims to provide a flexible, rule-based workflow for downscaling existing coarse-scale spatially explicit LULC scenario outputs to finer resolutions. We have developed ECOBRIDGE to fill the need in the environmental and ecological sector for a flexible system that can provide high-resolution datasets from coarser sources by integrating transferable scientific knowledge channelled in the form of transition rules. We structured the rule-based design of ECOBRIDGE into what can be described as an expert system. Expert Systems are part of the wider domain of Artificial Intelligence. They are designed to emulate the way expert humans carry out some tasks (Lucas & Van Der Gaag, 1991). At the core of Expert Systems there is a knowledge base, which contains the human expertise on the field in question, stored in a way that allows it to be used and processed efficiently. Expert Systems also include an inference engine, which is the set of rules and reasonings that drive the correct processing of the information in the knowledge base. ECOBRIDGE was designed to work efficiently over large (regional to national) extents and aimed at ensuring that the knowledge encapsulated in ECOBRIDGE was shareable and accessible to all. Additionally, like many developers of expert systems (Klyuchko, 2018), we also wanted to make a workflow which could be run in desktop-level devices such as minicomputers or dedicated workstations, but which would not require high levels of computing power or virtualisation.

2. Methods

The ECOBRIDGE workflow was originally developed to downscale existing UK-extent 1 km resolution scenarios (Malcolm et al., 2023) to finer resolutions that would allow input into process-based models of landscape use by a range of taxa (Gardner et al., 2024) and was based on a sequence of downscaling steps in ArcGIS applied by Blaydes et al. (in review).

2.1. Input LULC maps

To characterise LULCC, ECOBRIDGE requires four different input spatial datasets.

- a low-resolution baseline,
- a high-resolution baseline,
- a low-resolution scenario,
- and a polygon dataset of landscape parcels.

The polygon dataset ensures that the output landscapes retain the realism of the way landscapes are configured into discrete units (e.g. agricultural fields) and avoids artefactual hard boundaries at the edges of low-resolution grid cells. A user could simply use a vectorised version of the high-resolution baseline if an independent representation is not available.

For our study, we used the Land Cover Map 2020 (LCM2020) produced by UKCEH to supply requirements 1, 2 and 4. The LCM2020 is a suite of geospatial land cover datasets (raster and polygon) which describe the UK land surface in 2020. These were produced at the UK Centre for Ecology & Hydrology by classifying satellite images from 2020. We used the 1 km (Morton et al., 2022a) (dataset 1), 10m (Morton et al., 2022b) (dataset 2), and polygon (Morton et al., 2022c) (dataset 4) land cover maps.

2.2. Scenarios

To develop and test our workflow, we used 1 km resolution scenarios developed by Malcolm et al. (2023). These comprise 12 UK-extent LULC maps (11 scenarios plus a modelled baseline), with a thematic resolution similar to the ten Land Cover Map aggregate classes, but with additional classes introduced under scenarios (e.g. agroforestry, bioenergy crops). The LULC maps had been originally developed by rule-based extrapolation from LCM2020, so that spatial extent and resolutions aligned, and the classes followed the same numbering system. This allowed a robust test of the workflow, with large spatial extent, radical changes in LULC and the introduction of novel land use classes, without introducing complexities extraneous to the workflow (e.g. recoding LULC classes, matching spatial extents, projection and resolutions).

2.3. Expert knowledge and transition table

Rule-based downscaling models use *transitions*, i.e. sets of user-led conditions which define how changes will occur from an initial state to its projections under a given scenario (Lucas & Van Der Gaag, 1991). In our workflow, these transitions are defined in the form of a comma separated values (CSV) file provided by the user. We refer to this as the transition table. This is the fundamental route by which expert knowledge on LULCC is used to parametrise the workflow. It can be constructed by researchers and/or practitioners coming together to decide which LULCC transitions are likely to happen in real life and which land covers are unlikely to change, informed by local knowledge and/or by examination of historic changes (e.g. Redhead et al., 2020).

In ECOBRIDGE, the first row of the transition table CSV file is reserved for headers. In addition to the header row, the transition table must consist of 2 pairs of 2 columns. The first pair (Table 1, Low-Resolution Baseline Class and Low-Resolution Scenario Class) indicates the transition from the low-resolution baseline (column 1) to the low-resolution scenario (column 2). The second pair of columns deals with how high-resolution spatial data within that low-resolution transition (column 1 – column 2) will change from the high-resolution baseline (column 3) to the high-resolution scenario projection (column 4).

For instance, the first row in Table 1 indicates that, in low-resolution baseline pixels classified as class 2 which become class 6 pixels in the low-resolution scenario projection, high-resolution class 1 pixels remain unchanged.

2.4. Overarching workflow and development environment

At ECOBRIDGE's core is a geoprocessing workflow built on ArcGIS Pro's Modelbuilder programming platform (Fig. 1). The main geoprocessing workflow is complemented by five additional python scripts.

The downscaling workflow and algorithms at the core of ECOBRIDGE have been designed on the ArcGIS Pro environment. They have been tested and validated using the 3.2 version of the platform. Compatibility with other builds, particularly older versions, is not guaranteed. We used ArcGIS Pro Advanced edition, with the Spatial Analyst and Image Analyst extensions.

The ECOBRIDGE workflow has been run on both desktop (Windows 10 and 11) and virtualised environments successfully. Virtualisation has been carried out on a Parallels VM from a Mac OS host. To guarantee an accelerated performance, the ArcGIS Pro development environment for ECOBRIDGE was set up with a configuration which included using GPU processing by default. Before running ECOBRIDGE, it is recommended that users verify that the source datasets are aligned and share the same coordinate system. It is also recommended that the processing extent mirrors that of the required area of analysis. In ArcGIS Pro, this involved making sure that the environment Snap variable was configured to match one of the low-resolution datasets, and this is recommended best practice for this and similar platforms. This allowed us to guarantee that the results of the different stages of the workflow were aligned correctly to the source of change: the transitions at low-resolution level. Before executing the workflow, it is recommended to visually verify that the different layers align correctly using a map view.

2.5. Geoprocessing workflow

The ECOBRIDGE workflow starts by ingesting all required spatial inputs. In later stages of the workflow, the polygon dataset will be used to rearrange the raw reclassified pixels into structures that reflect the real landscape layout. By default, inbound image datasets are wrapped into an eight-bit Esri pixel grid.

Next, the transition table is ingested. The workflow expects the transition table to be a CSV file of four columns of integer values. The first two columns of the transition table are read, isolating the individual low-resolution transitions (column 1 and column 2). Then, for each individual pair of low-resolution transition values in columns 1 and 2, the pixels that match these values from the low-resolution baseline (column 1) and the low-resolution scenario (column 2) are extracted (Fig. 2), saving the output into two auxiliary raster files, which include the extracted values from column 1 and 2, respectively. Then, these two auxiliary raster files are subtracted. Subtracting the extracted raster files produces a raster file where overlapping pixels produce a numeric output, while the rest of the cells are Null. This allows us to map cells where a matching transition has taken place. The datasets resulting from the subtracting operations are stored in the geodatabase.

Table 1
Sample transition table, first three rows. The transition table used for testing and development of ECOBRIDGE had over 300 rows/rules.

Low-Resolution Baseline Class	Low-Resolution Scenario Class	High-Resolution Baseline Class	High-Resolution Downscaled Class
2	6	1	1
2	6	2	6
2	6	3	3

The workflow then iterates through the geodatabase and vectorises the raster datasets resulting from the subtraction process to create a series of templates or masks (Fig. 3). These masks, which match the location of each individual low-resolution transition, are then applied to the high-resolution dataset: they are used to clip it. These sections of the finer baseline are stored into the local main ArcGIS Pro geodatabase as individual raster datasets and are labelled in a way that reflects the low-resolution transitions that originated them to enable their identification in the next processing step.

Through this labelling, ECOBRIDGE can establish the low-resolution transition which originated each cell and, by revisiting the transition table and parsing the values in columns 3 and 4, can determine which high-resolution transitions should be applied to them. Thus, driven by the chains of changes specified in the transition table, cells undergo a pixel reclassification process (Fig. 4). Once this process has been completed, ECOBRIDGE runs a cleaning routine to delete previously created segmentation raster files, to free memory space and boost execution speed.

Next, ECOBRIDGE combines the reclassified clipped cells, overlaying them on the original fine-resolution baseline. In this way, areas without changes keep existing values: the reclassified areas are slotted into the correct locations, creating a complete mosaic of reclassified and original datasets. The resulting mosaic is the raw downscaled dataset, which is stored in the geodatabase as downscaled_output_RAW.tif.

At this stage, another cleaning routine is activated, and the remaining auxiliary datasets created during the execution are deleted. This optimization is complemented by an additional process, which consists of compacting the geodatabase to optimise performance.

The ECOBRIDGE workflow uses zonal statistics (Fig. 5) to summarise the higher-resolution majority pixel count for the downscaled output dataset, in relation to each parcel in the ingested polygon dataset. Once these figures have been calculated, the polygon data is updated and finally, a rasterisation function is called to turn this feature class dataset into a final raster file at the finer resolution: the resulting file keeps the landscape structure, but it also includes the downscaled information.

3. Results

3.1. ECOBRIDGE interface and execution

ECOBRIDGE can be accessed as an ArcGIS Pro toolbox within the ESRI platform of spatial software services. Users can integrate it into their ArcGIS Pro working environment. This integration can be carried out locally by accessing the.atbx file with the tools code. The tool User Interface (Fig. 6) is a simple menu which consists of five textboxes and a Run button. The different parameters can be dragged and dropped to the corresponding component, or they can be found by browsing through the folder system. In addition to specifying the different datasets needed to run the ECOBRIDGE workflow, users are also advised to plot them in ArcGIS Pro and make sure that the projections and processing extent are correctly configured.

ECOBRIDGE's execution running time depends on the datasets being processed, the transitions being implemented, and the equipment used. On a high-end GPU-enabled device, processing datasets covering the whole of the UK consistently took approximately 6 h. The user is

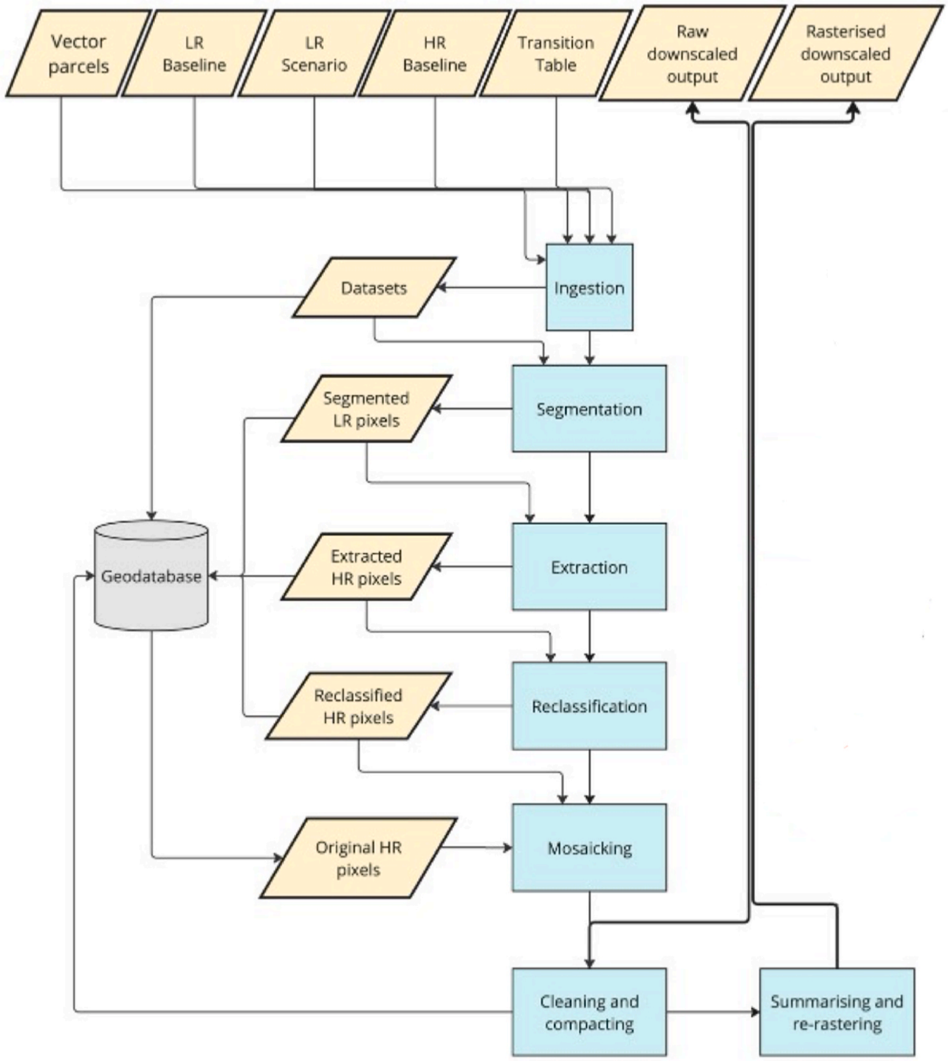

Fig. 1. Simplified flowchart of the ECOBRIDGE core workflow design. LR: Low Resolution, HR: High Resolution.

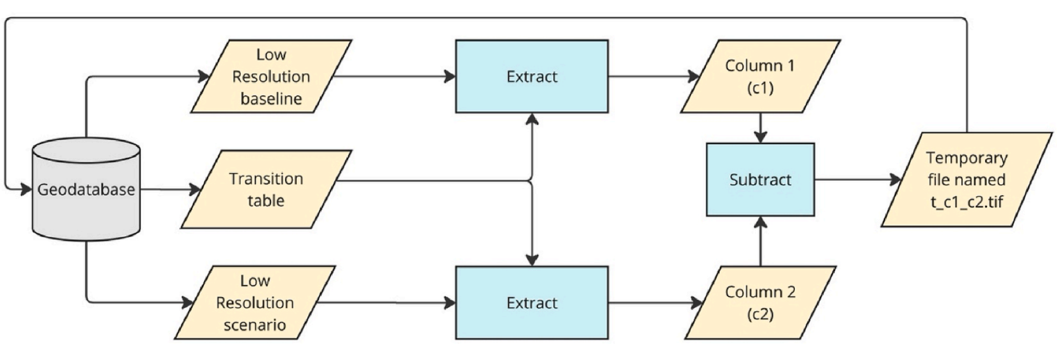

Fig. 2. Simplified flowchart of the segmentation stage.

informed of the software progress by a constant feed of messages indicating the stage at which the workflow is, and the operation being carried out.

The results of the execution of ECOBRIDGE are best exemplified in Figs. 7 and 8 below. Fig. 7 shows a 10 class, 1 km × 1 km Land Cover baseline for a sample area of Southern England (top right, A), and the 12-class scenario output for the same area (bottom left, B). In this, the increase of broadleaf and coniferous woodland is evident, together with the introduction of new land cover classes such as silvoarable regions in the north of the image. The bottom right image (C) in Fig. 7 shows the high-resolution (10 m) map for the same area. In Fig. 8, the changes driven by the baseline-scenario transitions are apparent in the increase of woodland to the detriment of improved grassland and arable land cover, and, to a lesser measure, in the presence of silvoarable cover. The top row (D, E) is also characterised by the presence of square patterns and sharp edges where transitions occurred and land cover in contiguous

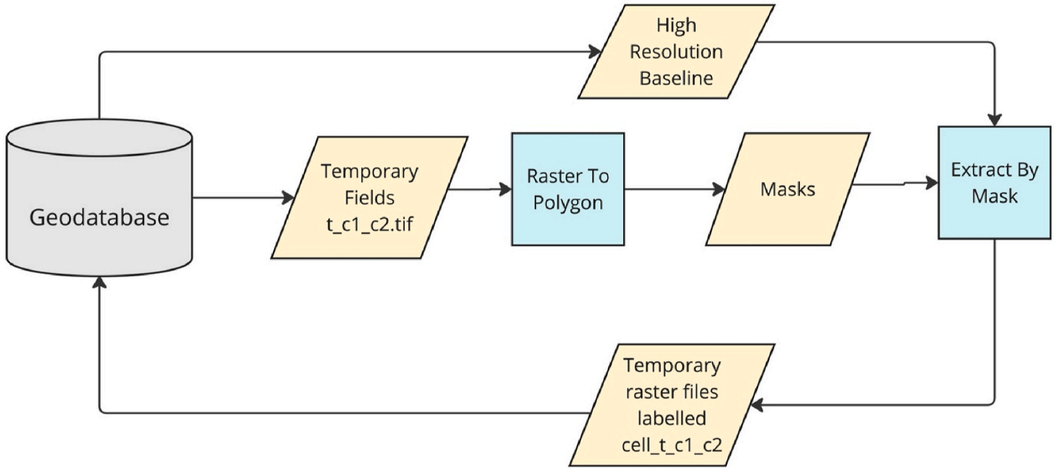

Fig. 3. – Simplified flowchart of the extraction stage.

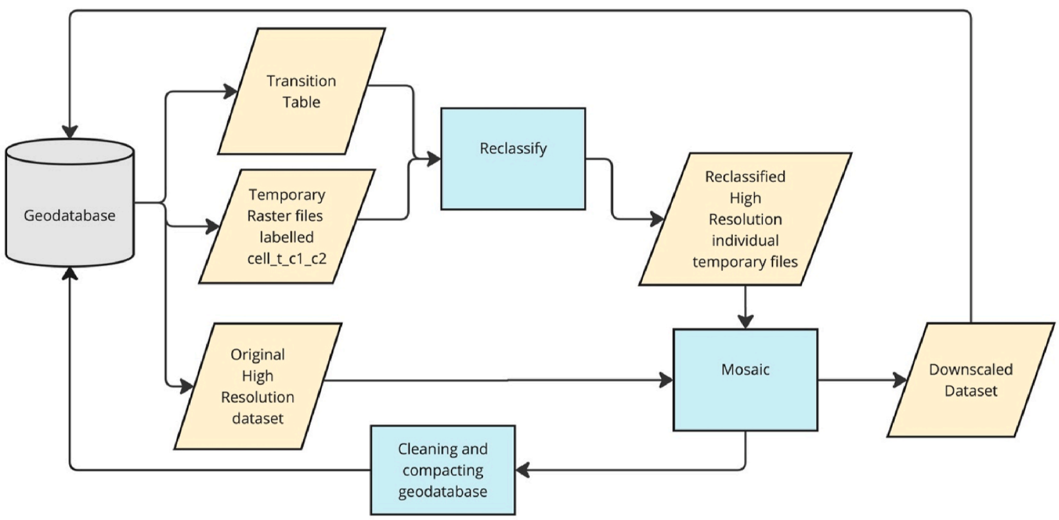

Fig. 4. – Simplified flowchart of the reclassification stage.

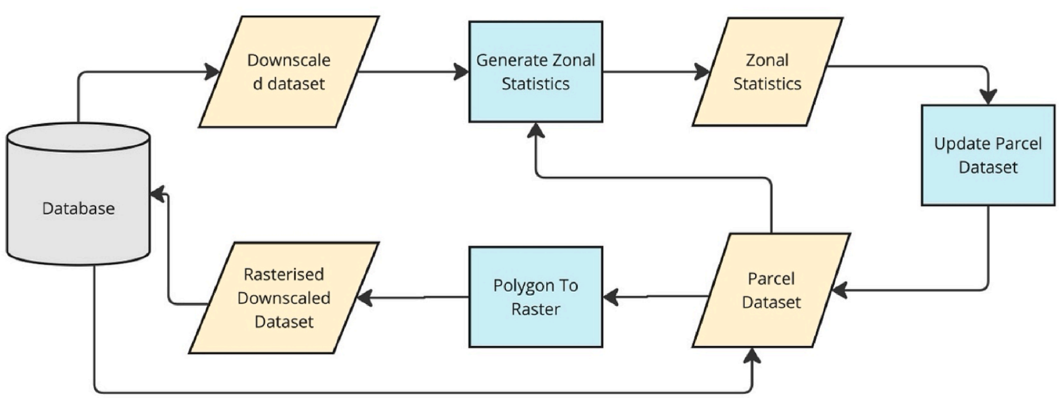

Fig. 5. Simplified flowchart of the rasterisation stage.

regions differ, while the bottom row (F, G) shows how the application of the rasterisation process of ECOBRIDGE helps to mitigate the appearance of sharp edges in the downscaled output. ECOBRIDGE reclassifies all polygons in the parcel dataset using the predominant underlying pixel class. Thus, it helps restore the original landscape features, delivering an artifact-free, natural-looking downscaled dataset (see Fig. 9).

4. Validation

The ECOBRIDGE workflow has been validated following a qualitative and quantitative approach, focusing on the detection of unwanted results or anomalies. The validation process cannot *per se* determine whether the changes that occur through the datasets are correct (since

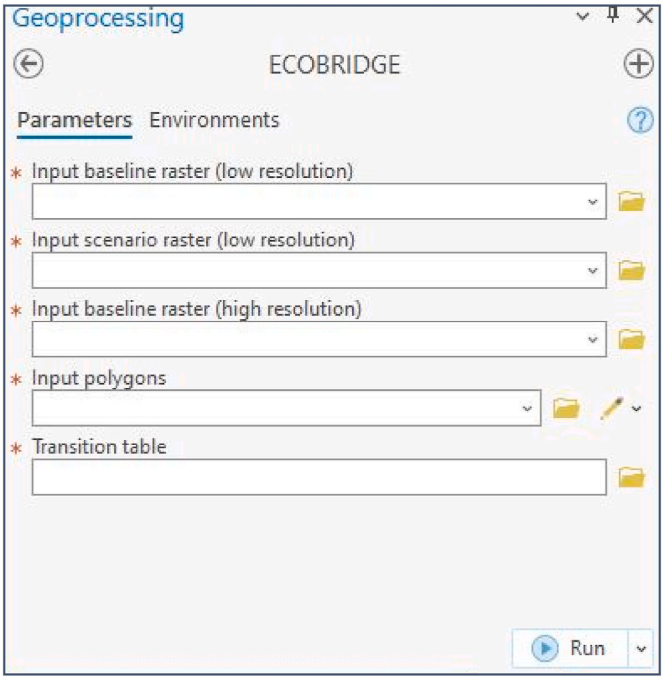

Fig. 6. Ecobridge graphical user interface.

scenarios produce hypothetical change and we have no actual change against which to compare it) but can help us confirm that all expected changes take place, that no changes take place in an unanticipated way and the ability of the tool to handle unexpected inputs in the transition table.

4.1. *Qualitative validation*

Qualitative validation consisted of carrying out a visual assessment of the downscaled results. This involved manually inspecting the four raster datasets, identifying the different transitions at play in both low- and high-resolution datasets, and checking that the expected value changes took place. This process lacks the automation and comprehensiveness of statistical or software-based methods but, like other authors particularly in the field of Earth Observation (Pulla et al., 2023), we found that this was a crucial step during the initial stages of development of the ECOBRIDGE workflow to verify that pixels were selected/omitted correctly for each given transition.

To carry out this manual verification of results we used the Create Accuracy Assessment Points workflow in the ArcGIS Pro Image Analyst dataset. A total of 500 accuracy assessment points were plotted on a section of the downscaled output of approximately 7500 km^2 in Southern England. Randomly distributed points were created for each class, according to the proportional area of the class. Zonal statistics were calculated for each accuracy assessment point to establish their overlapping pixel at different scales. Similar exercises at the UK scale were also carried out during various stages of ECOBRIDGE's development.

4.2. *Quantitative validation*

Additional checks were carried out to verify the correctness of the results. For example, we compared the changes in pixel counts between the low-resolution baseline and the scenario output datasets, and the changes which occurred between the high-resolution baseline and downscaled data (Fig. 9). These changes were compared across the two groups and datasets. As expected, proportional total count variation on the low-resolution datasets were mirrored by similar changes in the high-resolution images to within ±5 %.

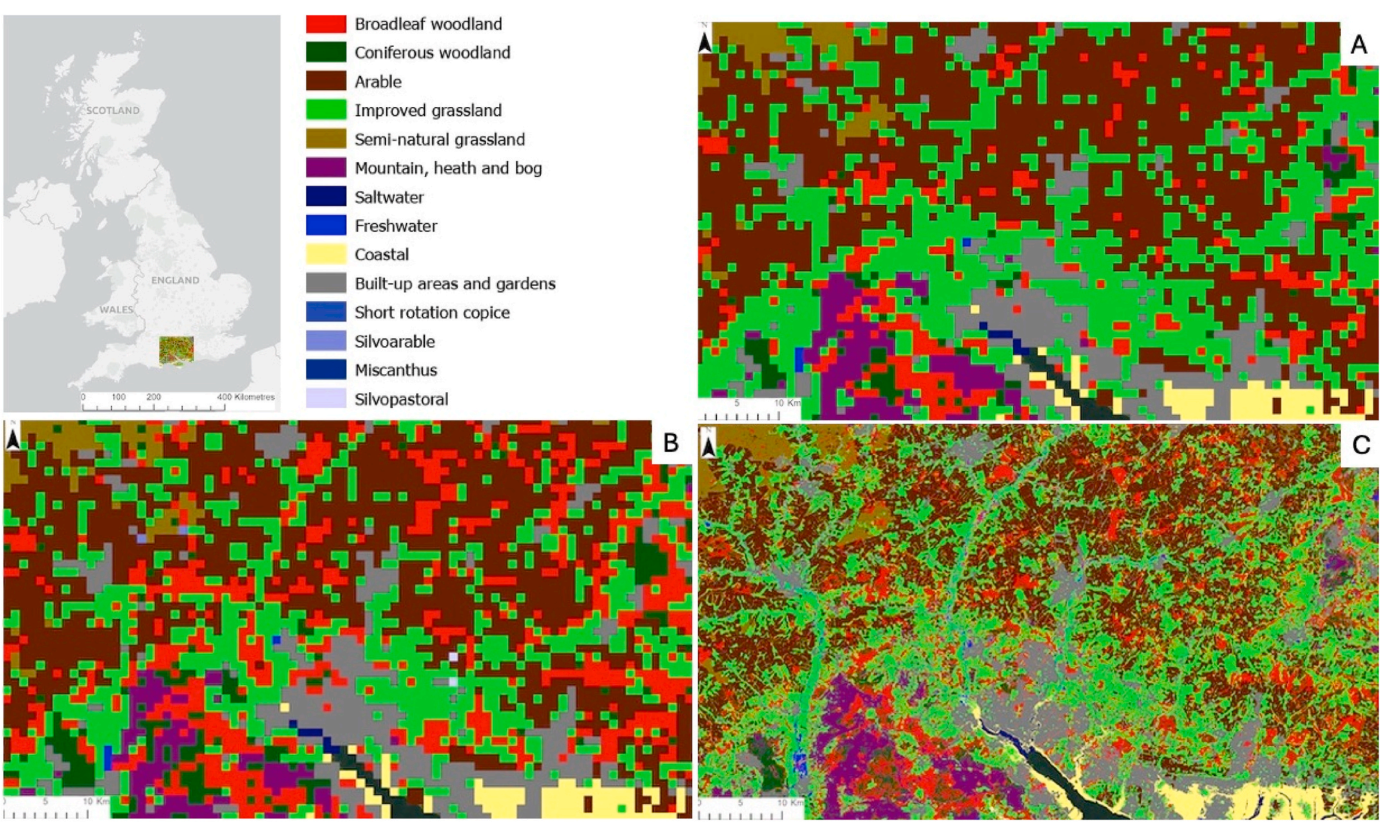

Fig. 7. – Legend and map showing location of the testing and validation area (top-left). The remaining three panels show input datasets to ECOBRIDGE: A) Low-resolution baseline, B) low-resolution scenario input, C) high-resolution baseline.

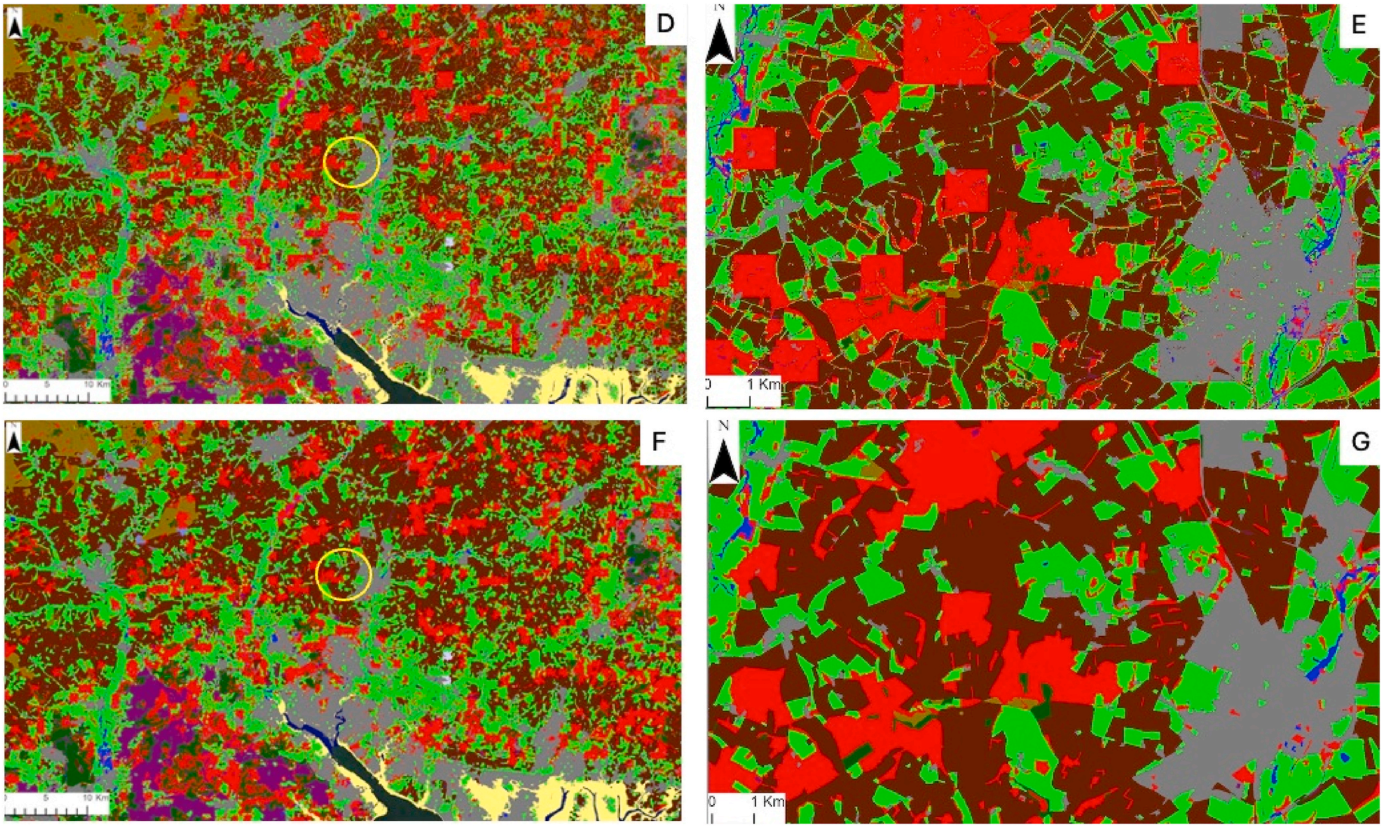

Fig. 8. Top row (D,E) shows raw downscaled output from ECOBRIDGE (D), with close-up view of yellow circled area (E). Bottom row (F, G) shows re-rasterised downscaled output (F), with close-up view of yellow circled area (G). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

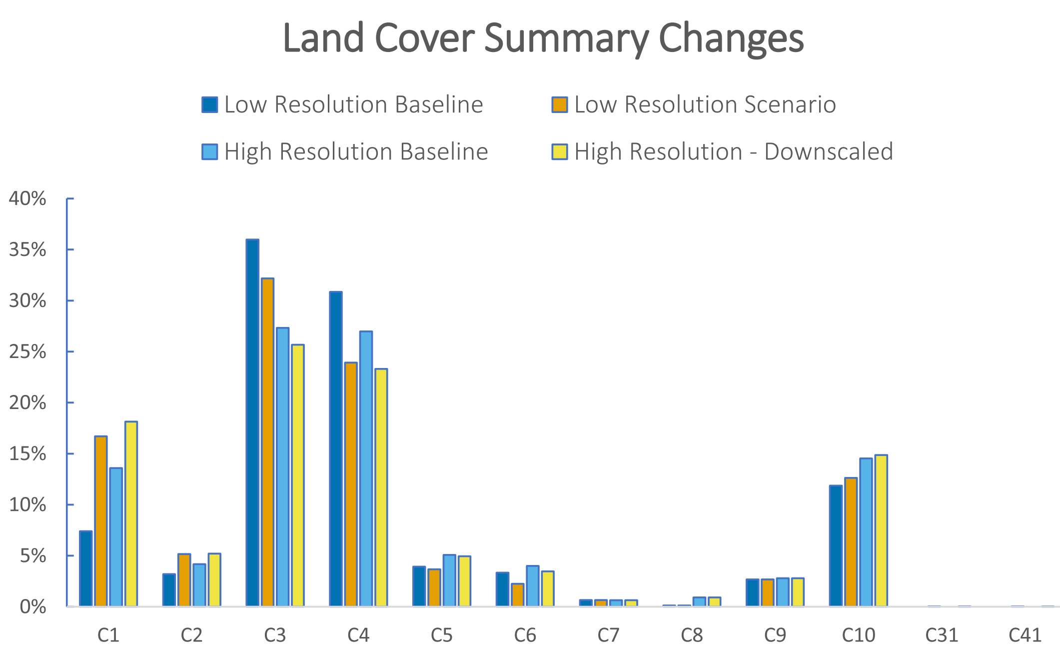

Fig. 9. – Bar plot of percentage cover of LULC classes in ECOBRIDGE coarse resolution inputs, and fine resolution input/output datasets for the test area. Category axis represents land cover classes from class 1 (C1) to class 41 (C41).

The results of the quantitative analysis were consistent with our expectations: changes in land cover values at low resolution were replicated by similar changes at high resolution. Some discrepancies are to be expected. In our example, the low-resolution scenario output is the result of a modelling process in which, among other impacts, some areas of arable and grassland cover (C3 and C4) become broadleaf woodland (C1). While the validation shows that this transformation occurs as expected at both high- and low-resolution levels, downscaling does affect the intensity of the change. This is to be expected: low-resolution models tend to have a more generalised impact compared to their high-resolution equivalent, since they tend to simplify and aggregate details. The high-resolution results reflect the fact that, while C3 and C4 are the majority classes in many 1 km pixels, these cells also include a variety of other classes (including C1) which only become apparent once the downscaling process has taken place.

4.3. Change-detection analysis

The ArcGIS Pro platform includes a set of tools for pixel change detection analysis. In particular, the Change Detection feature, within the Image Analysist extension, allows us to obtain a breakdown of all the changes produced between different raster files. In this way, we can establish the changes that occurred between the low-resolution baseline and scenario output and, crucially, the derived high-resolution transitions. This process produces a table of transitions which should exactly mirror the transition table: any erroneous transitions would be detected when comparing the combination results with the original transition table.

The Change Detection feature requires the Image Analyst extension. Users who lack access to that library can use the Combine feature to carry out a similar quantitative validation. This was used to create a table which included all pixel combinations for the four land cover datasets in question. In ArcGIS Pro, this feature requires the four land cover datasets and the extent and needs to be configured to consider the minimum possible cell size. By comparing the table produced by Combine with the transition table, we were able to confirm that no unexpected pixel changes had taken place. The only type of transitions shown by Combine which does not appear in the transition table are overlaps of same-value pixels at both high and low resolution. This is exemplified in the Sankey diagram below (Fig. 10), showing how, beyond the parameters specified by the transition table, all low-resolution baseline class 1 pixels overlap low-resolution scenario output class 1 pixels. Furthermore, as expected, the Sankey diagram shows how no changes at high-resolution occur, other than those indicated by the transition table. In this context, all high-resolution pixels in the baseline coincide with a high-resolution pixel of the same class in the downscaled output. Had the downscale process been unsuccessful or erroneous, changes both at low-resolution and high-resolution level would have followed additional, arbitrary combinations.

5. Discussion

5.1. Uses and limitations

ECOBRIDGE has been thoroughly tested on the Malcolm et al. (2023) scenarios, but its scope and application can include virtually any scenarios where baselines (low and high resolution) and transition table are available. For example, the workflow could be used to downscale datasets produced using the Shared Socioeconomic Pathways (SSPs) scenario frameworks (Brown et al., 2022; Riahi et al., 2017) as done by Blaydes et al. (in review). SSPs resolution depends on the model they are applied to, with most modelling applications ranging from hundreds to tens of kilometres.

ECOBRIDGE is not alone in the field of workflows or tools to downscale model outputs. Other examples include the Downscaler package, a command-based package to downscale species distribution based on statistical methods. The Statistical DownScaling Model (SDSM) (Wilby and Dawson, 2013) is a downscaling tool based on statistical methods, which focuses on downscaling climate datasets. SLEUTH (Clarke, 2008), consists of grids of cells which change according to a transition table. SLEUTH, however, focuses on urban growth scenarios, usually at a maximum resolution of 30m, requires specific, complex parameters, and employs historical information. The CLUE-S Model (Verburg et al., 2002) supports high-resolution datasets and it is also driven by a transition table, but requires extensive datasets and specialised parametrisations, increasing its complexity. Similarly, CA-Markov (Cellular Automata - Markov) is a powerful tool to simulate and predict LULCC, but it requires several historical and complex datasets to operate.

While undoubtedly useful, these tools are either highly specialised to a particular use case or require extensive parametrisation with complex data. ECOBRIDGE differs from these tools in that it allows expert knowledge on a specific field to completely govern LULCC predictions. The advantages of using ECOBRIDGE to downscale scenario outputs are therefore many. In general, downscaling requires fewer computing resources than applying complex models to fine resolution datasets to recreate scenarios from scratch. The fact that ECOBRIDGE does not involve high computing costs increases its flexibility. ECOBRIDGE can be applied at local, regional and country level according to the analysis required, without having to migrate to a more powerful computer platform. This flexibility is also highlighted in the way a user can adjust the transition table to obtain more nuanced outputs for different areas within a bigger extent. Thus, it is possible to run ECOBRIDGE exclusively

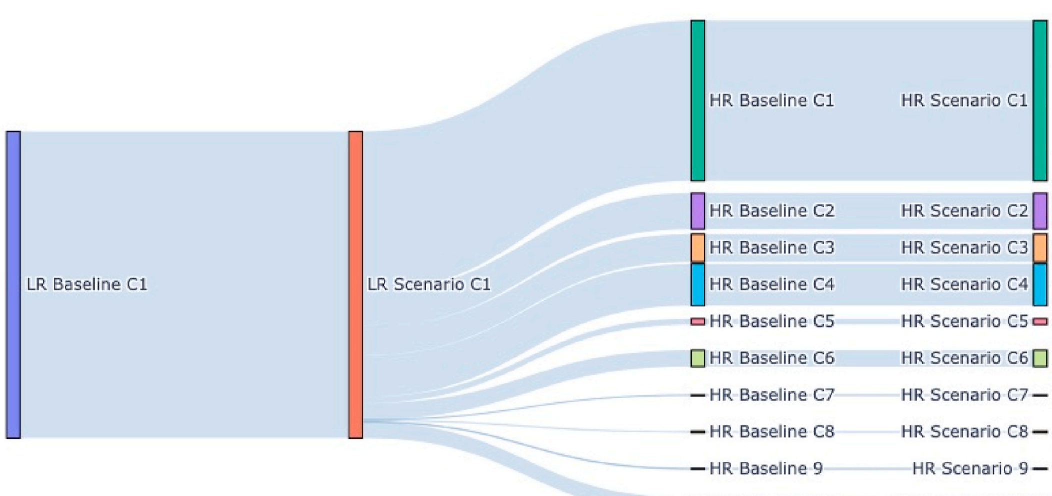

Fig. 10. Sankey diagram illustrating transition from low-resolution (LR) class 1 (C1) baseline pixels to LR scenario output C1 pixels, and subsequent transition from underlaying high-resolution (HR) class 1 to class 10 (C1 to C10) pixels to identical high-resolution scenario output pixels.

for regions which share common patterns and drivers of LULCC (Goodwin et al., 2022) through the creation of area-specific individual transition tables in combination with vector files for the areas in question. The workflow can also handle the introduction of new classes in the transition table (i.e. where new code is used for cells undergoing a specific combination of fine and coarse scale LULC transition) and the re-coding of LULC classes between baseline and scenario data (i.e. use of different integer codes to individual LULCs), provided care is taken when the user constructs the transition table to avoid human error.

While its simplicity and ease of use are some of the outstanding features of ECOBRIDGE, they are also its main limitation. Other parameters which could potentially enrich ECOBRIDGE outputs, such as those used by SLEUTH (Clarke, 2008), CA-Markov (Li et al., 2016), and CLUE-S (Verburg et al., 2002), are ignored by ECOBRIDGE: the tool relies exclusively on the quality of the expert knowledge provided. Where expert knowledge is insufficient to populate the rows of the transition table, determining which fine-scale changes take place within coarse-scale transitions, it may be possible to populate the table from literature or analysis of historic changes (Redhead et al., 2020), but in such situations there may be other, more appropriate tools to use that reflect this uncertainty (e.g. those based on statistical/probabilistic assignment). Adding probabilistic capabilities to the deterministic approach used in ECOBRIDGE has been identified as another way to enhance the workflow in potential future upgrades.

All data-based systems depend on the quality and availability of the information at their disposal for their correct performance, and ECOBRIDGE is no exception. While ECOBRIDGE can employ any raster baseline and scenario datasets, the quality of these data will ultimately define the quality of the downscaled outputs and their usability. This is an inherent weakness of any digital system which depends on input data for its results. However, where the user is aware of the potential for missing or erroneous data in the baselines, ECOBRIDGE can be used to help manage these issues successfully. By codifying known potential baseline inaccuracies or data voids within ECOBRIDGE's knowledge base (i.e. the transition table), the workflow can help to address some of these issues and act as a de facto error filter. For example, by specifying known implausible combinations of baseline and scenario pixels and producing specified downscaled pixel outputs to be used as error markers or 'canary' outputs, ECOBRIDGE can act as a QA and error detection tool.

A final limitation is the reliance of ECOBRIDGE on ESRI's ArcGIS Pro platform. While the use of this powerful environment has allowed us to accelerate the development of the tool, it limits the use of ECOBRIDGE to those with the required licences. Further investigation of implementing the ECOBRIDGE workflow on more openly available platforms is an obvious avenue for further, future development.

6. Conclusions

ECOBRIDGE forms a straightforward and flexible way for users to downscale spatial LULC scenario outputs, in an efficient and reproducible manner. The user interface and data requirements are simple, and this simplicity is also heightened by the use of a modern platform. ECOBRIDGE can contribute to propagating expert knowledge and enabling users to carry out LULCC model output analysis with increased accuracy and detail, helping the scientific community in understanding past and future LULCC trajectories at local level and beyond.

CRediT authorship contribution statement

Josep Serra Gallego: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Hollie Blaydes:** Writing – review & editing, Conceptualization. **Emma Gardner:** Writing – review & editing, Conceptualization. **Richard F. Pywell:** Writing – review & editing, Supervision. **J. Duncan Whyatt:** Writing – review & editing, Conceptualization. **John W. Redhead:** Writing – review & editing, Supervision, Data curation, Conceptualization.

Software availability

Name of software: ECOBRIDGE.
Repository: https://github.com/jogismeuk/ECOBRIDGE.git.
Developer: Josep Serra Gallego, UK Centre for Ecology & Hydrology, MacLean Building, Benson Lane, Crowmarsh Gifford, Wallingford OX10 8BB
Year first available: 2024.
Hardware required: GPU-enabled desktop or laptop computer.
Software required: ArcGIS Pro.
Public access.
Data availability: The low-resolution baseline (Morton et al., 2022a), high-resolution baseline (Morton et al., 2022b) and parcels (Morton et al., 2022c) datasets are available on the NERC Environmental Information Data Centre repository. The scenario dataset (Malcolm et al., 2023) used is not yet publicly available.
Cost: Free.

Declaration of competing interest

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

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Data availability

The authors do not have permission to share data.

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