



## Original Articles

## Effects of improved land-cover mapping on predicted ecosystem service outcomes in a lowland river catchment

Max Rayner<sup>a,\*</sup>, Heiko Balzter<sup>a,b,2</sup>, Laurence Jones<sup>c,3</sup>, Mick Whelan<sup>a,4</sup>, Chris Stoa<sup>d,5</sup><sup>a</sup> University of Leicester, Centre for Landscape and Climate Research, School of Geography, Geology and the Environment, University Road, LE1 7RH Leicester, UK<sup>b</sup> National Centre for Earth Observation, University of Leicester, University Road, LE1 7RH Leicester, UK<sup>c</sup> UK Centre for Ecology and Hydrology, Environment Centre Wales, Deiniol Road, Bangor, Gwynedd LL57 2UW, UK<sup>d</sup> The Game and Wildlife Conservation Trust, Allerton Project, Loddington, Leicester LE7 9XE, UK

## ARTICLE INFO

## Keywords:

Natural capital  
Ecosystem services  
Google earth engine  
Land-cover mapping

## ABSTRACT

Reliable quantification of ecosystem service (ES) provision in agricultural landscapes depends on accurate mapping of the spatial configuration of land-use and land cover (LULC). In this paper we explore the benefits of enhanced spatial and thematic resolution in LULC mapping in terms of predicting ecosystem services and associated natural capital-based land-use policies. Copernicus Sentinel-2 satellite images were processed using Google Earth Engine (GEE) to generate a LULC map at 10 m resolution, which was compared to existing datasets at 20 m, 25 m, and 100 m resolution in the River Welland catchment (Eastern England). Spatial resolution had a significant effect on the abundance and spatial configuration of land cover types. For example, detected woodland cover in the finest resolution dataset was 2x that in the coarsest data. Finer spatial resolution also allowed small, fragmented patches of woodland and grassland to be identified. ES provision (crop yield, carbon storage and pollinator abundance) was estimated from each map using the *Integrated Valuation of Ecosystem Services and Tradeoffs* (InVEST) model. The finest resolution map resulted in 21% lower predicted wheat production (due to lower estimates of cultivated land cover), 7% higher predicted carbon stocks and 43% higher predicted wild bee abundance compared to the coarsest resolution map. The estimated monetary value of ES provision increased by 23.2% between the 10 and 100 m dataset. We recommend that a LULC resolution of at least 10 m should be employed in agricultural landscapes to accurately capture ES provision. This can be achieved using GEE and could be used as a basis for the development of future natural capital policy.

## 1. Introduction

The intensification of farming practices beginning in the mid-20th century dramatically altered the landscape composition of Europe's agricultural regions (Stoa et al., 2009). Increasing intensification is often characterised by heavy reliance on machinery, high inputs of fertilisers and agrochemicals, increased field sizes, and a reduction in the number of crop rotations typically employed. Intensification is

recognised as a driver of changes to the supply of ecosystem services (ES) provided by agricultural landscapes (Mitchell et al., 2014), and a likely cause of observed reductions in biodiversity (Baker et al., 2012). Managing the environmental impacts of intensive agriculture and ensuring a sustainable supply of vital ES are important objectives of land use policy (Schulp et al., 2016), with governments and conservation organisations increasingly advocating for a natural capital approach to achieve this (Curnow, 2019). The natural capital approach recognises

**Abbreviations:** LULC, Land-use / Land-cover; GEE, Google Earth Engine; ES, Ecosystem Services; InVEST, Integrated Valuation of Ecosystem Services and Tradeoffs; MMA, Minimum Mapping Area.

\* Corresponding author.

E-mail addresses: [mjr59@leicester.ac.uk](mailto:mjr59@leicester.ac.uk) (M. Rayner), [hb91@leicester.ac.uk](mailto:hb91@leicester.ac.uk) (H. Balzter), [lj@ceh.ac.uk](mailto:lj@ceh.ac.uk) (L. Jones), [mjw72@leicester.ac.uk](mailto:mjw72@leicester.ac.uk) (M. Whelan), [cstoa@gwct.org.uk](mailto:cstoa@gwct.org.uk) (C. Stoa).

<sup>1</sup> ORCID: <https://orcid.org/0000-0002-5731-2115>.

<sup>2</sup> ORCID: <https://orcid.org/0000-0002-9053-4684>.

<sup>3</sup> ORCID: <https://orcid.org/0000-0002-4379-9006>.

<sup>4</sup> ORCID: <https://orcid.org/0000-0003-0277-9559>.

<sup>5</sup> ORCID: <https://orcid.org/0000-0002-8021-7888>.

<https://doi.org/10.1016/j.ecolind.2021.108463>

Received 18 June 2021; Received in revised form 18 October 2021; Accepted 7 December 2021

Available online 9 December 2021

1470-160X/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

the crucial role that habitats and ecosystem functions play in underpinning ES supply and the consequent benefits we get from the environment.

A monetary or non-monetary value can be attached to the ES that landscapes provide. This can help conceptualise the value of natural systems and increase society's motivation to protect them (Bateman et al., 2013). A key component of this approach is the characterisation of landscape composition and associated ES provision. This can be performed with spatially referenced numerical models such as the *Integrated Valuation of Ecosystem Services and Tradeoffs* model (InVEST) (Sharp et al., 2020), which predict ES provision from actual or hypothetical land-use/land-cover (LULC) configurations. These predictions can then be used to help inform land-use policy and communicate ES values (Cord et al., 2017). Models can simulate both (i) the physical processes occurring in different habitats and landscape features and (ii) the stocks associated with the area of different habitats and features to which ES quantities or values are related (e.g. carbon stocks under different land-covers) (Crossman et al., 2013; Sharps et al., 2017). InVEST is a widely used modelling package that currently supports nineteen different ES models. InVEST is free to access and its component models are relatively simple in design and implementation which facilitates the engagement of non-experts and allows them to be run in data poor locations (Vorstius and Spray, 2015). However, the simplicity of InVEST's models may also make them sensitive to data resolution effects (Bagstad et al., 2018).

Predicting the magnitude and direction of these effects is difficult (Rioux et al., 2019). For example, Grafius et al., (2016) modelled ES provision in urban environments using InVEST and found that moving from coarser (25 m) to finer (5 m) resolution datasets increased the predicted provision of carbon storage modelled (stocks) while decreasing modelled rates of soil erosion, and pollination (processes). In comparison Rioux et al., (2019), also modelling an urban environment, found that all three ES estimates considered (carbon storage, urban cooling and pollination) increased at finer resolutions. Thus, resolution effects on ES estimates are not consistent. Further research is, therefore, needed in a variety of environments and for a range ES in order to better understand how these effects might influence model outputs and associated decisions.

The effects of spatial resolution on modelled ES principally relate to its influence on landscape composition and associated landscape metrics (spatial statistics such as the number, size, shape and distribution of habitat patches (Fichera, Modica and Pollino, 2012; McGarigal, 1995). Previous studies have linked LULC spatial resolution with variation in landscape metrics (Saura, 2004; Wu et al., 2002) and estimations of supply and flow of ES (Rioux et al., 2019). Such issues are of concern to modellers and policy makers, as many ES are affected by both the abundance and configuration of habitats across the landscape (Gardner et al., 2019; Thomas et al., 2020; Santana et al., 2017). Accurately representing on-the-ground landscape composition within LULC datasets is, therefore, a crucial potential control over ES model performance.

Until relatively recently, the spatial resolution of national LULC maps was limited by access to sufficient high-quality satellite imagery and the computational demands of classifying it (Carrasco et al., 2019). These limitations have been addressed to some extent by increased availability of high-quality, high-resolution data (e.g. from the European Space Agency's Copernicus Sentinel-2 platform) which can be processed using Google Earth Engine (GEE), allowing accurate LULC mapping at 10 m resolution at national, or even continental scales (Ghorbanian et al., 2020; Li et al., 2020). Automated classification algorithms have also been developed in GEE; allowing maps to be produced at time intervals matching the requirements of environmental monitoring (Morton et al., 2020). These developments have the potential to improve land-use decision making and help address some of the more pressing environmental issues of our time, such as the conflict between intensive agricultural production and the sustainable provision of ES from farmed landscapes (Power, 2010). By opening access to a huge repository of data and providing the cloud-computing environment to process and

analyse it, GEE has supported rapid developments in the state-of-the-art for LULC mapping, and spatial analysis for environmental science (Gorelick et al., 2017; Wang et al., 2020).

In this paper we explore the influence of spatial resolution in LULC data on derived ES. The paper has three main objectives:

- (1) To quantify the effects of improved spatial resolution in LULC mapping on five landscape composition metrics: number of patches, mean patch area, total patch area, edge length of patches, and the proportion of like-adjacencies of patch pixels.
- (2) To compare the effects of LULC spatial resolution on ES predicted using InVEST. Specifically, we look at wheat production (an example of a provisioning service), pollinator abundance across four guilds of wild bee species, and carbon stocks. This bundle of ES provides a policy context for the resolution effects explored i. e., balancing food security with climate change mitigation and biodiversity conservation.
- (3) To make recommendations for LULC datasets used in natural capital assessments, specifically focused on balancing the provision of food security with climate change mitigation and biodiversity conservation.

Although recent work has explored the effects of spatial resolution on estimates of ES supply (Grafius et al., 2016; Rioux et al., 2019), these have focussed on urban environments and relied on fine resolution satellite data that are not freely accessible, or have artificially degraded the resolution of a single fine resolution LULC dataset. Here, we compare a new generation of free and open access datasets derived from the Sentinel-2 satellite archive against widely available coarser resolution datasets, investigating potential resolution effects within an agricultural landscape.

Modellers and policy makers are more likely to choose LULC datasets from those that are readily available, particularly where costs are limiting. Therefore, a comparison of different available datasets (which vary by resolution) may better-inform their utility for future land-management policy compared with a specific investigation of resolution effects achieved through degrading the resolution of a single dataset.

## 2. Materials and methods

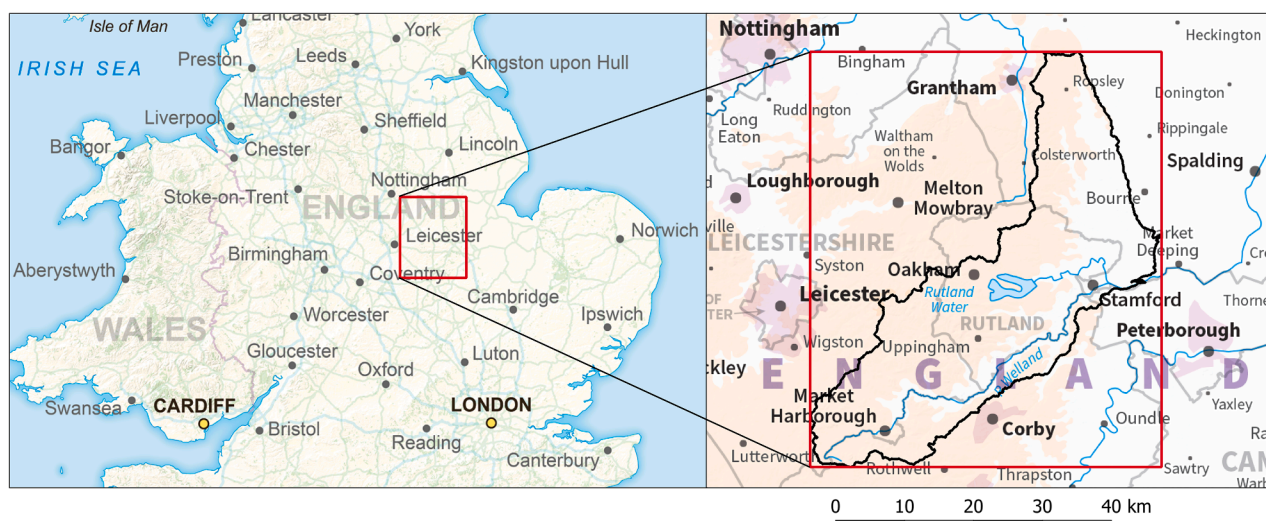
### 2.1. Study area

Our study was conducted in the 1,045 km<sup>2</sup> Upper Welland Catchment, UK (52.6°N, 0.6°W Fig. 1). The land cover is predominantly agricultural with 29.7% covered by grazed or cut grassland, 52.9% by arable land and 9.1% by woodland (Rayner, 2020). The remainder is made up of roads, settlements, and water bodies.

### 2.2. LULC maps

Four gridded LULC datasets were selected for analysis in this study ranging in spatial resolution from 10 m to 100 m. One was a bespoke LULC dataset created for this study in GEE using Sentinel 2 imagery (S2LC2018). This was compared with (i) Land Cover Map 2018 (LCM2018) produced by the UK Centre for Ecology and Hydrology (CEH) (Morton et al., 2020); (ii) Land Cover Map 2015 (LCM2015) also produced by CEH (Rowland et al., 2017); (iii) CORINE Land Cover Map 2018 (CLC2018) produced by the Copernicus Land Monitoring Service. Details of each dataset are shown in Table 1.

S2LC\_2018 was produced by a random forest classification of a cloud-free mosaic of level 2A (bottom of atmosphere radiance) Sentinel-2 imagery collated and processed in GEE (data available via Rayner, 2020). The training dataset was created in QGIS v3.6.1 by user interpretation of the Sentinel-2 mosaic, combined with reference to physical crop maps of the region provided by local landowners, and the 2018



**Fig. 1.** The location and boundary of the Upper Welland Catchment (outlined in black) within the United Kingdom (UK). The River Welland follows the southern border of the catchment, with Rutland Water, the UK's largest artificial reservoir, occupying the middle of the catchment.

**Table 1**

Technical details of the raster format LULC datasets included in the analysis. Note that LCM2018 has a minimum mapping area equal to its pixel size; as there are no post classification steps to filter map artefacts by a minimum size.

LULC dataset	Spatial resolution (m)	Minimum mapping area (MMA)	Sensors utilised
S2LC_2018	10	0.2 ha	Sentinel-2
LCM2018	20	0.04 ha	Sentinel-2
LCM2015	25	0.5 ha	Landsat-8
CLC2018	100	25 ha	Sentinel-2 and Landsat-8

Crop Map of England produced by the UK Rural Payments Agency. This method means that it is possible to account for different crop types within the thematic resolution of the final map.

Random forest classification is a widely used method and provides a good balance between classification accuracy and computational demand (Breiman, 2001). The mosaic was composed of eight images captured between 1st May 2018 and 30th September 2018 which corresponds with the period in arable crop phenology which most easily allows them to be differentiated. The random forest classification was based on the fiftieth percentile value of eight bands from the Sentinel-2 mosaic. The initial classification was then error corrected in QGIS v3.6.1. First, the raster was sieved to remove raster polygons less than twenty pixels giving an MMA of 0.2 ha. Although this process will remove some correctly classified linear landscape features of interest, it was deemed a good compromise to reduce the demands of the subsequent manual correction step. Manual correction of the remaining obvious classification errors was completed using the Thematic Raster Editor plugin for QGIS (ThRasE v. 20.3.23). S2LC\_2018 has an overall classification accuracy of 92.1% and  $\kappa$  of 0.91 (Rayner, 2020). The classification methods and accuracy assessments of the three comparison LULC maps are detailed in the Supplementary Information (S1).

### 2.3. Landscape metrics

Five landscape metrics were calculated from each LULC dataset for the woodland, grassland, and cultivated area classes (Table 2) in QGIS v3.6.1 using Landscape Ecology Statistics (LecoS) v1.9.0 (Jung, 2016), a Python plugin based on FRAGSTATS.

We focus our analysis of landscape composition on three land covers common to all four LULC datasets analysed, which are frequently present in agricultural landscapes: woodlands, grasslands, and cultivated

**Table 2**

Descriptions of the landscape metrics calculated.

Landscape metric	Unit	Description
Number of patches	Count of individual patches	The total number of patches of each landcover class. A 'patch' is an individual raster polygon and cannot be smaller than the MMA of the dataset.
Land cover	Square kilometres	The total area of landscape covered by each landcover class.
Mean patch area	Hectares	The total area of each landcover class divided by the total number of patches.
Edge length	Kilometres	The total length of the outside edges of all habitat patches. Larger values, when comparing the same landcover class between datasets, indicate greater levels of fragmentation.
Like adjacencies	Percentage of class PIXELS	The proportion of cell adjacencies within a landcover class that are "like" adjacencies i. e., pixels adjacent to those of the same landcover class. Lower values indicate less aggregation of the landcover class.

(arable) areas. Both woodland and grassland are important habitats for wildlife, providing materials and processes that support many ecological functions and associated ES, such as pollination, pest control (Mitchell et al., 2014), hydrological ES (Thomas et al., 2020), and the provision of biodiversity (Gardner et al., 2019). Cultivated areas cover 27% of the UK's land surface (Rae, 2017), are a vital resource in maintaining food security, and are a significant contributor to the UK's economy.

### 2.4. Crop production model

Each LULC map was used in separate runs of the InVEST v3.9.0 carbon storage, crop production, and pollinator abundance models (Sharp et al., 2020). InVEST's crop production model is stock-based and empirical, built on observed global crop yields data for 175 crops. It relates crop cover in the user's LULC map to global data from Monfreda, Ramankutty and Foley (2008) via a lookup table. S2LC\_2018 differentiates between five crop types (cereals, field beans, oilseed rape, maize, and potatoes). However, the LCM2015, LCM2018 and CLC2018 datasets group all cultivated areas into a single class. To allow for a more direct comparison between the datasets we collated all crop types from S2LC\_2018 into a single class and used this version alongside the other datasets. We modelled the cultivated area class as only growing winter



wheat (*Triticum aestivum*: the most common arable crop grown in the region), using this as a proxy for all other crops.

InVEST's directory contains a global climate map and a climate percentile yield table. First the model clips the climate map to the extent of the LULC map supplied by the user and reclassifies it using data from the percentile yield table to produce four raster maps of percentile crop yields (25th, 50th, 75th and 95th percentile). These are then interpolated to the same resolution as the LULC map. LULC classes indicated as not growing the crop of interest from the landcover to crop lookup table are masked out. The yield values are then summed and tabulated.

Model accuracy was assessed by comparing predicted yields of wheat with UK averages for 2018 (DEFRA, 2019). This was deemed sufficient to check the model was predicting realistic yields. The economic value of modelled wheat yields was estimated using the mean price index of London wheat for 2018 obtained from the Agriculture and Horticulture Development Board website (AHDB, 2021).

## 2.5. Carbon storage model

InVEST's carbon storage model is the second stock-based model assessed in this study. The model is, again, empirically-based and relates each LULC class to a lookup table containing carbon values in  $\text{Mg ha}^{-1}$  for four pools of carbon: above ground (plant biomass), below ground (live root biomass), soil organic carbon and dead organic matter (dead surface biomass). The model calculates total carbon stocks based on these values and the total area of each LULC class within the dataset. Carbon values for the LULC classes were taken from Sharps et al., (2017), who collated values for UK landcovers based on a review of published figures. Carbon stores for above and below ground live biomass in cultivated areas were set to zero, as they do not remain in the landscape long enough to be considered a stock. The carbon pool values we used were validated by Sharps et al., (2017) against field data collected in the UK (Glanville et al., 2017; Smart et al., 2017). Although they were found to exceed measured values by 51%, they were of the same order of magnitude (Sharps et al., 2017). Since this study is primarily focussed on understanding the relative differences between LULC datasets rather than on predicting absolute amounts, these values were, therefore, considered adequate.

The InVEST carbon model cannot calculate sequestration rates unless two LULC maps are entered into the model representing an earlier and later date. We could not do this when modelling a single year. Instead, we predicted a monetary value for the carbon sequestered by the landscape's woodland in one year. We based this on (i) the avoided value of removing 1 Mg of carbon by other means in 2018 (£69  $\text{Mg}^{-1}$ ) published by the Office for National Statistics (2020), (ii) average carbon sequestration rates by woodlands in England assessed under the Woodland Carbon Code (Forestry Commission, 2019), (iii) and the area of woodland present in each of the four LULC datasets we modelled.

The Woodland Carbon Code is a set of standards by which UK woodlands are judged based on sequestration rates and other measures, and feeds into natural capital accounting methods such as Office for National Statistics (2020). We took projected sequestration rates for the 27 verified projects in England (to better match climatic conditions and species assemblages of our study area) and divided this figure by the total area of those projects, to estimate an annual sequestration rate per hectare ( $5.77 \text{ Mg C ha year}^{-1}$ ).

## 2.6. Pollinator abundance model

The InVEST pollinator abundance model is process-based and simulates the nesting and foraging behaviours of wild bee populations across the landscape to produce an index of pollinator abundance. The model is fully described in Lonsdorf et al., (2009) but it is useful to include an overview here.

The model works on the assumption that for wild bee populations to persist in the landscape they require adequate nesting sites, and food

(floral resources) within foraging distance of those nesting sites. The model first calculates an index of pollinator supply for each guild, and for every cell, indicating where in the landscape pollinators are likely to originate from. The index is based on the nesting resources in that cell, the floral resources within foraging range, and the relative abundance of each guild across the landscape. The index of supply is then used to calculate an index of abundance, which indicates where pollinators are active across the landscape. The index of abundance is a product of the index of supply and available floral resources in each season, weighted by each guild's relative activity during that season.

In this study, we follow Gardner et al., (2020) and model four guilds of wild bees: ground nesting solitary bees, cavity nesting solitary bees, ground nesting bumblebees and tree nesting bumblebees. The indices for each guild and landcover within the guild table and landcover biophysical table were taken from "expert opinion" values used in Gardner et al., (2020). We were able to set specific floral resources and nesting availability scores for the crop classes in S2LC\_2018 as this dataset differentiates between several arable crop types. For the aggregate crop classes in the other LULC datasets we determined a best estimate based on the mix of crop types across the region and the range of expert opinion scores for these crop types given by Gardner et al., (2020). Relative abundance values were taken from the relative abundance of each guild within the national survey reported by Gardner et al., (2020).

## 3. Results

### 3.1. Landscape metrics

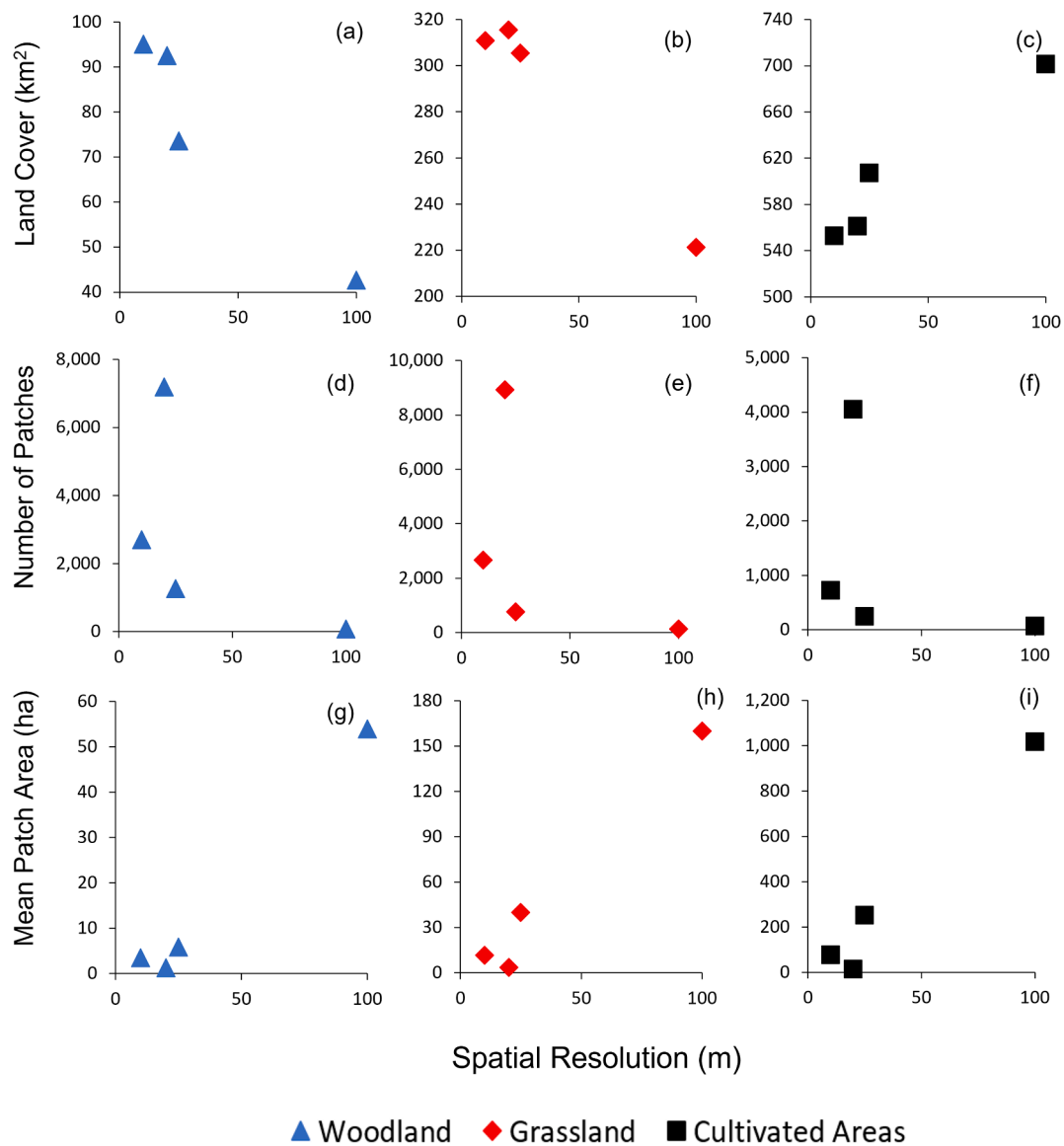
The total estimated landcover proportion of woodland is substantially lower in the coarser spatial resolution datasets. More than double the amount of woodland is estimated using the S2LC\_2018 and LCM2018 datasets than in the CLC2018 data, with 9.1% at 10 m, 8.9% at 20 m, 7.1% at 25 m and 4.1% at 100 m resolution (Fig. 2a). Grassland cover estimates also decreased at 100 m resolution (29.8% at 10 m, 30.2% at 20 m, 29.2% at 25 m and 21.1% at 100 m Fig. 2b). As the spatial resolution degrades, large areas of woodland and grassland are aggregated into the cultivated area classes with estimated cultivated area increasing from 52.8% at 10 m to 67.1% at 100 m (Fig. 2c).

The number of patches of all three LULC classes decreases at coarser spatial resolutions (Fig. 2d, e and f), except in the case of LCM2018 which has a much higher number of patches of each habitat type. Patch numbers in LCM2018 far exceed the next highest from S2LC\_2018, these high values are explained by the number of single pixel patches present across the landscape in LCM2018 (Fig. 3). This is also reflected in the mean patch areas for each LULC class, with LCM2018 at 20 m resolution consistently having the lowest values (Fig. 2g–i).

Spatial resolution effects were also observed for LULC-class configuration. Woodland, grassland, and cultivated areas become more dispersed at finer resolutions, with LCM2018 exhibiting the greatest levels of dispersion in all three classes (Fig. 4). Comparing metrics between LCM2018 and CLC2018 highlights this dispersion effect. Estimated edge lengths of woodland, grassland, and cultivated areas indicate that the LULC patches are significantly less aggregated in LCM2018 (Fig. 4a–c). The contrast between the two datasets is greatest in woodland, as this is the LULC class that is present in smaller, less regularly shaped patches in the real landscape. The proportion of like-adjacencies also increases with coarser spatial resolution, highlighting how pixels of woodland, grassland and cultivated areas are more likely to be present in larger, more aggregated patches in the coarser resolution datasets (Fig. 4d–f). Woodland is the most dispersed class across all four LULC datasets followed by grassland and cultivated areas.

### 3.2. Predicted ecosystem services provision

The predicted supply of regulating services (pollinator abundance and carbon storage) is higher when using the finer resolution datasets



**Fig. 2.** Landscape metrics relating to the abundance of woodland, grassland, and cultivated areas across the four LULC datasets with different spatial resolution.

and decreases as the resolution degrades. Conversely, the supply of provisioning services (wheat production) increases as the resolution degrades (Fig. 5).

Estimates of carbon stocks were far lower at 100 m resolution compared with the other three LULC datasets. However, estimates of carbon stocks at 20 and 25 m were marginally higher than at 10 m, despite higher woodland cover in the latter dataset.

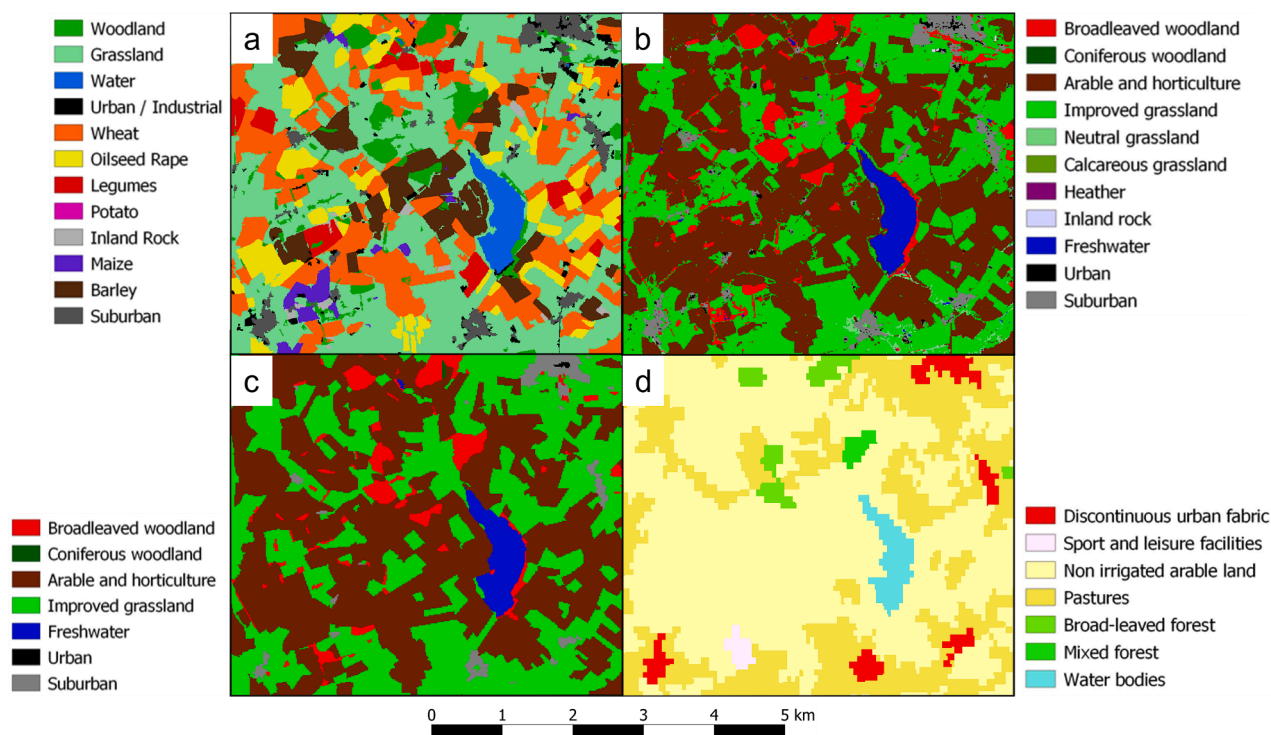
Predicted wheat production increased significantly with coarser resolution datasets (Fig. 5). We compared modelled values to average national yields from 2018 of  $7.8 \text{ Mg ha}^{-1}$  (DEFRA, 2019) and found that the 95th percentile values were the closest fit. We estimated monetary values for 95th percentile wheat production, and carbon sequestration by the catchment's woodlands (Table 3).

The estimated monetary value of wheat production increased by 27.1% between the 10 m and 100 m resolution datasets, while the estimated monetary value of carbon sequestration decreased by 55.1% between the same resolutions. In total, the estimated monetary value of the ES increased by 23.2% between the 10 and 100 m datasets.

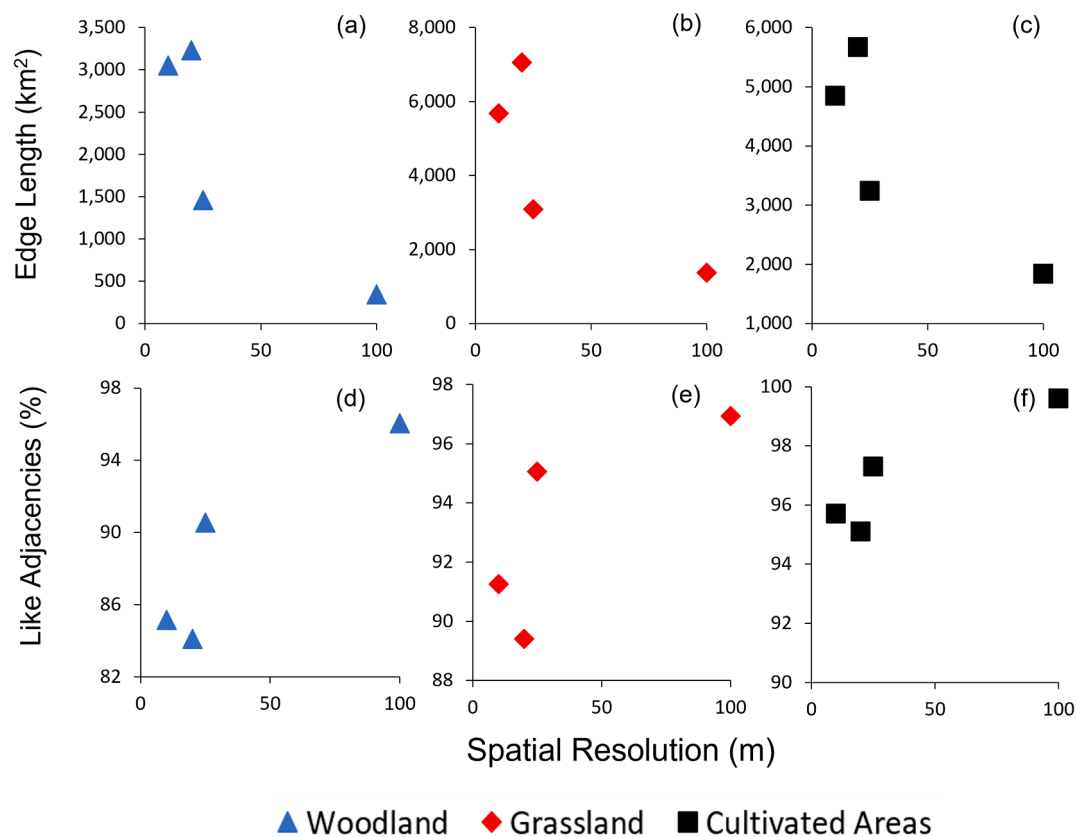
The predicted mean abundance of all wild bees decreased by 1.47 individuals  $\text{ha}^{-1}$  as the spatial resolution degraded from 10 m to 100 m (Fig. 5). When scaled across the region this equates to a difference of

approximately 150,000 individuals. Ground nesting bumblebees were the most abundant predicted guild, followed by ground nesting solitary bees (Fig. 6b), tree nesting bumblebees, and cavity nesting solitary bees (Fig. 6a). Degrading the resolution from 25 m to 100 m had less of an impact on modelled abundance for all four guilds, compared with the degradation from 10 m to 25 m.

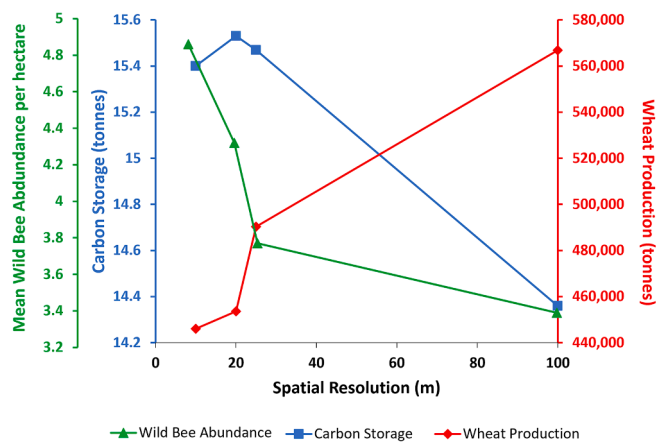
While averages are useful for assessing the overall effect of resolution on modelled pollinator abundance, comparison of spatial patterns more effectively communicates the impact of different spatial resolutions and associated landscape composition on the abundance of the four guilds across the landscape (Fig. 7). The ability to differentiate crop covers in S2LC\_2018 means that crops with better floral resources, such as oilseed rape or field beans, can be accounted for explicitly in the model, creating regions of higher predicted abundance relative to the other datasets (Fig. 7a). The presence of smaller woodland and grassland patches spread across the landscape in S2LC\_2018 and LCM2018 (Fig. 7a and b) also helps create areas of higher abundance. These features are missing in LCM2015 and CLC2018 (Fig. 7c and d).



**Fig. 3.** Zoomed area maps of a sample region of the study area as represented by (a) S2LC\_2018, (b) LCM2018, (c) LCM2015 and (d) CLC2018 highlighting the variation in landscape composition and thematic resolution between the different datasets.



**Fig. 4.** Landscape metrics values for the fragmentation of woodland, grassland, and cultivated areas across the four LULC datasets.



**Fig. 5.** Resolution effects on ecosystem services modelled. Wild bee abundance is given as the mean combined abundance per hectare of all four modelled guilds. Wheat production shows the 95th percentile of modelled yields.

**Table 3**

Estimated monetary value of wheat production, and carbon sequestration by the catchment's woodlands.

LULC dataset	Wheat production	Carbon sequestration	Total value
S2LC 2018	£75.84 million	£3.79 million	£79.63 million
LCM2018	£77.11 million	£3.69 million	£80.80 million
LCM2015	£83.36 million	£2.93 million	£86.29 million
LCM2018	£96.37 million	£1.70 million	£98.07 million

## 4. Discussion

### 4.1. Resolution effects on LULC mapping and ecosystem service assessment

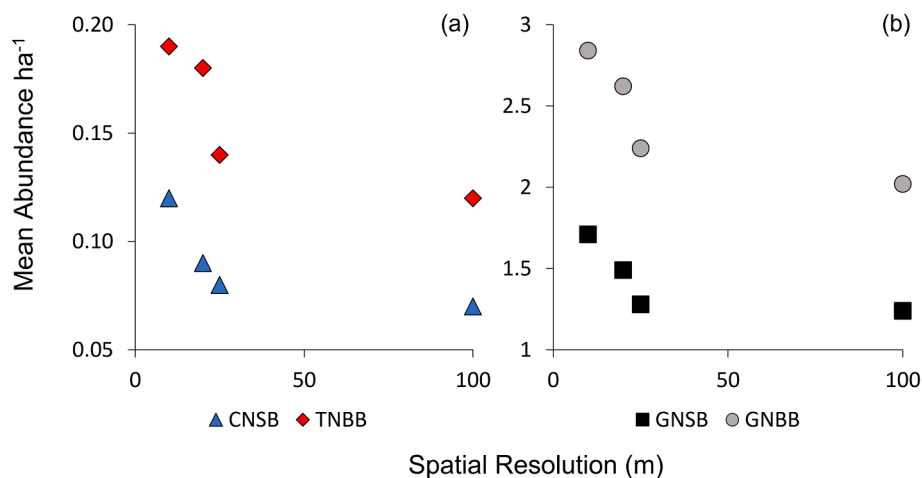
Our analysis of the effects of spatial resolution on landscape metrics has, perhaps unsurprisingly, shown that the finer resolution LULC maps produced from Sentinel-2 imagery characterise the landscape very differently to coarser resolution LULC maps in terms of the abundance of different land covers, but also in terms of their distribution across the landscape. As resolution degrades the dominant land covers increase in proportion while the less abundant, more fragmented land covers decrease in proportion. Most striking was the substantial difference in predicted areas of woodland and cultivated land between the finest and coarsest resolution maps. This is due to the way that the classification is

aggregated by larger MMUs in LCM2015 and CLC2018, meaning that smaller, more linear woodland patches are the first features to be dissolved from the dataset as land covers are aggregated. These differences are primarily due to the use of finer resolution Sentinel-2 imagery in the GEE-derived datasets, which capture smaller landscape features in the classified maps (Li et al., 2020). Rioux et al., (2019) reported similar effects in an urban environment when the resolution of a single LULC dataset was degraded in increments from 1 to 15 m, with impervious surfaces increasing in proportion (+10% in residential zones and + 6% in commercial zones) while the proportion of vegetated land covers decreased (-15% in residential zones and -46% in commercial zones).

### 4.2. Stock-based ecosystem service models

The 100% increase in woodland and  $\approx 20\%$  decrease in cultivated area between the coarsest and finest LULC maps significantly affected the stock-based ES model outputs (carbon storage and wheat production). Grafius et al., (2016) found similar resolution effects on InVEST's carbon storage model in urban environments when comparing just two spatial resolutions, with higher carbon storage values predicted at 5 m resolution ( $9.32 \text{ kg C m}^{-2}$ ) compared with 25 m ( $7.17 \text{ kg C m}^{-2}$ ). Rioux et al. (2019) also found that carbon storage decreased as they degraded the original resolution of their LULC dataset. In urban environments, this pattern is explained by the greater landscape detail captured in residential areas at finer resolutions which better identifies garden land covers and, hence, increases estimated carbon storage. In our study, the ability to better characterise land covers at finer resolutions was also the main cause of differences in modelled carbon stores. However, the land covers of importance and the way they were aggregated at the various resolutions differed in our agricultural region, compared with those from urban environments.

For the same soil type, woodland and long-term grassland tend to have substantially higher soil organic carbon concentrations compared with long-term arable rotations (Guo and Gifford, 2002). This reflects a higher annual return of photosynthate to the soil, and a lower rate of mineralisation in grassland and woodland systems due to reduced physical disturbance and aeration. In agricultural landscapes, the woodland and grassland patches that exist within the matrix of cultivated areas represent a major store of carbon across the landscape. However, despite our 10 m dataset having the greatest area of woodland, the 20 m and 25 m datasets had marginally higher values of total carbon storage. For LCM2018 (20 m) this can be explained by the larger number of grassland patches which were predicted across the landscape. Some of these patches were single pixels within the middle of patches of cultivation, many which are likely to be artefacts. In contrast, the post



**Fig. 6.** Mean predicted abundance per hectare of the four guilds of wild bees for each LULC dataset: Cavity nesting solitary bees (CNSB), tree nesting bumblebees (TNBB), ground nesting solitary bees (GNSB), and ground nesting bumblebees (GNBB).

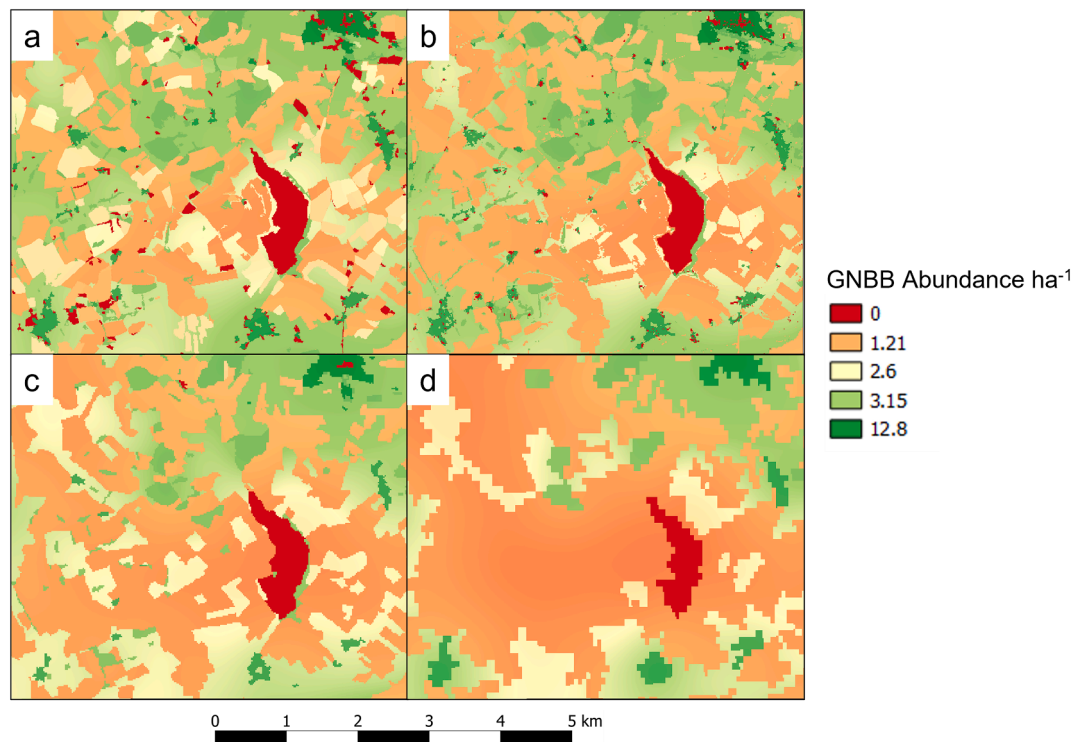


Fig. 7. Spatial output of the InVEST pollinator abundance model showing abundance per hectare of ground nesting bumblebees (GNBB) modelled from (a) S2LC\_2018, (b) LCM2018, (c) LCM2015, and (d) CLC2018.

classification processing of S2LC\_2018 (10 m) meant that these single pixel features were removed from the final map, and replaced with pixels of the crop type from adjacent fields. In the case of LCM2015 (25 m), the relatively high value for carbon storage can be explained by a lower predicted area of urban, suburban, and industrial land covers compared with S2LC\_2018 (39 km<sup>2</sup> in S2LC\_2018 and 54 km<sup>2</sup> in LCM2015). Much of the extra area of these land covers identified by S2LC\_2018 was in the form of isolated agricultural buildings and hard standings, as well as major transport infrastructure (roads and railway lines). These features (which are assigned zero carbon storage in the model's lookup table) were either too small in area, or too linear in shape to be captured in the LCM2015 data. Roads, railway lines, and isolated rural buildings were mostly replaced with grassland and cultivated area land covers in this dataset.

The aggregation of woodland and grassland classes into cultivated areas accounts for the higher values of total wheat production modelled at coarser resolutions. Unlike carbon storage, modelled wheat production consistently increased with coarser spatial resolution because its supply is dependent on a single LULC class that is dominant across the landscape, in large, continuous areas. Carbon storage values were affected by multiple LULC classes, present across the landscape in a larger variety of configurations and abundances, which interacted more subtly as spatial resolution decreased. The large differences in estimates of crop production between the four resolutions highlight the potential to overvalue this ES when estimates are based on coarse resolution datasets.

#### 4.3. Process-based ecosystem service models

Resolution effects on estimates of ES are not consistent and can vary depending on the landscape of interest, and the scale at which resolutions are compared. We found that predicted pollinator abundance consistently decreased with reduced spatial resolution, in line with previously reported results from urban environments (Rioux et al., 2019). Grafius et al., (2016) found the opposite relationship for

InVEST's index of pollinator supply in an urban environment, with 9% of habitat at 25 m resolution exhibiting index values > 0.25 compared with 6% at 5 m resolution.

InVEST's pollinator model is sensitive to the configuration of land-covers across the landscape, not just their total areas, unlike the stock-based models (such as for carbon storage), which would always return the same result for any number of randomly generated landscapes with the same proportions of land cover. The indices of supply and abundance are influenced by the assigned scores of nesting and floral resources for each LULC class. In addition, these indices are weighted by distance, with near resources being given greater weight than those further away. As such, hot-spots of floral and nesting resources (and, therefore, abundance) can be created where land-covers with high scores in these indices are proximal.

Our parameterisation of the model assigned high nesting and floral resource value to woodland, grassland, and suburban land-covers (with slight variations between the four guilds modelled), and lower values to the cultivated land-covers. The exception was S2LC\_2018 which differentiates between five different crop types. In this case, higher floral and nesting resource scores were assigned to some crop types that are known to provide such resources for the wild-bee guilds we modelled (e.g. oil seed rape, *Brassica napus*, which flowers in spring). For the remaining LULC datasets, we had to set lower scores for cultivated areas, because specific crop types were not explicitly identified, showing that for some ES models the thematic resolution of the map is as important as the spatial resolution for overall model performance.

The smaller woodland, grassland and suburban features that were present across the landscape in the S2LC\_2018 and LCM2018 data created "hot spots" of high pollinator abundance within the dominant low abundance areas of cultivation. The linear nature of many of these features helped create corridors between hot spots, distributing the benefits of pollinator abundance more widely across the landscape. The inclusion of more "pollinator-friendly" crop types in S2LC\_2018 amplified this effect.

After the resolution had degraded beyond a certain point the



predicted effect on pollinator abundance lessened, with only a small reduction in modelled abundance between LCM2015 at 25 m and CLC2018 at 100 m. The effects of the spatial scale of management intervention on ES supply are not always linear, and may sometimes exhibit sigmoidal, exponential or saturation like relationships (Lindborg et al., 2017). Degrading spatial resolution is analogous to investigating different scales of management intervention (through changing proportions of land-covers), and it is possible that the negative effects of degrading resolution on pollinator abundance reach a saturation point at a level between 25 and 100 m resolution. Beyond these resolutions, it is possible that changes to land cover composition occur at scales greater than the foraging and flight distances of the wild bee species we modelled.

#### 4.4. Uncertainty in the valuation of ecosystem service provision

We estimated monetary values for crop yields in this study because crop production easily lends itself to economic valuation. This valuation can facilitate the comparison of different ES estimates by framing them in understandable and consistent units. However, valuing climate regulation based on the component of the carbon budget that InVEST models (the static stocks of carbon across the landscape, not sequestration) introduces substantial uncertainty into the valuation. Terrestrial carbon stocks are obviously hugely important for global climate regulation, but it can be argued that the actual sequestration of carbon from the atmosphere represents the final benefit to society provided by the climate regulation ES (Beaumont et al., 2014). This would make sequestration the appropriate metric to value, rather than stocks. Indeed, when using carbon stocks, there is a risk of overestimating value as factors such as temporal and spatial variation in sequestration rate are not taken into account (Beaumont et al., 2014).

Whilst it is possible to estimate carbon sequestration in InVEST, this is not possible for a single year. For this reason, we estimated carbon sequestration based on the total area of the region's woodland cover. This method has been used previously in similar landscapes (Brainard et al., 2009). The monetary value derived was based on the 'avoided costs' of sequestering carbon by other means (Office for National Statistics, 2020). Another option might have been to use the social cost of carbon (Ricke et al., 2018), although this can also be difficult, due to the varied impacts of climate change on different countries (Ricke et al., 2018).

The results of our monetary valuation raise several considerations for policy and decision makers. If ES provision were considered purely in monetary terms, it could be argued that the higher values of provision modelled in the 100 m dataset are the most beneficial to society. However, drawing this conclusion would likely lead to problematic trade-offs in the bundle of ES, particularly when balancing climate regulation with food security and the protection of biodiversity. The value of carbon sequestration fell as resolution degraded, but this was masked by greater increases in the value of crop production. The land cover changes associated with the 100 m resolution estimates of provision were also associated with reduced pollinator abundance, which would likely have additional effects on crop production. Clearly, policy and decision makers need to interpret more than just monetary values when determining land use interventions as part of natural capital programmes.

## 5. Conclusion and recommendations

Agricultural landscapes are becoming crucial areas for policy intervention as societies seek to balance food security requirements with climate change mitigation and attempt to reverse losses of biodiversity (Seddon et al., 2020). Three primary concerns for policy and decision makers are (i) the accuracy of spatially explicit models used to estimate ES provision, (ii) the costs and availability of data used to populate these models, and (iii) the methods or metrics used to quantify or value ES

provision.

The accuracy of ES models can be affected by the spatial and thematic resolution of the LULC datasets. We believe that 10 m is the best currently pragmatic scale at which to model agricultural ES supply across the landscape. Thanks to the availability of Sentinel-2 data, which can be easily processed in the GEE cloud-computing environment, 10 m resolution imagery can generate LULC datasets at regional and national scales. These data products can capture many of the smaller landscape features in agricultural environments that we have identified as important sources of ES supply, leading to better estimations from both process-based and stock-based ES models, better estimations of associated natural capital and, hence, potentially better-informed policy and decision making (DEFRA, 2020). GEE also enables LULC mapping at regular time intervals, which will be an important component of monitoring policy impact as it will allow for modelling of ecosystem service supply at regular intervals. If LULC interventions (e.g. modifications in crop covers or management practices intended to improve ES such as soil carbon sequestration or enhanced biodiversity) are modelled at the field or single-farm scale, then finer resolutions may be desirable. However, such datasets are still limited by significant financial and technical barriers.

We have shown here that thematic resolution can be as important as spatial resolution. For example, the ability to differentiate between several crop types in S2LC2018 increased estimates of pollinator abundance across the landscape. We, therefore, recommend that ES assessments in agricultural environments are based on LULC datasets which are able to differentiate between different crop types.

ES models, such as InVEST, have their limitations. For example, the carbon storage model is empirical and cannot currently account for dynamic changes in carbon stores reflecting the balance between emission and sequestration (resulting, for example, from changes to cultivation practices in the same crop type, such as low- or no-till). Similarly, the crop production model cannot account for landscape factors influencing yield such as slope angle, soil properties, weather, nutrient availability or the prevalence of pests and diseases. Despite this, we believe these models can still usefully contribute to policy making and monitoring because they can assess the approximate magnitude and direction of changes in ES supply resulting from proposed policy interventions. In addition, their simplicity and limited data requirements mean they can be employed with low cost.

InVEST's carbon storage model has been validated for the UK (Sharps et al., 2017). In addition, InVEST has water quality and water balance models, which have also been validated, and could also be included in the bundle of ES considered in landscape decision making frameworks (Redhead et al., 2016). Future research should aim to establish the validity of the remaining InVEST ES models for landscapes subject to potential policy interventions (e.g. farm subsidy and incentive schemes).

We believe that it is not always appropriate to frame ES supply solely in monetary terms. Natural capital policies are beginning to adopt this position too, with intrinsic and cultural values of ES being given greater prominence (DEFRA, 2018). Whilst metrics or indices of ES supply will almost always be an essential component of natural capital or "payment for ecosystem service" policies, we should move away from discussing ES supply in purely economic terms.

#### CRediT authorship contribution statement

**Max Rayner:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Heiko Balzter:** Conceptualization, Methodology, Writing – original draft. **Laurence Jones:** Conceptualization, Writing – original draft. **Mick Whelan:** Conceptualization, Writing – original draft. **Chris Stoate:** Conceptualization, Writing – original draft.

## 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.

## Acknowledgements

This research was supported by the Central England NERC Training Alliance (CENTA) Doctoral Training Partnership (Grant Reference: NE/L002493/1). H. Balzter was partly supported by the NERC National Centre for Earth Observation (NCEO).

## References

- AHDB Cereals and Oilseeds markets Available at: <https://ahdb.org.uk/cereals-oilseeds-markets> 2021 Accessed: March 2021.
- Bagstad, K.J., Cohen, E., Ancona, Z.H., McNulty, S.G., Sun, G.e., 2018. The sensitivity of ecosystem service models to choices of input data and spatial resolution. *Appl. Geogr.* 93, 25–36.
- Baker, D.J., Freeman, S.N., Grive, P.V., Siriwardena, G.M., 2012. Landscape-scale responses of birds to agri-environment management: a test of the English Environmental Stewardship scheme. *J. Appl. Ecol.* 49 (4), 871–882. <https://doi.org/10.1111/j.1365-2664.2012.02161.x>.
- Bateman, I.J., Harwood, A.R., Mace, G.M., Watson, R.T., Abson, D.J., Andrews, B., Binner, A., Crowe, A., Day, B.H., Dugdale, S., Fezzi, C., Foden, J.o., Hadley, D., Haines-Young, R., Hulme, M., Kontoleon, A., Lovett, A.A., Munday, P., Pascual, U., Paterson, J., Perino, G., Sen, A., Siriwardena, G., van Soest, D., Termansen, M., 2013. Bringing ecosystem services into economic decision-making: land use in the United Kingdom. *Science* 341 (6141), 45–50.
- Beaumont, N.J., Jones, L., Garbutt, A., Hansom, J.D., Toberman, M., 2014. The value of carbon sequestration and storage in coastal habitats. *Estuar. Coast. Shelf Sci.* 137, 32–40.
- Brainard, J., Bateman, I.J., Lovett, A.A., 2009. The social value of carbon sequestered in Great Britain's woodlands. *Ecol. Econ.* 68 (4), 1257–1267.
- Breiman, L., 2001. Random forests. *Machine learning* 45 (1), 5–32.
- Carrasco, L., O'Neil, A.W., Morton, R.D., Rowland, C.S., 2019. Evaluating combinations of temporally aggregated Sentinel-1, Sentinel-2 and Landsat 8 for land cover mapping with Google Earth Engine. *Remote Sens.* 11 (3), 288.
- F. Commission Provisional Woodland Statistics Available at: [https://www.forestresarch.gov.uk/documents/7212/PWS\\_2019.pdf](https://www.forestresarch.gov.uk/documents/7212/PWS_2019.pdf) 2019 Accessed: March 2021.
- Cord, A.F., Brauman, K.A., Chaplin-Kramer, R., Huth, A., Ziv, G., Seppelt, R., 2017. Priorities to advance monitoring of ecosystem services using earth observation. *Trends Ecol. Evol.* 32 (6), 416–428.
- Crossman, N.D., Burkhard, B., Nedkov, S., Willemen, L., Petz, K., Palomo, I., Drakou, E. G., Martín-López, B., McPhearson, T., Boyanova, K., Alkemade, R., Egoh, B., Dunbar, M.B., Maes, J., 2013. A blueprint for mapping and modelling ecosystem services. *Ecosyst. Serv.* 4, 4–14.
- Curnow, J., 2019. Environmental economics in UK environmental policy: Defra's 25 Year Environment Plan. *J. Environ. Econ. Policy* 8 (4), 353–358. <https://doi.org/10.1080/21606544.2019.1601135>.
- DEFRA A Green Future: Our 25 Year Plan to Improve the Environment Available at: [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/693158/25-year-environment-plan.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/693158/25-year-environment-plan.pdf) 2018 Accessed: March 2021.
- DEFRA Farming Statistics - Final crop areas, yields, livestock populations and agricultural workforce At 2018 Available at: [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/869062/structure-jun2018-final-uk-28feb20.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/869062/structure-jun2018-final-uk-28feb20.pdf) 2019 Accessed: March 2021.
- DEFRA The Path to Sustainable Farming: An Agricultural Transition Plan 2021 to 2024 Available at: [https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment\\_data/file/954283/agricultural-transition-plan.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/954283/agricultural-transition-plan.pdf) 2020 Accessed: March 2021.
- Fichera, C.R., Modica, G., Pollino, M., 2012. Land Cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. *Eur. J. Remote Sens.* 45 (1), 1–18.
- Gardner, E., Breeze, T.D., Clough, Y., Smith, H.G., Baldock, K.C., Campbell, A., Garratt, M.P., Gillespie, M.A., Kunin, W.E., McKerchar, M. and Memmott, J., (2020). 'Reliably predicting pollinator abundance: Challenges of calibrating process-based ecological models'. *Methods in Ecology and Evolution*, 11(12), pp.1673–1689.
- Gardner, E., Hesselberg, T., Grabowska-Zhang, A., Hughes, J., 2019. The effect of woodland area on avian community composition in a fragmented southern UK landscape and associated management recommendations. *Bird Study* 66 (3), 293–305.
- Ghorbanian, A., Kakooei, M., Amani, M., Mahdavi, S., Mohammadzadeh, A., Hasanlou, M., 2020. Improved land cover map of Iran using Sentinel imagery within Google Earth Engine and a novel automatic workflow for land cover classification using migrated training samples. *ISPRS J. Photogramm. Remote Sens.* 167, 276–288.
- Glanville, H.C., Reinsch, S., Cosby, B.J., Emmett, B.A., Marshall, M.R., Smart, S.M., Winterbourn, J.B., Jones, D.L., 2017. Soil carbon data in the Conwy catchment in North Wales 2014. NERC Environ. Inform. Data Centre.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* 202, 18–27.
- Grafius, D.R., Corstanje, R., Warren, P.H., Evans, K.L., Hancock, S., Harris, J.A., 2016. The impact of land use/land cover scale on modelling urban ecosystem services. *Landscape Ecol.* 31 (7), 1509–1522.
- Guo, L.B., Gifford, R.M., 2002. Soil carbon stocks and land use change: a meta analysis. *Glob. Change Biol.* 8 (4), 345–360.
- Jung, M., 2016. LecoS – A Python plugin for automated landscape ecology analysis. *Ecol. Inf.* 31, 18–21.
- Li, Q., Qiu, C., Ma, L., Schmitt, M., Zhu, X.X., 2020. Mapping the land cover of Africa at 10 m resolution from multi-source remote sensing data with Google Earth Engine. *Remote Sensing* 12 (4), 602.
- Lindborg, R., Gordon, L.J., Malinga, R., Bengtsson, J., Peterson, G., Bommarco, R., Deutsch, L., Gren, Å., Rundlöf, M., Smith, H.G., 2017. How spatial scale shapes the generation and management of multiple ecosystem services. *Ecosphere* 8 (4), e01741.
- Lonsdorf, E., Kremen, C., Ricketts, T., Winfree, R., Williams, N., Greenleaf, S., 2009. Modelling pollination services across agricultural landscapes. *Ann. Bot.* 103 (9), 1589–1600.
- McGarigal, K. (1995) FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. US Department of Agriculture, Forest Service, Pacific Northwest Research Station.
- Mitchell, M.G.E., Bennett, E.M., Gonzalez, A., Banks-Leite, C., 2014. Forest fragments modulate the provision of multiple ecosystem services. *J. Appl. Ecol.* 51 (4), 909–918.
- Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochem. Cycles* 22 (1), n/a–n/a.
- Morton, R.D.; Marston, C.G.; O'Neil, A.W.; Rowland, C.S. (2020). 'Land Cover Map 2018 (20m classified pixels, GB)'. NERC Environmental Information Data Centre. (Dataset). <https://doi.org/10.5285/b3dfc4c7-c9bd-4a02-bed8-46b2a41be04a>.
- Office for National Statistics UK Natural Capital Accounts: 2020 Available at: <https://www.ons.gov.uk/economy/environmentalaccounts/bulletins/uknaturalcapitalaccounts/2020> 2020 Accessed: March 2020.
- Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. *Philos. Trans. R. Soc. B Biol. Sci.* 365 (1554), 2959–2971.
- Rae, A. (2017) A Land Cover Atlas of the United Kingdom. DOI: <https://doi.org/10.15131/shef.data.5266495.v1>.
- Rayner, M. (2020). 'Fine resolution land cover map of the Upper Welland Catchment, UK for 2018'. NERC Environmental Information Data Centre. (Dataset). <https://doi.org/10.5285/63b748ee-22a4-42ca-8a34-20321f6ab8af>.
- Redhead, J.W., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T.H., Bullock, J.M., 2016. Empirical validation of the InVEST water yield ecosystem service model at a national scale. *Sci. Total Environ.* 569–570, 1418–1426.
- Ricke, K., Drouet, L., Caldeira, K., Tavoni, M., 2018. Country-level social cost of carbon. *Nat. Clim. Change* 8 (10), 895–900.
- Rioux, J.-F., Cimon-Morin, J., Pellerin, S., Alard, D., Poulin, M., 2019. How land cover spatial resolution affects mapping of urban ecosystem service flows. *Front. Environ. Sci.* 7, 93.
- Rowland, C.S.; Morton, R.D.; Carrasco, L.; McShane, G.; O'Neil, A.W.; Wood, C.M. (2017). 'Land Cover Map 2015 (vector, GB)'. NERC Environmental Information Data Centre. (Dataset). <https://doi.org/10.5285/6c6c9203-7333-4d96-88ab-78925e7a4e73>.
- Santana, J., Reino, L., Stoate, C., Moreira, F., Ribeiro, P.F., Santos, J.L., Rotenberry, J.T., Beja, P., 2017. Combined effects of landscape composition and heterogeneity on farmland avian diversity. *Ecol. Evol.* 7 (4), 1212–1223.
- Saura, S., 2004. Effects of remote sensor spatial resolution and data aggregation on selected fragmentation indices. *Landscape Ecol.* 19 (2), 197–209.
- Schulp, C.J.E., Van Teeffelen, A.J.A., Tucker, G., Verburg, P.H., 2016. A quantitative assessment of policy options for no net loss of biodiversity and ecosystem services in the European Union. *Land Use Policy* 57, 151–163. <https://doi.org/10.1016/j.landusepol.2016.05.018>.
- Seddon, N., Chausson, A., Berry, P., Girardin, C.A., Smith, A., Turner, B., 2020. Understanding the value and limits of nature-based solutions to climate change and other global challenges. *Philos. Trans. R. Soc. B* 375 (1794), 20190120.
- Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., Chaumont, N., Denu, D., Fisher, D., Glowinski, K., Griffin, R., Guannel, G., Guerry, A., Johnson, J., Hamel, P., Kennedy, C., Kim, C.K., Lacayo, M., Lonsdorf, E., Mandle, L., Rogers, L., Silver, J., Toft, J., Verutes, G., Vogl, A.L., Wood, S., Wyatt, K., 2020. InVEST 3.9.0 User's Guide. The Natural Capital Project. Stanford University, University of Minnesota, The Nature Conservancy and World Wildlife Fund.
- Sharps, K., Masante, D., Thomas, A., Jackson, B., Redhead, J., May, L., Prosser, H., Cosby, B., Emmett, B., Jones, L., 2017. Comparing strengths and weaknesses of three ecosystem services modelling tools in a diverse UK river catchment. *Sci. Total Environ.* 584–585 (Supplement C), 118–130.
- Smart, S.M., Reinsch, S., Mercado, L., Blanes, M.C., Cosby, B.J., Glanville, H.C., Jones, D. L., Marshall, M.R., Emmett, B.A., 2017. Plant aboveground and belowground standing biomass measurements in the Conwy catchment in North Wales (2013 and 2014). NERC Environ. Inform. Data Centre.
- Stoate, C., Baldi, A., Beja, P., Boatman, N.D., Herzog, I., van Doorn, A., de Snoo, G.R., Rakosy, L., Ramwell, C., 2009. Ecological impacts of early 21st century agricultural change in Europe—a review. *J. Environ. Manage.* 91 (1), 22–46.
- Thomas, A., Masante, D., Jackson, B., Cosby, B., Emmett, B., Jones, L., 2020. Fragmentation and thresholds in hydrological flow-based ecosystem services. *Ecol. Appl.* 30 (2) <https://doi.org/10.1002/eap.v30.210.1002/eap.2046>.

Vorstius, A., Spray, C.J., 2015. A comparison of ecosystem services mapping tools for their potential to support planning and decision-making on a local scale. *Ecosyst. Serv.* 15, 75–83.

Wang, L., Diao, C., Xian, G., Yin, D., Lu, Y., Zou, S. and Erickson, T. A. 2020. A summary of the special issue on remote sensing of land change science with Google earth engine. Elsevier.

Wu, J., Shen, W., Sun, W., Tueller, P.T., 2002. Empirical patterns of the effects of changing scale on landscape metrics. *Landsc. Ecol.* 17 (8), 761–782.