Comparing conservation land acquisition strategies using agent-based models

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Abstract

Most unprotected biodiversity is found outside state-owned protected areas, so developing effective conservation initiatives on privately and communally-owned land is critical. Conservationists have a long history of working with these landowners and their actions can be divided into two broad categories. The first is where they agree to take over responsibility for management, either by buying the land or agreeing on long-term leases. The second is where they "rent" the land for conservation and pay people to manage their land appropriately, often through agri-environment schemes. However, we still know relatively little about the effectiveness of these two approaches. Here we use an agent-based modelling approach to investigate the biodiversity outcomes over time of different land acquisition scenarios, based on varying buying and renting budgets and different levels of landowner willingness to engage with the conservation authority. We found that buying land always led to better conservation outcomes, with biodiversity scores being 23.4 times higher when 100% of the budget was for buying compared to when 100% of the budget was for renting. This was mostly because buying land ensured it was managed in perpetuity, allowing the biodiversity value of each land parcel to increase over time. We also found that land-owner willingness to sell or rent their land had a large impact on results, with biodiversity scores varying by 28 times depending on the level of support. Our modelling system will next be used to incorporate more sophisticated measures of biodiversity value and investigate other scenarios for developing ecological networks on privately-owned land, such as longer-term rental agreements and conservation stewardship agreements. In this way we hope to guide future conservation policy to develop large-scale conservation areas in England and inform global strategies that account for biodiversity and stakeholder preferences when designing ecological networks.

Introduction

Expanding protected area coverage has been a central goal of international conservation policy for decades, so that more than 15% of the terrestrial realm is now under some type of protection (Lewis et al., 2019). Despite this, biodiversity continues to decline. Key voices in the international conservation community are now calling for further increases to produce more representative networks that include important areas for biodiversity, arguing for 30% coverage targets by 2030 (Dinerstein et al., 2019). Past progress has often depended on protecting land owned by the state, but this is no longer tenable because some countries have relatively little state-owned land, and in those that do it often covers remote, economically marginal areas that are already over-represented in protected area networks (Joppa & Pfaff, 2009). In addition, many governments struggle to fund the management of their existing protected land and so need the private and NGO sector to share the costs (Waldron et al., 2020). This means any plans to reduce biodiversity loss must involve conserving more privately- or communally-owned land through new protected areas or other effective area-based conservation measures (Maxwell et al., 2020).

Conservationists already have a long history of working with landowners and their actions can be divided into two broad categories (Schöttker, Johst, Drechsler, & Wätzold, 2016). The first is where they “buy” land, either by purchasing the land or agreeing on long-term leases for conservation, and take over responsibility for its management (Armsworth & Sanchirico, 2008; McDonald-Madden, Bode, Game, Grantham, & Possingham, 2008). Under this strategy, the land is usually managed for biodiversity conservation and associated co-benefits (e.g., recreational activity, eco-tourism). The second is where they “rent” the land for conservation by paying the land-owners to manage the land for biodiversity (Ferraro & Kiss, 2002; Engel, Pagiola, & Wunder, 2008). This renting approach can cover a range of incentives (Merenlender, Huntsinger, Guthey, & Fairfax, 2004; Kamal, Grodzińska-Jurczak, & Brown, 2015) but the most well-known are agri-environment schemes, which pay farmers to produce biodiversity and/or ecosystem service benefits. The annual budgets for these two approaches are large, with governments and NGOs spending billions of dollars on land purchase (e.g. Iftekhar, Tisdell, & Gilfedder, 2014; Nolte, 2018) and governments also spending billions of dollars on contracts with private landowners for conservation benefits (Batáry, Dicks, Kleijn, & Sutherland, 2015). Research on these two approaches has largely focused on conservation outcomes, showing that for both protected areas and agri-environment schemes that performance can vary widely and depends on adequate resourcing and well-designed management (Kleijn et al., 2006; Batáry et al., 2015; Gill et al., 2017). There has been much less research comparing the costs and the benefits of these two approaches, so there is little to guide conservation agencies when deciding whether to invest in buying or renting land for conservation. Here we use an agent-based modelling approach to help address this important topic.

Agent-based models simulate the actions and interactions of autonomous agents (Ferber, 1999). They are particularly useful for understanding the influence of human decision-making on land use and land management as they can account for mechanistic and spatially explicit factors (Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Brown et al., 2014). This is important when trying to understand the benefits of different conservation land acquisition strategies because landowner willingness can be a major constraint on achieving conservation goals (Guerrero, Knight, Grantham, Cowling, & Wilson, 2010; Knight et al., 2011; Sorice et al., 2013), and plays a key role in determining where conservation actions are best focused (Tulloch, Tulloch, Evans, & Mills, 2014). Using these models can also help understand the cost-effectiveness of the different schemes and the extent to which they develop conservation landscapes with long-term biodiversity benefits (Miteva, Pattanayak, & Ferraro, 2012; Drechsler, Johst, & Wätzold, 2017). This is particularly relevant because conservation budgets are often limited and time-bound, so developing ecological networks by working with individual landowners is not straightforward (Wätzold, Drechsler, Johst, Mewes, & Sturm, 2016). We developed an agent-based modelling system named CELMA (Comparing Environmental Land Management Approaches) to compare the effectiveness of "buying" land for conservation versus "renting" it for conservation through agri-environment schemes.

Here we describe CELMA and how it was used to inform ongoing discussions about conservation land acquisition policy in England. These issues are particularly relevant for England, where most land is privately owned and the current conservation area network is fragmented and over-represents areas with low agricultural potential (Shwartz et al., 2017). The UK Government has recognised these limitations and is committed to developing nature networks that address these problems (Defra, 2018). We used CELMA to investigate how the interactions between economic, conservation and contract parameters impact conservation outcomes. The model includes variables such as agricultural value of the land unit, landowner willingness to sell or rent their land and land acquisition budgets. We then measured the relative importance of these three variables in producing higher value conservation landscapes using generalised linear modelling and identified the conditions under which conservation agencies should invest more in buying or renting land.

Methods

Overview of the agent-based model

CELMA is a set of Python code that simulates the decision-making processes made by conservation agencies and by landowners, where the latter have the option to sell their land unit to the conservation agency, rent their unit for conservation under some type of agri-environment or stewardship agreement, or decline any offers. The measure of portfolio value is a simple conservation score based on the area of land under conservation management, the patch sizes of this managed land and the length of time each land unit has been managed for conservation (Supplementary material). Each simulation, known as a "run", begins with CELMA importing the setup data and scenario parameters and setting the willingness characteristics of each landowner (Table 1). Thus, CELMA can be used to compare results from different conservation scenarios, where each scenario is based on the same set of user-defined economic, conservation and contract parameters. The reason for specifying more than one run is that CELMA uses a stochastic approach to define a number of the economic and willingness values and so each run is likely to identify a different portfolio of land units.

For each run, CELMA begins by producing the initial land unit portfolio that specifies which land units are protected (Figure 1). The next steps in the algorithm involve calculating the amount of funding available for buying and renting land and identifying landowners who are willing to sell or rent their land. CELMA then loops through this list of willing landowners to identify the best properties to add to the portfolio, until there is insufficient funding to buy or rent any more land units (Figure 1). The final part of each iteration is to update and record the portfolio details. This process is then repeated for the number of times specified by the user, with the final step of reporting the characteristics of the final portfolio at the end of the run. The number of iterations in each run is the equivalent to the number of years, so setting an iteration value of 100 makes CELMA model changes over a 100-year period. Once CELMA has completed the specified number of runs for each scenario it reports the median value of all the runs in each scenario for each output, as well as the characteristics of the "best" portfolio, which is the run in each scenario with the highest final conservation score.

CELMA uses three input files. The pu.csv file is a text file that lists the unique identifier value of each land unit used in the analysis, its agricultural quality value and whether it is a protected area (i.e. already part of the network of land under conservation). The bound.csv file contains details of shared boundaries between the different land units, following the format of the Marxan systematic conservation planning software boundary file by listing for each boundary the ID value of the first land unit, ID value of the second land unit and the length of shared boundary (Ball, Possingham, & Watts, 2009). The scenarios.csv file lists the different parameters used in each scenario and the setup.txt file specifies where the other files are stored, where the outputs should be saved and the number of runs and iterations in each scenario.

CELMA uses a number of parameters (Table 1, **Error! Reference source not found.** and Supplementary Materials) but there are several key aspects to highlight. First, the value of each land unit depends in part on the annual global gross margin, which is a proxy for the profitability of a set area of land under a given crop with average productivity. The initial value is specified by the user but it then changes over time based on an autoregressive order one (AR1) model. The AR1 model calculates the gross margin so the values tend towards a mean but vary each year based on the change compared to the previous year and a random effect (Mills, 1991). Second, at the beginning of each run the willingness to sell and willingness to rent parameters are set for each landowner. The range of these parameters for the population of landowners is specified by the user for each scenario and CELMA uses this to assign specific values to each landowner for each run (Supplementary materials). These parameters define the likelihood that a landowner will accept an offer in a particular year to buy or rent, given the value of the offer in comparison to the value of their land. The annual lists of willing sellers and renters are produced by calculating a random number with a uniform distribution between 0 and 1 for each land unit, and if the probability of the landowner willingness to sell or rent is greater than the random number then the land unit is included in the respective list. This process is designed to make the process more realistic, reflecting examples where unwilling landowners are forced by circumstance to engage (e.g. because of ill health) or where willing landowners end up not getting involved (e.g. because of administrative errors). Third, the CELMA algorithm chooses the best land unit to buy and then the best unit to rent, and then repeats the process until the buying and renting budgets are insufficient to acquire more land. New land units that neighbour existing land units in the conservation portfolio are preferentially selected.

Setting the shared parameters for the land acquisition scenarios

We based all the analyses on 900 hexagonal land units, each with an area of 1 ha. We created these land units using the Create Grid function in QGIS (QGIS.org, 2019) and give each hexagon a unique identifier value. To replicate the common phenomenon where land quality shows a spatial gradient, we calculated a land quality index score by applying a linear scale so that the X coordinate of each hexagon's centroid ranged between 92 to 103 and then added a random number based on a uniform distribution between -5 and 5. We used these data to produce the unit.csv file and the CLUZ plugin (Smith, 2019) for QGIS to produce the bound.csv file.

A number of parameters were used in every run of every scenario: the area of each land unit was set as 1 ha and the initial annual gross margin value as £347 per hectare, based on data from the UK on farming wheat (Lang, 2009); the annual gross margin change parameters was set as 0.88 for ϕ and $\sigma 2$ as 2.149 based on trial and error to show similar patterns to long-term time series on wheat prices (Solar & Klovland, 2011); the cost of conservation management was set as £210 per hectare based on UK data (Armsworth, Cantú-Salazar, Parnell, Davies, & Stoneman, 2011) and a discount rate of 4%; the proportion of units that were set as protected was 0.05 (equating to 45 units); the habitat restoration response variable r was set as 0.5, which meant it took 10 years for a habitat patch to be more than 99% restored and so was similar to restoration times for some wetlands; the willingness correlation value was 0, so each landowner's willingness to sell and rent parameters were not correlated; we used 50 runs and each run consisted of 100 iterations, with each iteration representing a year.

Setting the individual parameters for the land acquisition scenarios

We used 400 different scenarios based on different combinations of four parameters. For the proportion of the conservation acquisition budget assigned to buying and renting parameter, we used five parameter values: 0:1, 0.25:0.75, 0.5:0.5, 0.75:0.25 and 1:0. For both the selling willingness parameter values and renting willingness parameter values we set r as 11.5 and used four different willingness b values that we named: Reluctant (b = -0.8), Neutral (b = -0.65), Positive (b = -0.5) and Enthusiastic (b = -0.35). We selected these values based on trial and error so that for the most extensive portfolios, more than half of the available land units would be under some type of conservation management at the end of each run. These b values meant the median probability of a landowner accepting an offer that equalled the opportunity cost was 0.0001 for the Reluctant scenario, 0.0006 for the Neutral scenario, 0.003 for the Positive scenario and 0.018 for the Enthusiastic scenario (Figure 2). For the proportion of land under conservation in the rental agreements we used values of 0.2, 0.4, 0.6, 0.8 and 1.

Analysing the output data

We used the CELMA outputs to investigate how proportion of budget assigned to buying, willingness to sell, willingness to rent and proportion of land in the rental agreements influenced the median final conservation score of the 50 portfolios produced in each of the 400 scenarios. We analysed the data in R version 4.0.3 (R Development Core Team, 2020). Due to over-dispersion in the outcome variable, we used a generalised linear model with a quasi-poisson error distribution and a log link function. We identified the significant factors and then reran the analysis to identify any significant interactions between these important factors.

Results

The median conservation score for each scenario ranged between 50.8, based on 0 sold land units and 3 rented land units at the end of the 100 years (Buy budget = 0%, Rent budget = 100%, Rented proportion of farm = 0.2, Sell willingness = Neutral, Rent willingness = Reluctant, Figure 3A) and 2551.9, based on 599 sold land units and 0 rented land units at the end of the 100 years (Buy budget = 100%, Rent budget = 0%, Rented proportion of farm = 0.2, Sell willingness = Enthusiastic, Rent willingness = Neutral, Figure 3C). As an illustration of scenario with a balance between sold and rented land units, when the Buy budget and Rent budget were both 50%, the rented proportion of farm was 0.2 and landowners were Enthusiastic about selling and renting then the median score was 722.4, with 129 sold land units and 140 rented land units at the end of the 100 years (Figure 3B). The generalised linear model found that the final conservation score was determined by the proportion of budget assigned to buying, willingness to sell and willingness to rent and their interactions (Table 2; Table 3; Figure 4), whereas proportion of land under rental contract was not important.

The times series data show the greatest initial increase in conservation scores generally occurred in scenarios where willingness to rent was high (Figure 4B, 4C), but conservation scores after 100 years were generally highest when willingness to buy was high (Figure 4A, B, C). Initial and final conservation scores tended to decrease with decreasing budgets for buying and this was most pronounced when the rental budget was 100% of the total conservation budget (Figure 4E). When willingness to sell was Reluctant then scenarios where 25% of the budget was assigned to buying land generally produced the highest conservation scores (Table 3).

Discussion

Billions of dollars are spent on conservation land acquisition each year (Batáry et al., 2015) but there is little research on which acquisition approaches are most effective at increasing the area of land under conservation (Nolte, Vos, & Schöttker, 2019). Landowner support is likely to be a key factor and so we developed CELMA, an agent-based model to investigate the best funding strategy under different willingness scenarios. Here we discuss the factors that influenced which scenarios produced the best conservation outcomes and then outline ways in which this approach could be adapted to inform future work.

Understanding the factors that produced high conservation scores

Our model showed that the conservation benefit of land acquisition policies can vary widely, differing by three orders of magnitude over a 100-year period (Figure 3). The statistical analysis showed that this was driven by the influence of three of the factors we varied in the scenarios: proportion of the budget spent on buying or renting land, landowner willingness to sell their land and landowner willingness to rent their land. The impact of budget was the most obvious, as increasing the budget proportion for buying land produced the largest conservation gains. This supports results from other studies from Africa, Europe and North America that buying land has higher conservation benefit in the long-term, mostly because the benefits from buying land are in perpetuity (Curran, Kiteme, Wünscher, Koellner, & Hellweg, 2016; Schöttker & Wätzold, 2018; Schöttker & Santos, 2019). These gains are most apparent in the long-term, as while there were some examples of high rental budget scenarios performing well during the first decade, sustained increases to high levels were dependent on high budgets for buying (Figure 4).

The influence of landowner willingness to sell and rent also emerged clearly from the results. When willingness to sell and rent were both low, so was the final conservation score. This is best illustrated by comparing results from scenarios based on a 50% Buy: 50% Rent budget, as the conservation score when willingness to sell and rent were both Reluctant is 13% of that when willingness to sell and rent were both Enthusiastic (Figure 4C). This highlights the importance of landowner willingness and supports previous work showing this can have critical impacts on conservation outcomes (Knight et al., 2011; Adams, Pressey, & Stoeckl, 2014). Less widely discussed are the impacts of landowner willingness to choose between mutually exclusive options. This is shown by the importance of the interaction between willingness to sell and rent in our statistical analysis (Table 2) and our finding that the highest conservation scores came from scenarios where landowners were more willing to sell than rent (Figure 4). This occurred because when willingness to sell and rent were both high, some landowners ended up renting when they would have been similarly interested in selling, resulting in a lower conservation score. This would have been even more of an issue if we had specified a positive correlation between landowner willingness to sell and rent (Supplementary material Figure S8). In such situations the behaviour with the highest conservation benefits was often crowded out (Parker & Thurman, 2011).

Our results can also identify the most suitable funding strategies for a specific scenario. In particular, we can identify how best to divide up conservation land acquisition budgets given different levels of landowner willingness. We found that even when willingness to sell was low, it was generally better to assign 25% of the budget to buying (Table 3). Thus, a key finding was that the best funding strategy always involved assigning some of the budget to buying land, even when landowners were 18 times more likely to accept a rent offer that matched the opportunity cost, i.e. when willingness to sell was Reluctant and willingness to rent was Enthusiastic (Figure 2). As willingness to sell increased then increasing the percentage of budget for buying produced higher conservation scores, so that once willingness to sell was Positive then assigning 100% of the budget to buying produced the highest, or almost equal highest scores. This emphasises the importance of developing conservation instruments that appeal to landowners (Moon & Cocklin, 2011; Broch, Strange, Jacobsen, & Wilson, 2013; Selinske, Coetzee, Purnell, & Knight, 2015), using behaviour change research to identify suitable incentives and minimise barriers to implementation (Smith, Salazar, Starinchak, Thomas-Walters, & Veríssimo, 2020).

The area of land included in the rental agreement was the only factor that did not have an important impact on the final conservation scores. This was likely because the offers made to landowners in CELMA were based on opportunity costs, so the loss of earnings from conserving more land would be balanced by an increase in rental payments. We might have expected the conservation scores to be slightly higher when more land per farm was rented, as this could have produced slightly larger patches of conserved land. However, this was not the case and probably arose because the algorithm preferentially made offers to landowners with units adjoining existing conservation land and because rented land was less likely to be conserved in the long-term and so help accrue a higher conservation score. More importantly, we also assumed there was no relationship between land under the rental agreement and willingness to rent, whereas a number of studies have shown landowners are less willing to sign up to contracts that cover a large part of the farm (Lienhoop & Brouwer, 2015; Trenholm, Haider, Lantz, Knowler, & Haegeli, 2017).

Future work to inform practice

Many of the parameters we used in the scenarios were based on values from the UK, so that they reflected a realistic situation. In particular, we used UK values for the annual global gross margin (Lang, 2009), the cost of conservation management (Armsworth et al., 2011), contract length and protected proportion (Shwartz et al., 2017). We used a habitat restoration response value that mimicked that of wetlands, leading to some conservation scores levelling off within the 100-year study period because all the land with willing landowners had been bought and enough time had elapsed for each land patch to have the maximum conservation value. This produced higher conservation scores than if we had used a value that mimicked the slower restoration of habitats like woodland, but had little influence on the relative benefits of each scenario (Supplementary Material Figure S7). We also set that unspent funds for buying were carried over to the next year, which is common conservation policy but favoured the buying of land as it allowed funds to build up.

Our model was much less realistic in terms of how it measured conservation value and so identified acquisition priorities, as it assumed that each land unit had equal conservation potential, giving higher priority to units that would increase conservation area network patch size. While this reflects some types of agri-environment payment where any landowner can apply to fund activities such as maintaining hedgerows or leaving field margins uncleared, many rental agreements and almost all purchase agreements target land based on the biodiversity they contain (McDonald-Madden et al., 2008). Future agent-based models could account for this complexity by calculating conservation scores based on the presence of different biodiversity elements, e.g. priority species and habitats. This would be particularly useful for modelling land-owner responses to different rental schemes, which in most countries provide a set payment for a particular activity or outcome (Armsworth et al., 2012). It should also be possible to model the impacts of different land purchase strategies although this should account for two additional aspects. First, conservation agencies commonly make purchasing decisions based on the biodiversity value of the land and the likelihood that better units will be available in the near future, so models would need to define the agencies biodiversity goals, mirroring the systematic conservation planning approach (McDonald-Madden et al., 2008). Second, conservation agencies are often willing to pay more for land units with higher conservation value, increasing landowner willingness to sell but also often driving up prices (Armsworth, Daily, Kareiva, & Sanchirico, 2006; Lennox & Armsworth, 2013).

Our modelling also used a simple approach to model landowner willingness to sell and rent. We assumed that the willingness parameters for a land unit remained constant during the 100-year period and that these values were independent. Changing this in the model would be straightforward, and we have already modelled the impact of landowners who are willing to sell also being more willing to rent, showing that this reduced conservation scores because renting behaviour further crowded out selling behaviour (Supplementary Material Figure S8). A more important issue would be parametrising the model based on real-world data, as landowner willingness had a large impact on our modelling results and so using realistic values is a critical next step. In particular, it would be important to see how willingness varies based on the type of conservation management involved and the different components of contract agreements, as this is likely to differ with contract length, area of land involved and bureaucratic burden (Lienhoop & Brouwer, 2015; Santos, Clemente, Brouwer, Antunes, & Pinto, 2015).

Our results have shown very clearly that buying land for conservation produces much stronger conservation outcomes than renting, but landowner willingness to sell or rent is a more important factor than the budgets allocated to these two alternative strategies. Our work also suggests that the CELMA agent-based model could be modified to inform a whole range of policies based on different agri-environment, covenant or purchase schemes. Such work would have to be context specific and ideally build on conservation best practice, with implementation agencies explicitly setting out their objectives for the different schemes and collecting data on how their target audience is likely to respond to the different policy instruments. Despite the time and costs involved in setting objectives and collecting such data, the investment is likely to be extremely worthwhile given the millions of dollars that are often spent. It would also build an important evidence base to identify general trends and develop theories, helping ensure increased effectiveness for every conservation land acquisition strategy.

Acknowledgements

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Table 1: User-defined economic, conservation and contract parameters used in the CELMA agent-based model.

Analysis parameter	
Number of runs	Number of times CELMA undertakes an analysis for a specified scenario (based on the same set of parameters).
Number of iterations	Number of times CELMA goes through the iterative process in each run. If one iteration represents a year then setting 100 iterations means CELMA measures changes over a 100-year period.
Economic parameter	
Initial annual global gross margin	Initial profitability of a land unit with “average” land quality.
Average annual gross margin	Profitability of a land unit with “average” land quality in a given year. This value fluctuates each year, based on the autoregressive order one (AR1) model.
Land quality index	Relative economic value of a land unit. This is multiplied by the annual gross margin to give the potential gross margin for each land unit.
Annual conservation grant	Total annual budget for conservation.
Management cost per hectare	Cost of managing one hectare of land under conservation for one year. This depends on the patch size, with larger patches costing less to manage per hectare.
Buy budget proportion	This is the proportion of the acquisition budget assigned to buying land, where the acquisition budget is the annual conservation grant minus the annual management budget. Any unspent funds accrue over time.
Rent budget proportion	This is the proportion of the acquisition budget assigned to renting land, where the acquisition budget is the annual conservation grant minus the annual management budget. Any unspent funds do not accrue over time.
Conservation parameter	
Protected proportion	Proportion of land units given Protected status at the beginning of each run. These land units are randomly assigned at the beginning of each run.
Habitat restoration response value	This determines the conservation value of a land unit’s patch of habitat, based on the length of time the unit has been managed for conservation.
Contract parameter	
Contract length	Duration of the rental contract, after which the contract is only renewed if the land unit owner is willing to rent and there is sufficient budget.
Willingness to sell parameters	Two parameters are assigned to each landowner at the beginning of each run that defines their likelihood of accepting a buy offer of a certain value. The user specifies the range of willingness values for the population of landowners in each scenario.
Willingness to rent parameters	Two parameters are assigned to each landowner at the beginning of each run that defines their likelihood of accepting a rent offer of a certain value. The user specifies the range of willingness values for the population of landowners in each scenario.
Willingness correlation factor	This specifies the extent to which the willingness of a landowner to sell their land is correlated with their willingness to sell it.

Table 2: The model coefficients of variables that explained the median final conservation scores of the different CELMA scenarios. Willing sell = Landowner's willingness to sell; Willing rent = Landowner's willingness to rent; Buy budget proportion = proportion of budget assigned to buying land, which is the mirror of the proportion of budget assigned to renting land.

	Estimate	Std. Error	Z-value	P-value
(Intercept)	3.104	0.592	5.246	< 0.001
Willing sell	-3.275	1.131	-2.895	0.004
Willing rent	-6.844	0.943	-7.260	< 0.001
Buy budget proportion	6.4983	0.786	8.273	< 0.001
Willing sell * Willing rent	-10.5212	1.865	-5.641	< 0.001
Willing sell * Buy budget proportion	8.367	1.573	5.319	< 0.001
Willing rent * Buy budget proportion	5.636	1.270	4.436	< 0.001
Willing sell * Willing rent * Buy budget proportion	8.256	2.615	3.157	0.002

Table 3: Ranking of scenarios from their conservation score based on the proportion of their budget assigned for buying land for conservation for each willingness to sell, willingness to rent combination, e.g. when willingness to sell and rent were both Reluctant then the scenario with 25% of the budget assigned for buying land produced the highest conservation score. Values in brackets show the median conservation score for the 100 runs per scenario.

	Rent: Reluctant	Rent: Neutral	Rent: Positive	Rent: Enthusiastic
Sell: Reluctant	25% (93.09) 75% (92.99) 50% (92.88) 100% (90.65) 0% (52.76)	25% (103.07) 50% (102.8) 75% (102.52) 100% (91.08) 0% (61.03)	50% (138.36) 25% (138.13) 75% (133.65) 100% (90.19) 0% (87.78)	25% (208.58) 50% (198.72) 75% (187.09) 0% (107.42) 100% (90.15)
Sell: Neutral	75% (295.06) 50% (292.24) 100% (288.17) 25% (285.87) 0% (53.15)	25% (314.78) 75% (313.87) 50% (308.99) 100% (286.13) 0% (61.5)	50% (369.08) 75% (367.61) 100% (287.64) 25% (272.52) 0% (88.59)	50% (454.32) 75% (452.91) 100% (287.16) 25% (285.81) 0% (105.89)
Sell: Positive	75% (1281.91) 100% (1279.19) 50% (1263.4) 25% (1059.2) 0% (52.82)	100% (1286.69) 75% (1275.28) 50% (1247.16) 25% (915.81) 0% (60.77)	100% (1272.22) 75% (1247.98) 50% (834.46) 25% (457.95) 0% (87.65)	100% (1285.39) 75% (1260.39) 50% (663.44) 25% (343.17) 0% (105.82)
Sell: Enthusiastic	100% (2533.97) 75% (2470.32) 50% (2272.44) 25% (1329.73) 0% (53.18)	100% (2538.06) 75% (2406.9) 50% (2080.19) 25% (1122.31) 0% (61.88)	100% (2530.13) 75% (1801.04) 50% (1079.5) 25% (536.45) 0% (87.82)	100% (2538.68) 75% (1493.65) 50% (726.43) 25% (380.29) 0% (105.94)

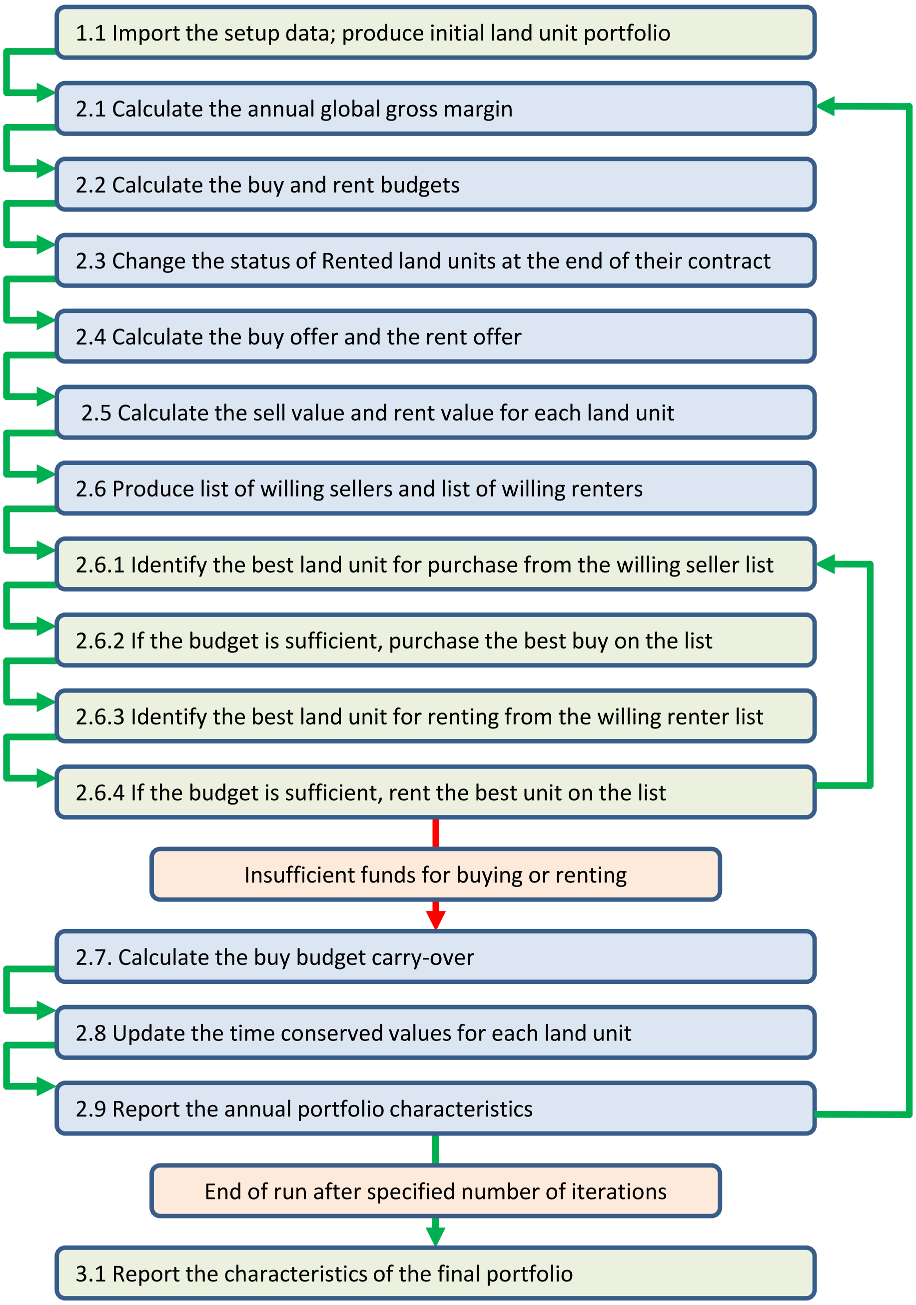

Figure 1: The steps involved in the CELMA algorithm to select the best land units to buy and rent each year, given the available budget. The best land units for buying and renting were identified based on the extent to which they would increase the conservation score of the ecological network through increasing the network's total and patch size area.

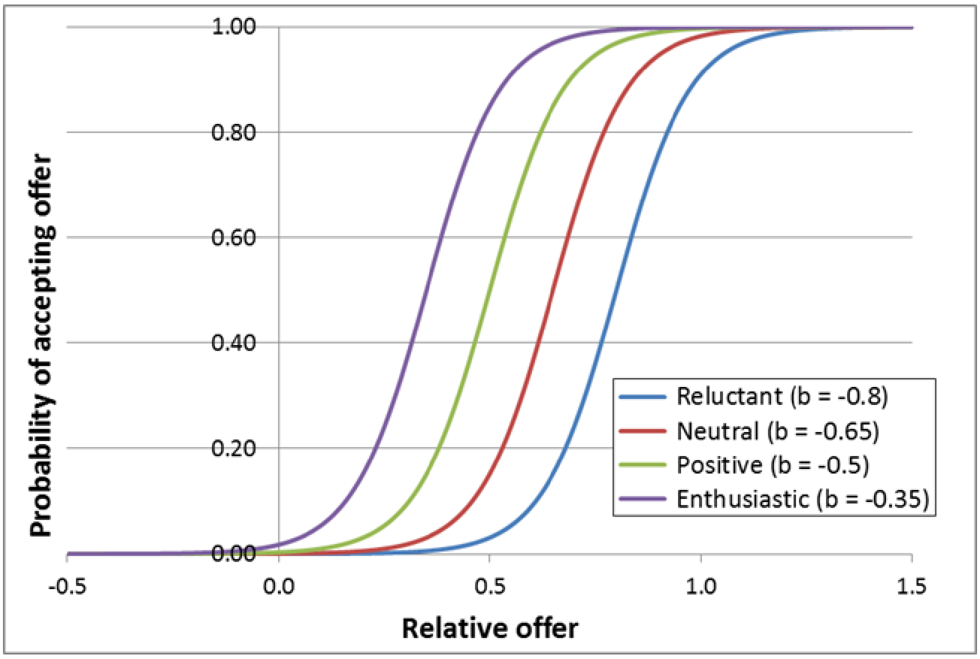

Figure 2: Probability curves of a landowner accepting an offer based on the ratio of the offer to the opportunity cost. A relative offer of 0 means the manager was offered the opportunity cost; a relative offer of 1 means the manager was offered double the opportunity cost.

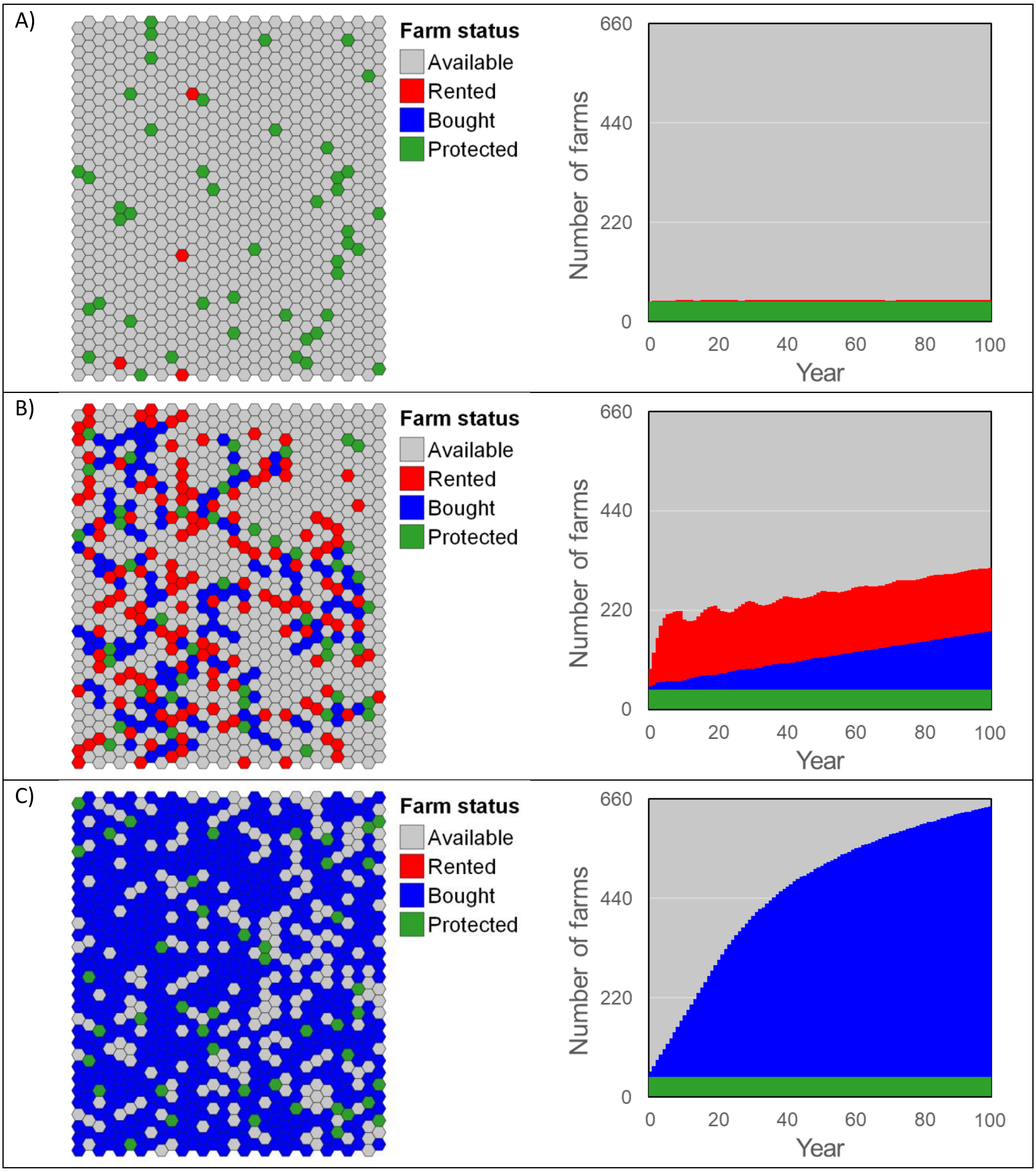

Figure 3. Illustrative details of three CELMA outputs under three different scenarios. A) Annual income = £100K; Buy 0%: Rent 100%; Sell = Reluctant; Rent = Reluctant. B) Annual income = £100K; Buy 50%: Rent 50%; Sell = Positive; Rent = Positive. C) Annual income = £100K; Buy 50%: Rent 50%; Sell = Positive; Rent = Positive. F) Annual income = £100K; Buy 100%: Rent 0%; Sell = Enthusiastic; Rent = Enthusiastic

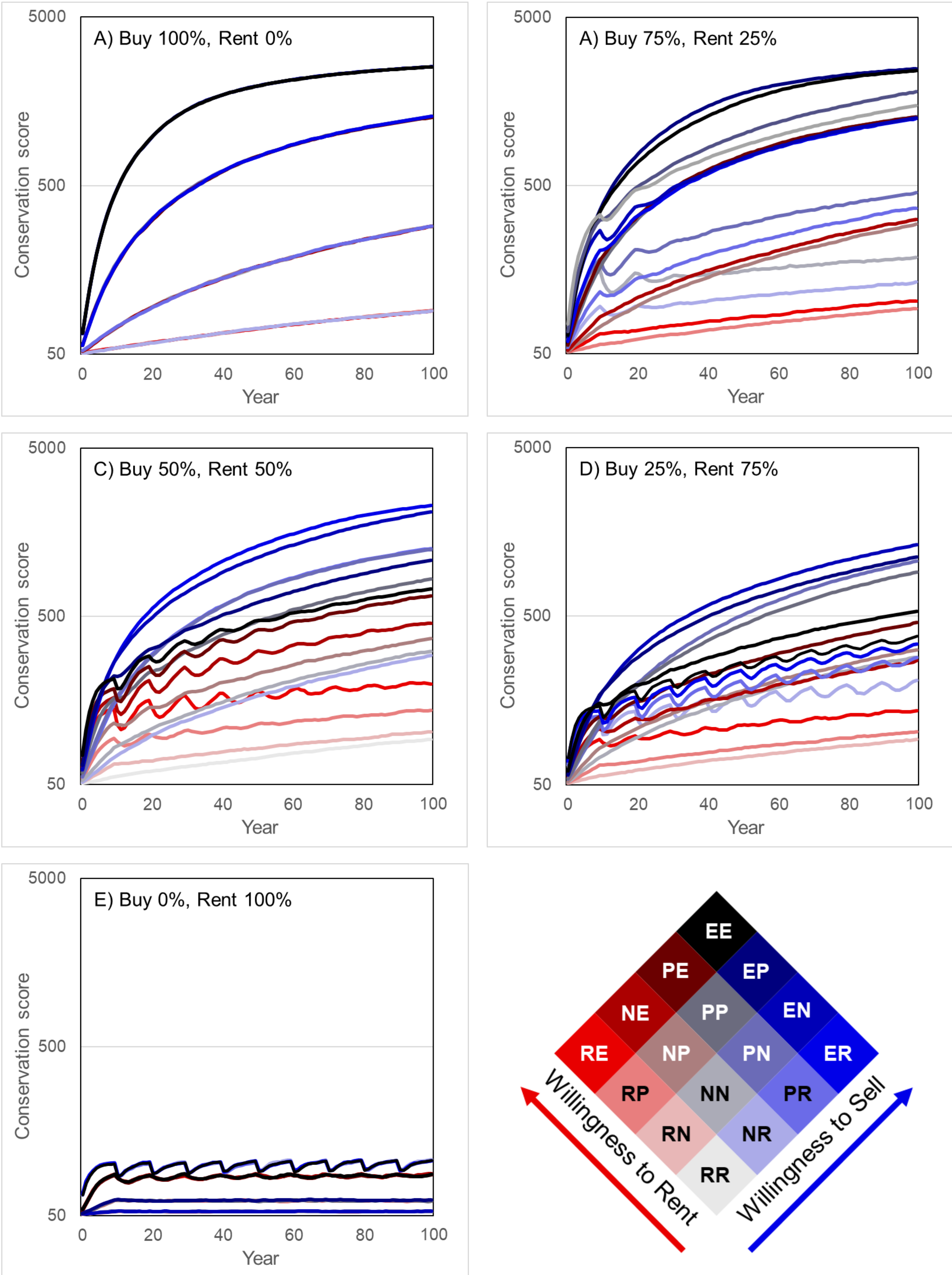

Figure 4: Conservation score over time for the five different funding scenarios based on percentage of budget assigned for buying and renting. Each line colour shows whether the land owner is Reluctant (R), Neutral (N), Positive (P) or Enthusiastic (E) to sell or rent their land, e.g. RP = Reluctant to sell, Positive about renting. Each line is the mean of the five different scenarios with the same Buy/Rent and willingness values but different proportions of land under rental contract.