Adapting genetic algorithms for multifunctional landscape decisions: a theoretical case study on wild bees and farmers in the UK

Article

Supplemental Material

Supporting Information: Adapting genetic algorithms for multifunctional landscape decisions: a theoretical case study on wild bees and farmers in the UK

Ellen Knight, Heiko Balzter, Tom D. Breeze, Julia Brettschneider, Robbie D. Girling, Alex Hagen-Zanker, Mike Image, Colin G. Johnson, Christopher Lee, Andrew Lovett, Sergei Petrovskiy, Alexa Varah, Mick Whelan, Shengxiang Yang, Emma Gardner

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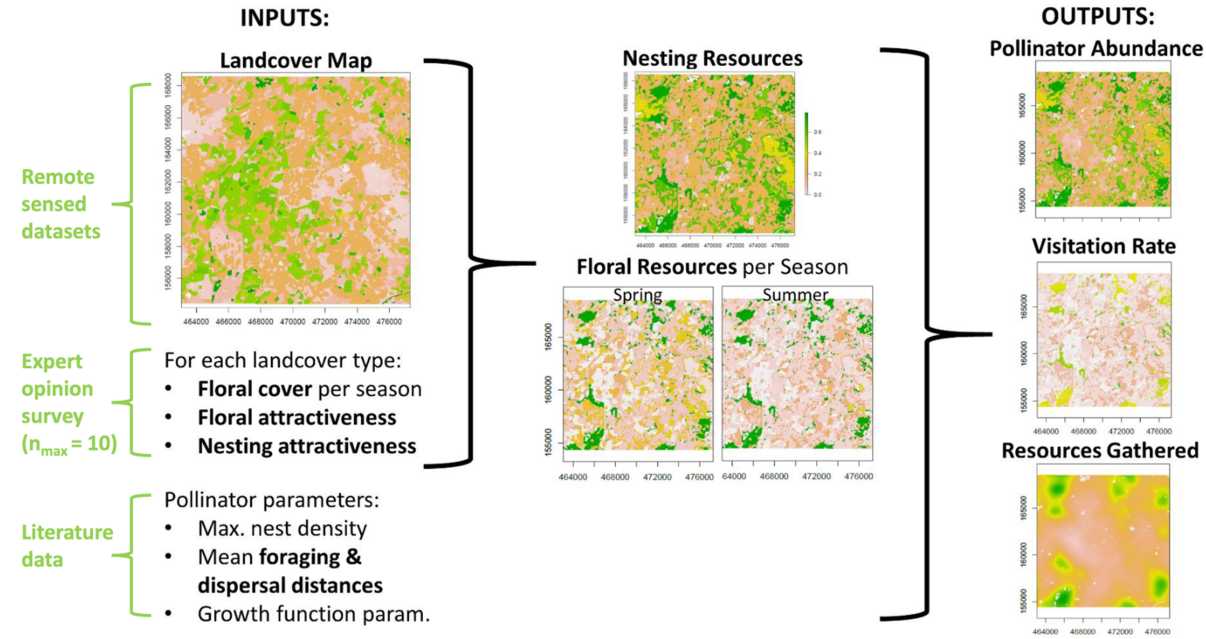

Figure S1 *Overview of the Poll4pop model, which was parameterised and validated for four bee guilds in the UK by Gardner et al. (2020): ground-nesting bumblebees, tree-nesting bumblebees, ground-nesting solitary bees and cavity-nesting solitary bees. The model predicts bee abundance across a given landscape by simulating the processes of central-place foraging, population growth and female dispersal. This is seasonally-resolved and can be simulated across multiple years, although only one year is simulated within the NSGA-II algorithm in our experiments. The NSGA-II fitness functions use the output visitation rate rasters for spring and summer to calculate a fitness score for bees and to modify crop yields when calculating the fitness score for farm income (see Fig.S5).*

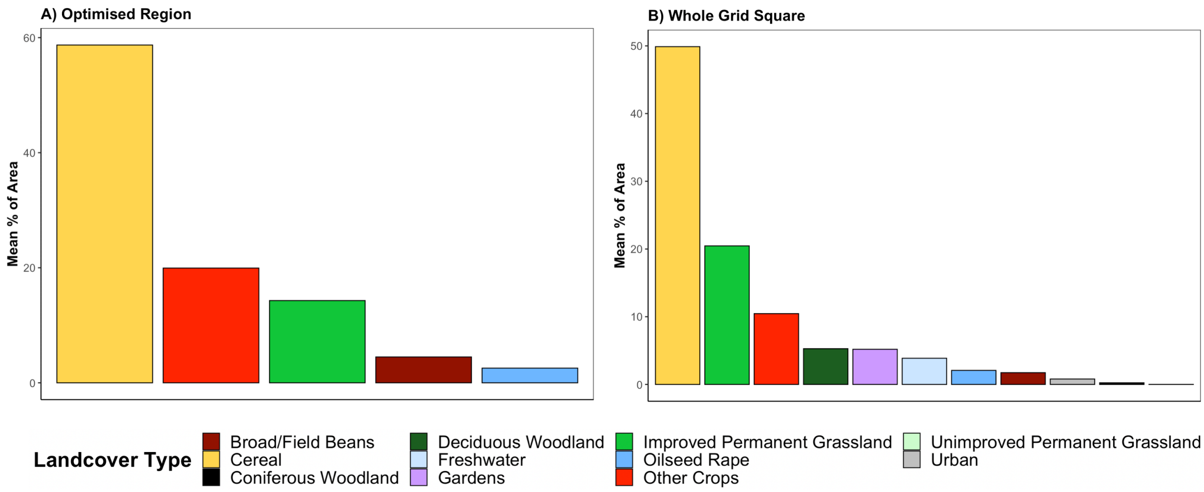

Figure S2 *Landcover proportions of the original 10x10 km SK86 grid square used as reference landscape in our optimisation experiments. A) shows the proportions of each landcover within the optimised region, which included all fields (n=303) within a 2 km buffer of the centre of the grid square which originally contained either arable crop or improved permanent grassland. B) shows the proportions of each landcover across the whole grid square.*

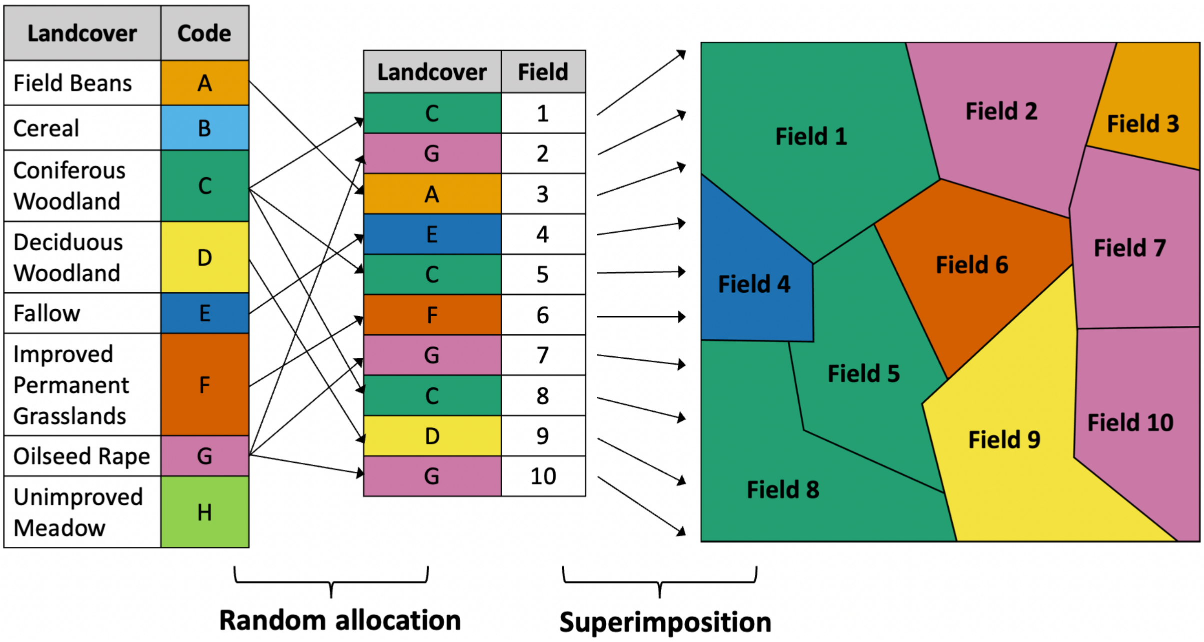

Figure S3 *Landscape initialisation process.*

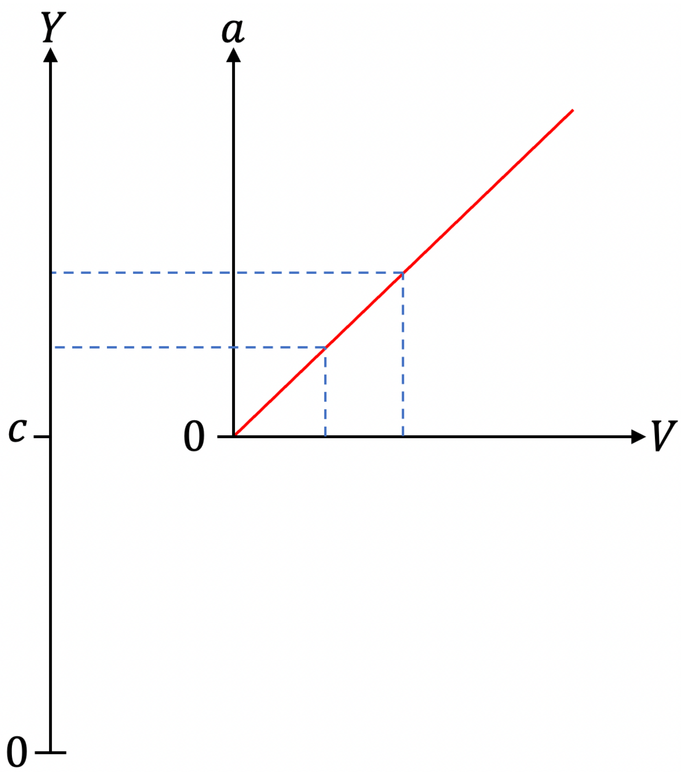

Figure S4 *Visualisation of the derivation of Equation 1.*

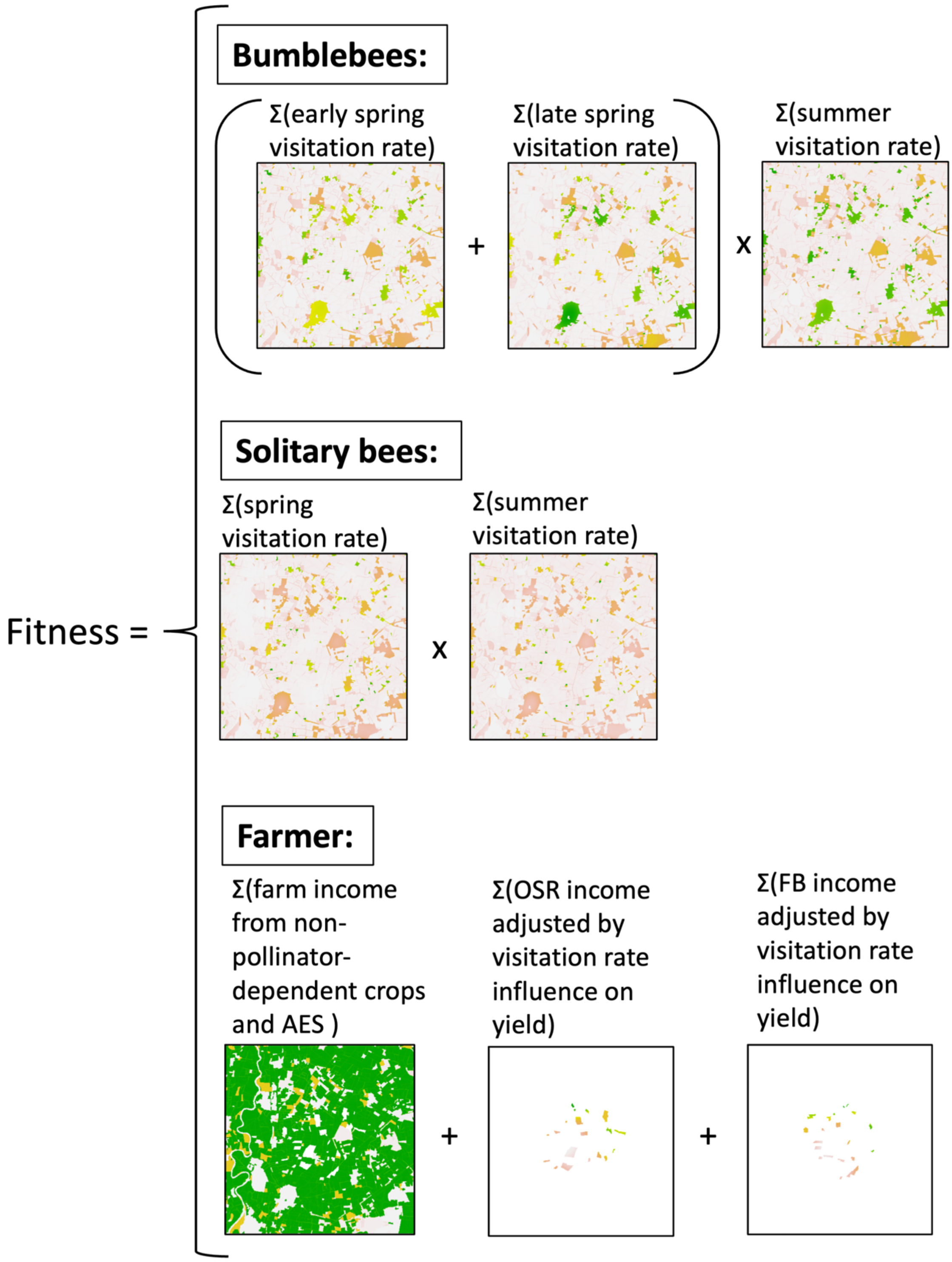

Figure S5 *Visualisation of how the fitness function calculates scores for each objective, using the output 10x10 km rasters with 25 m pixel resolution. Totals are therefore calculated as the sum of 160000 pixel values for each raster. The derivations for the visitation-dependent adjustments to OSR and FB yield are given below.*

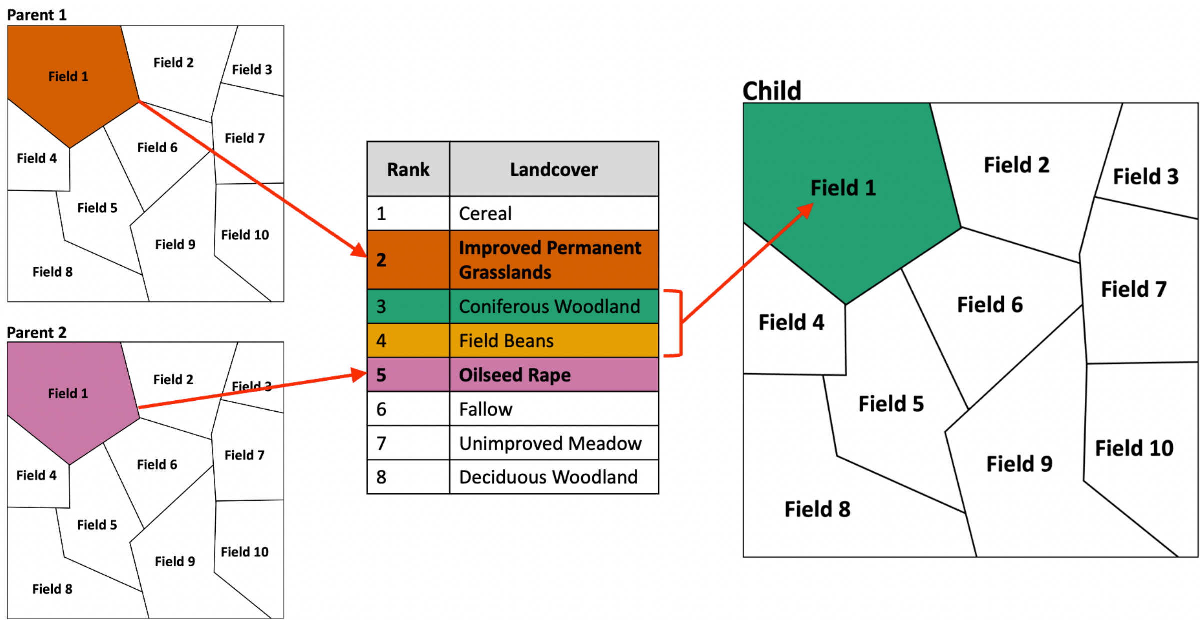

Figure S6 *The crossover process, which occurs for each field if a specified crossover probability (default value = 0.7) is met. Landcovers in the table are ranked by an average of Poll4pop-defined nesting and floral scores for each guild of bee. If the crossover probability is met for a field, the landcover in the child field is selected from those ranked in-between the two parent landcovers on this scale. If the two parent landcovers are next to each other on the scale, one is selected at random from them both. If both parent landcovers are the same, the child landcover will also be the same.*

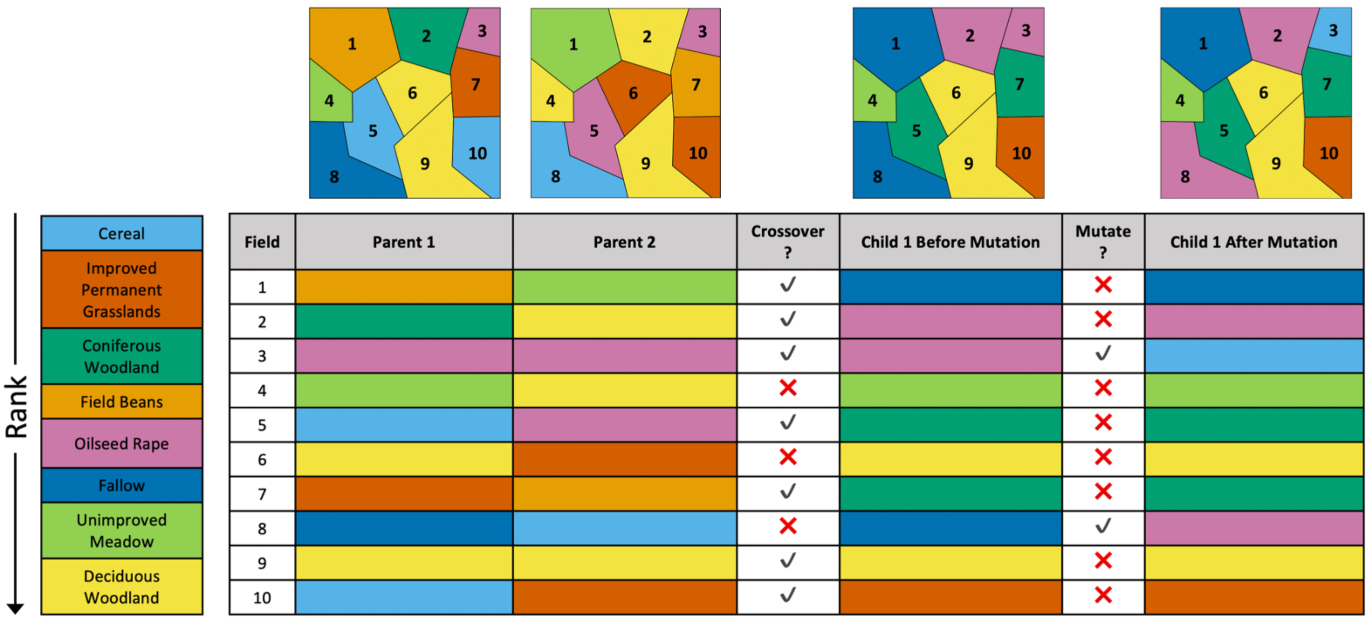

Figure S7 *Summary of the crossover and mutation process. Landcovers in the lefthand table are ranked by an average of Poll4pop-defined nesting and floral scores for each guild of bee. Note the landcover configuration of Child 1 is based on Parent 1, and only gains characteristics of Parent 2 during when the crossover probability for a field is met. If the mutation probability for a field in the child landscape is met (default value = 0.2), a new landcover is randomly assigned to that field.*

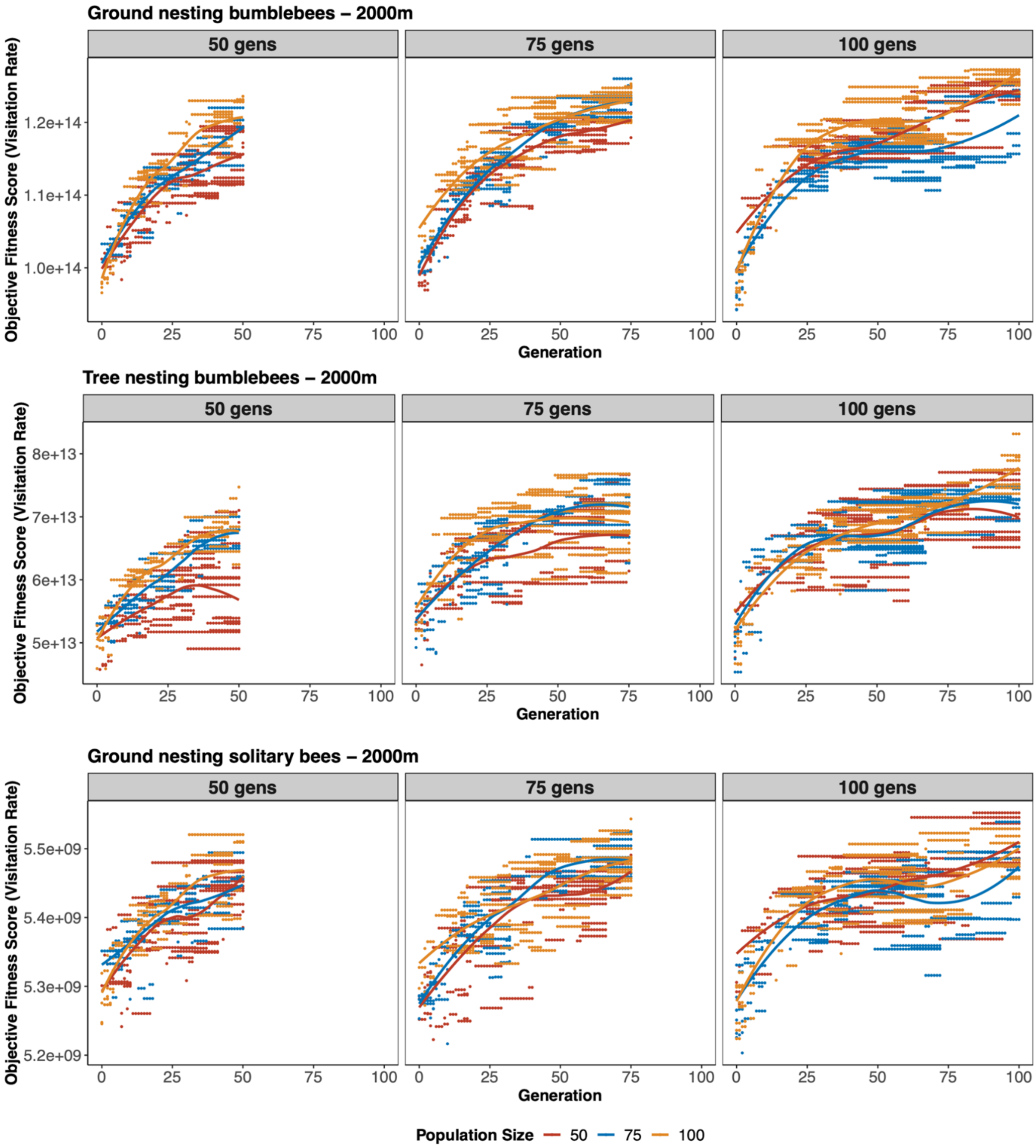

Figure S8 *To ensure the choice of population size and generations parameters was sensible, preliminary investigations were executed in which multi-objective optimisations with different combinations of population size and maximum number of generations were run. 1 repeat was executed for each combination of population size and number of generations. For each objective, fitness scores of the Pareto rank 1 landscapes for each generation were plotted. Visual inspection was used to compare the curves for each repeat (higher maximum scores are more desirable). Ideally, the gradient of the curve should flatten towards the end of the optimisation as a global optimum is reached, however trade-offs between different objectives can alter this shape.*

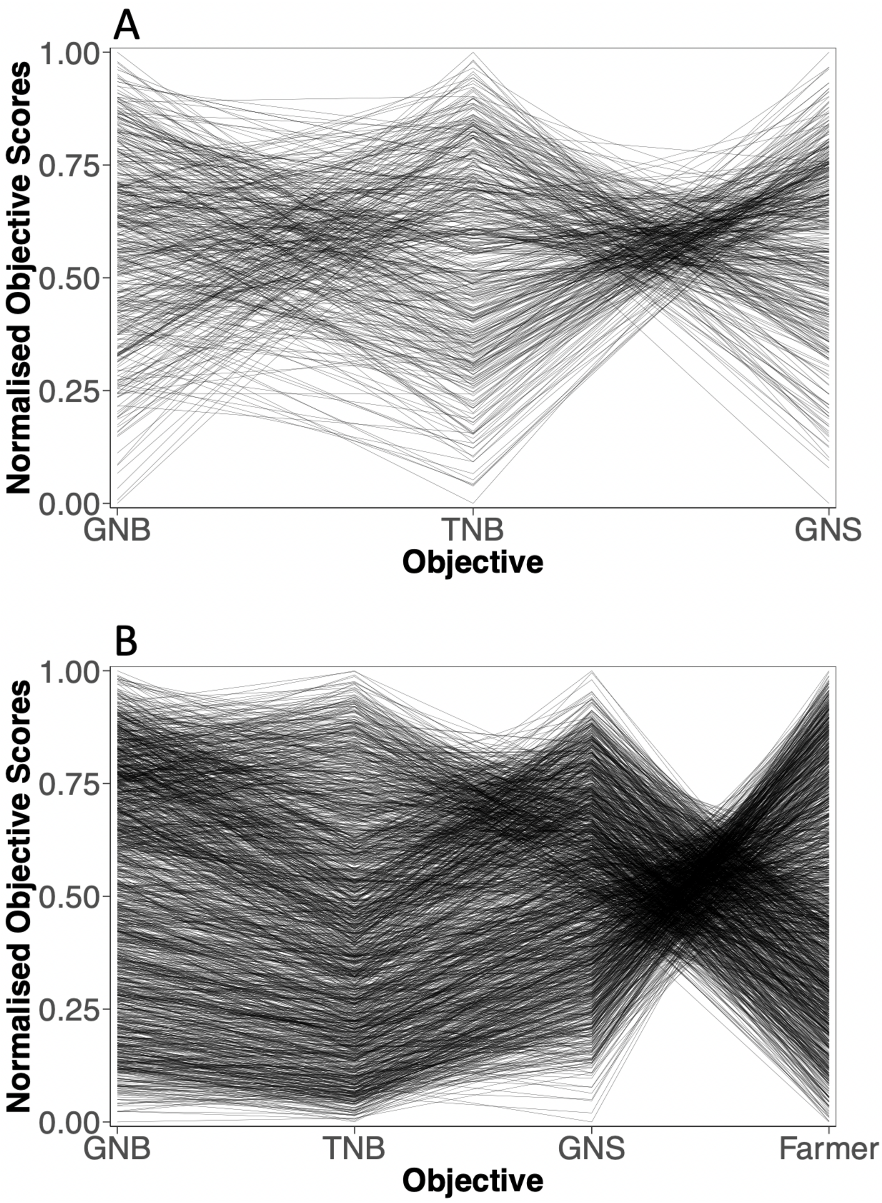

Figure S9 *A) Normalised objective fitness scores for final landscapes of multi-objective optimisations including only bees. B) Normalised objective fitness scores for final landscapes of multi-objective optimisations including bees and the farmer. For A) and B), the fitness of individual landscapes within the final population is normalised so that the fittest landscape for each objective in the multi-objective optimisation will have a value of 1, and the least fit a value of 0. Each line represents one landscape. Higher density of crossed lines between objectives therefore represents increased conflict between the needs of those actors. See Table S3 for sample sizes.*

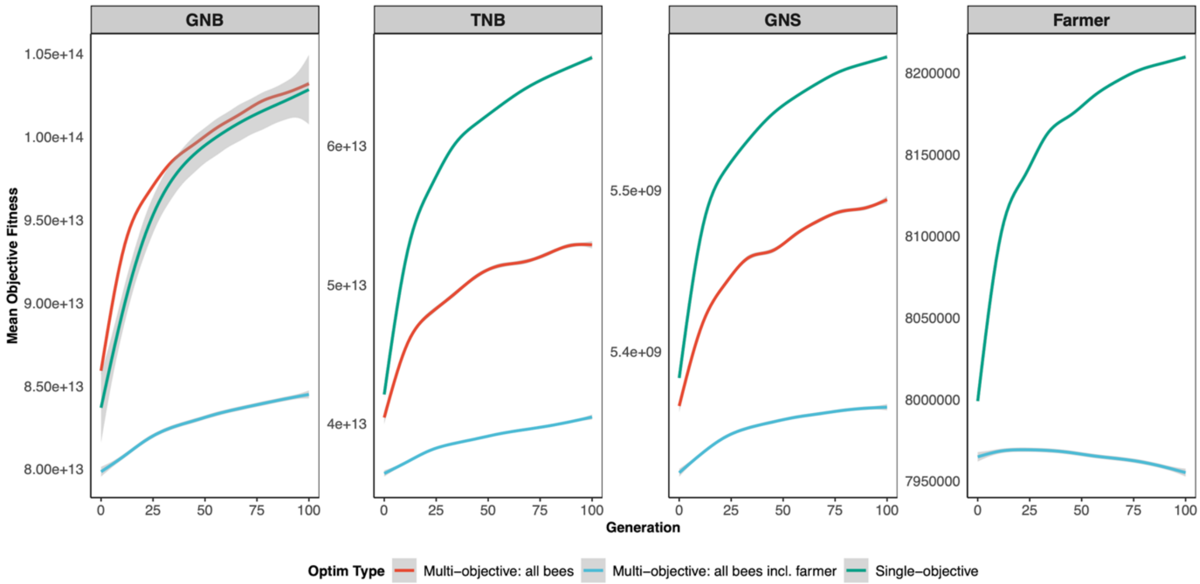

Figure S10 *Evolution of mean fitness score for each objective in each generation, separated by the type of optimisation being carried out. Mean is taken from all rank 1 landscapes in each generation for multi-objective optimisations and rank 1-3 landscapes in each generation for single-objective optimisations, for all replicate runs. Shaded areas represent standard error on the mean fitness of included landscapes in each generation (negligible in some cases). Number of repeats denoted in Table S3. Y axes units are omitted because they differ between bee objectives (GNB/ TNB/ GNS units = visitation rate) and the farmer objective (landscape income in GBP).*

Supplementary Tables

Table S1 *Mean of foraging kernels of bee guilds used in the optimisation process, as defined by the Poll4pop model (Gardner et al., 2020).*

Guild	Foraging distance (m)
Ground-nesting bumblebees	530
Tree-nesting bumblebees	530
Ground-nesting solitary bees	191

Table S2 *Values and of origins of subjective NSGA2R algorithm parameters, as used in all optimisation experiments.*

Parameter	Value	Justification
Population size	50	Validated during preliminary parameter trials to check for convergence (Fig.S7).
Tournament size	5	Slight increase of default (2) to increase efficiency.
Generations	100	Validated during preliminary parameter trials to check for convergence (Fig.S7).
Crossover probability	0.7	Default value.
Mutation probability	0.2	Default value.

Table S3 *Number of completed optimisations and final population landscapes analysed for each objective (i.e 'end-user' of the optimised landscape) and radius. Objective abbreviations stand for: ground-nesting bumblebees (GNB), tree-nesting bumblebees (TNB), ground-nesting solitary bees (GNS). Only Pareto rank 1 landscapes were taken from the final population of multi-objective optimisations, and rank 1-3 landscapes taken from single-objective optimisations because these can only have one landscape at each rank by definition.*

Objective(s)	Radius (m)	Number of optimisations	Number of Highly-Ranked Landscapes Analysed
GNB	2000	15	45
TNB	2000	25	75
GNS	2000	23	72
Farmer	2000	25	75
GNS + TNB + GNS	2000	25	461
GNS + TNB + GNS + Farmer	2000	25	1250

Adapting the NSGA-II algorithm for single-objective optimisations

The NSGA-II algorithm, which typically deals with multi-objective optimisations, was adapted to conduct single-objective optimisations by simply specifying the same objective twice in the algorithm arguments. Therefore, two equal fitness scores are output by the fitness function of the algorithm for each landscape in each generation. This changes the way individuals are ranked because if one solution has a higher score than another then it automatically has Pareto dominance. Therefore, for example, each generation of a single-objective optimisation with a population of 50 landscapes would have 50 separate Pareto ranks. This contrasts to multi-objective optimisations where there would be many landscapes within the same rank. However, the overall optimisation process is not affected by this distinction and the algorithm will still produce a final population of 50 optimised landscapes.

Adjusting pollinator-dependent crop yield according to visitation rate

Equation S1 (broad/field beans):

$$a = 0.592V$$

Equation S2 (oilseed rape):

$$a = (1 - e^{-V}) \cdot e^{-0.0152}$$

Where:
a = yield adjustment value of crop in specified pixel (tonnes per ha)
V = total visitation rate of GNB, TNB and GNS to specified pixel (visits)

From Equations S1 and S2, Equation 1 is derived as follows:

$$a = mV$$

Where m is a constant with units (tonnes per ha per visit).

In this equation the intercept is assumed to be 0, however we know this not to be true as the crops will produce some yield regardless of visitation. Therefore, the intercept value will be the yield produced with no visitation to the crop, meaning:

$$Y = a + c$$

Where:
Y = crop yield (tonnes per ha)
a = yield adjustment value of the crop (tonnes per ha)
c = crop yield with no visitation (tonnes per ha)

$$\therefore Y = mV + c$$
$$\therefore c = Y - mV$$

As we know the national mean crop yield (Y_0) and predicted visitation rates for the real-life landscape (V_0):

$$c = Y_0 - mV_0$$
$$\therefore Y = mV + Y_0 - mV_0$$
$$\therefore Y = Y_0 + mV - mV_0$$
$$\therefore Y = Y_0 + (a - a_0) \qquad \textit{(Equation 1)}$$