Estimating the Accuracy of Camera Trap Methodologies with an Agent Based Movement Model.

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Abstract

Within European cities there are established populations of Eurasian Badgers (*Meles meles*) that were engulfed by urban expansion. These relict populations are popular with city people, but also cause issues with human conflict and require careful management, requiring a detailed understanding of their urban ecology. Camera traps can be used to analyse spatial activity but come with caveats and suitable reference data to assess the accuracy is difficult. Here I show that an Agent Based Model (ABM) can be used to test the effectiveness of a camera trap methodology in urban badgers. I found that the camera trap method was relatively effective, but lower than a standard 95% confidence interval. The only alteration of camera trap methodology that proved effective was increased trapping effort. These results demonstrate that whilst camera trapping is a generally effective, it can vary in accuracy and ABM is useful for adding improvements. Future enhanced iterations of the model could investigate a broader range of the factors being investigated with camera traps. Furthermore, loading study areas into the model and improving it with the use of 'tuning' data could allow it to test a range of scenarios that can be compared to the real world data.

Introduction

Following the Industrial Revolution, the urban habitat began a rapid expansion into the surrounding rural areas (McKinney, 2002). As the habitat shifted it resulted in the diminished range of many rural species (McKinney, 2002; Radeloff et al., 2005), with a notable effect on mammalian carnivores (Woodroffe & Ginsberg, 1998; Woodroffe, 2000; Cardillo et al., 2004). However, some of these carnivores were able to adapt with the change, in that they managed to remain as relict populations within the cities greenspaces (Bateman and Flemming 2012). One of these relicts is the Eurasian Badger, *Meles meles,* which has kept a foothold in the urban fringes of cities in Europe (Geiger, et al 2018) and the United Kingdom (Cresswell Harris, 1988). The badgers were likely able to adapt because their plastic mesocarnivore diet (Zabala et al, 2002) could include anthropogenic food whilst they used greenspaces (Clements, Neal & Yalden, 1988) and anthropogenic structures (Ward et al, 2016) in sett building.

The establishment of badgers within urban ecosystems can cause human conflict or ecological issues. The anthropogenic conflict has been linked with these animals because they raid bins and allotments (Harris, 1984) and can harm/kill domestic pets (Harris, 1984) and hedgehogs (Doncaster, 1992). Furthermore, their sometimes-extensive sett structures can destabilise urban structures (Ward et al 2016). The badger population is also known as a reservoir for Bovine TB (Meylan, 2013), which has caused social issues and ecological controversy (Woodroffe et al, 2006), historically and currently.

Despite this, the public opinion on badgers is generally positive (Soulsbury 2015). In some cases, city dwellers actively encourage badger activity by leaving food out at night (Harris, 1984). This gives badgers a capacity as a flagship species for urban people that grow ever more dissociated with wildlife (Miller, 2005). As research and public opinion on badgers expands, policy makers have responded by rejecting lethal control measures (Ward et al, 2016) and revising culling protocols (Woodroffe et al, 2006). This leaves a situation where management strategies must balance a public desire for relict badger populations to remain whilst minimising the damage they can cause. In order to best hone such management strategies for the badger, a continued and detailed understanding of this urban animal's ecology is needed.

One particular aspect of their behavioural ecology is their spatial activity, which can be studied to indicate what areas of their range are being utilized. A common methodology for this is camera traps, which automatically record photo or video data on either a timer or if a sensor is triggered (for review see (Sollmann, 2018). Camera traps can also be used for surveys on mammals that are either rare or elusive (Bowkett, Rovero and Marshall, 2008). Studies using camera traps have been able answer a wide range of questions on these animals' ecology, which would be difficult or impossible to address otherwise (O'Connell, Nichols and Karanth 2010).

Applied to urban badgers, camera trap studies have helped demonstrate that activity rates (badger photograph rate ÷ cameras survey time) have a positive relationship with woodland habitats and light pollution, and a negative relationship with open grassland and anthropogenic effects (Mallinson, 2021). This study also showed preliminary indications of the effect badgers have on hedgehogs as they reveal that there is virtually no overlap in hedgehog and badger activity. This type of data has management implications in terms of the areas of the parks the badgers are using and the degree of badger exploitation within surrounding urban area. It also demonstrates the ecological consequences of badger presence and how aspects like park lighting and visitors could be affecting the badgers or their prey.

However, the camera trap methodology entails caveats and assumptions. This is primarily because relationships with factors like habitat or human activity can be influenced by sampling as well as ecological processes (Hamel, 2013). A common example of this is where denser forested habitats show higher activity than open grassland because animals moving through forest areas typically follow specific pathways (Sollmann, 2018) and so are more likely to trigger the camera. Camera trap sampling can also be very sensitive in regard to the amount of time the traps are installed for, and the frequency of images collected.

Furthermore, it is difficult to know the most effective number of cameras, how long to run them for and what spatial distribution without comparative reference data. In the case of urban badgers, radio telemetry tracking data can be used to see how the badger movements align with the spatial activity.

This can work with surveys of setts to create detailed reference of the badger's home ranges (like those in Jackson-Matthews, 2017), which can then be added as covariates to camera trap analyses.

In the absence of reference data set, an alternative way to analyse camera trap methodology is to simulate a wide range of data, and test how the methodology copes in different scenarios. A simple example of this is in Rowcliffe, et al (2011) where data from a simulated distribution of the original data was used to estimate biases. A more complex approach is with a correlated random walk (CRW) model, where the movements represent individuals moving on a grid that is then virtually sampled. For example, in their camera trap metanalysis by Broadley et al, (2019) simulations demonstrated that whilst detection rates were related to true abundance, the movement of the animals could cause up to a 30% change in these abundance estimations. A similar random walk model used was also used to evaluate camera trap results and methodology for jaguar density estimates in Belize by Borchers, et al (2014). The model was then used to investigate issues of independent sampling when using camera traps, to estimate jaguar densities, rerunning simulations with different camera densities to estimate bias.

These random movement models are a derivative of Agent Based Models (ABMs), which have a wide variety of designs and can be used to test a broad range of questions. Beyond methodology and experimental design, an ABM can also test hypothetical scenarios and presenting predictions based on virtual experiments. In Toger et al, 2018 the spatial movements of urban wildlife were simulated, but in the place of a CRW used a combination of the maze solving A* algorithm and optimal foraging theory to direct city foraging wild boar agents. This is just one of a large range of different types of movement ABMs used in ecology, as reviewed in McLane et al, (2011).

The use of ABMs to test methodology or run virtual experiments, is not mutually exclusive and using both simultaneously makes an effective tool that can work in parallel with fieldwork. The movements of the virtual are initially designed using data and research on the species' behavioural ecology and environment. Predictions are then be made about their behaviour by testing scenarios within the simulation, and virtual sampling can be used to see what the best fieldwork methodology is for detecting these trends in the field. The results of this fieldwork can be then used to improve the parameters and design of the original ABM.

This technique of using simulations like agent based models to test methodology is known as "Virtual Ecology" (VE), as coined in a review on the subject in Zurell, et al (2010). A virtual world is created in parallel to the real world, sampled and then analysed with statistical modelling. Generally speaking, this VE technique works best at ruling out methodologies rather than supporting them. If the sampling fails to detect the trend in the virtual world is likely will not work in the real world, but a success in the virtual world does not guarantee it works in the real world. This is because models are simplifications by design, and any number of unaccounted for confounding factors in the real world can bias a sampling method.

In order to investigate and improve the methodology and design of Mallinson (2021), I have developed a badger movement ABM. The design of the ABM is focused on testing methods under different scenarios of badger behaviour. This includes an investigation into how changing the number of traps, the trapping effort (number of days left running) and arrangements improve the accuracy, i.e. methods ability to detect trends. As a reference, I will have a 'complete' data set which contains every pixel in the environment. Both data sets will then be analysed with the same statistical models. The behavioural scenarios being tested will focus on different badger habitat preferences and see how effective the original camera trap methodology is at detecting these preferences. Further scenarios then investigate how modifications to this methodology affect the ability to detect behavioural trends.

Methodology

Note for clarity, objects in a model will be underlined and italicised, so as to make clear from the generic use of the word (e.g. *Badger* animal and simulated badger). The term 'model' used in this paper will refer to the Agent Based Model rather than the statistical model, unless clearly specified otherwise. Simulation refers to one of multiple operations performed by a specified version of the Agent Based Model.

Original Camera Trap Methodology

The original camera trap data analysed in Mallinson (2021) were based on surveys by the Zoological Society of London (ZSL) from 2017 to 2019. Cameras were placed at intersections of a 150km2 grid. Images were tagged manually by Lovell (2020). Habitat classifications were assigned to camera trap by Lovel (2020) using Google satellite and street view (Google, 2020), the Digimap habitat class data (EDINA, 2020), and the phase 1 habitat survey classification (Joint Nature Conservation Committee, 2010).

Programs

The agent-based model was programmed in Netlogo 6.2.0 (Wilensky, 1999), which is a specifically tailored program for building agent-based models. Netlogo allows the creation of a grid-based world of 'patches' which is occupied by objects called 'turtles'. Patches and turtles can be programmed to have a number of specified values. Different loops can then be programmed to allow turtles to have movement attributes like speed and heading. Netlogo also uses a 'seed' system which allows the user to rerun an identical simulation by specifying what 'seed' of random numbers are used. Statistical analysis was done in R coding language (R Core Team, 2021), using raster (Hijmans, 2021), dplyr (Wickham et al, 2021), MASS (Venables & Ripley, 2002), and Performance (Lüdecke et al, 2021) packages. Plots were produced with ggplot2 (Wickham, 2016) and figures in GIMP (GIMP Development Team, 2019)

World generation

The world was generated to only include habitat class as an attribute, using the proportions of each habitat classified in (Lovell 2020). These were 60% grassland, 14% woodland, 16% scattered trees and ~ 10% built-up. Scrubland was too small to be worth including in the model. The built-up area was split into 2% concrete, 2% building and 6% roads which was based on the ratio of buildings to roads from a rasterized version of the OS vector map (EDINA, 2020).

Objects and their data

During simulation the world contained 5 different types of object: *Setts*, *Badgers*, *Nodes*, *Food-Patches* and Meals. During the setup phase, *Setts* are placed randomly in either a woodland or scrubland habitat, as badgers have a strong preference for building their setts within these habitats (Ward et al, 2016). Badgers were then randomly created in *Setts*. *Nodes* were set as a 30m x 30m grid and were used for creating waypoints for the badger's memory of Food-Patches. *Food-Patches* were created randomly across the study area, and when the simulation began, they would produce one *Meal* per night.

Data recording

In order to generate data for analysis, patches were populated with records of the movements of any *Badgers* at every step. This created the complete reference data set where every single movement of every *Badger* is stored on the environmental grid. To produce camera data, cameras record all of the data populated in the patch that they are on.

General setup

Each simulation 'night' was run for 5 hours, based on the average nightly activity time of *Badgers* (Palphramand et al, 2007). There was a total of 300 steps representing 300 minutes per night. *Badgers* will teleport back to their *Setts* once the 300 steps have finished. The simulation was run for 14 nights as this was the average trapping effort in original surveys. The scale of the pixels was 10m x 10m which made up an 800m x 800m study area which was the average size of study area in Mallinson (2021). The default number of *Badgers* was 20 individuals spreads across 3 *Setts*, based on a population density of 31.4 badgers per km2 from Raveral (2018) and the sett surveys of Home Park in Jackson-Matthews (2017). 50 *Food-Patches* were then placed randomly across the study area.

Behaviour: summary

In summary, the *Badger* behaviour was a loop, shown in Figure 1, would be repeated 300 times per night. The first step is any patches with a *Badger* on will record data on that Badger. Next *Badgers* would check if they had any waypoints they can use. If they do, they will set their heading towards the waypoint, otherwise they will set a random heading.

Then *Badgers* will check if there is a *Meal* within 50m. If this is the case, they will set speed from a pareto distribution with $\boldsymbol{\mu} = 3$ and then check if there is a barrier to their speed. If there are no Meals, they will set speed from a pareto distribution with $\boldsymbol{\mu} = 1$ and then run a cost evaluation followed by a barrier check. If the distance to a barrier was less than the distance the *Badgers* speed (the distance it was about to move forwards), then the *Badgers* speed would be set to the distance to the barrier.

The *Badgers* would then delete any waypoint *Nodes* within 20m from their temporary list of waypoint *Nodes* and consume any *Meals* within 13m. Finally, they would move forward at the speed in the direction of the final heading. The loop would then begin again and create memory oriented movement dynamics.

Behaviour: Core movement

The core movement of the *Badgers* was a composite random search strategy (CRSS), outlined in Nolting (2013). This is a form of Levy walk (Mandelbrot 1982), where the heading at each step is entirely random, and the distance moved in that step (speed parameter) is taken from a bounded Pareto distribution (Amoroso, 1938).

By taking speeds from the pareto distribution, the majority of step lengths are shorter with the large steps becoming increasingly rare. When combined with a random heading at each step, this generates a 'fractal' searching pattern shown in Figure 2 which is reminiscent of the movement patterns of a foraging animal searching for food patches (Nolting, 2013).

The composite addition of the CRSS is designed to mimic a switch in searching behaviour when non -proximate cues (i.e. smell) indicate food is nearby. In the Pareto equation, $p(l) \sim l^{-\boldsymbol{\mu}}$ the parameter $\boldsymbol{\mu}$ can be between 1 and 3 which will adjust the distribution of speeds that are randomly taken from it. At $\mu = 1$ there is a higher frequency of larger speeds resulting in a ballistic 'inter-patch' movement Figure 2. When $\mu = 3$ the movements are mostly shorter giving a Brownian 'intra-patch' movement Figure 2. The switch between $\boldsymbol{\mu} = 1$ and $\boldsymbol{\mu} = 3$ is triggered by being within 50m of a *Meal* based on the patch sizes used in Mellgren and Roper (1986). The Pareto equation used in my model was a truncated pareto (Aban, Meerschaert and Panorska, 2006) with the maximum speed of 240m in a minute, set as the average max speed in Palphramand, Newton-Cross and White (2007). The minimum speed was 2 metres in a minute which averaged out the badger's speed to the 90m per minute mean speed shown in Palphramand, Newton-Cross and White (2007).

Behaviour: Barriers

To make buildings impassable structures I used a barrier checking function shown in Figure 3, which would ensure the maximum speed taken from the pareto distribution was always limited to the distance to the nearest barrier directly in front of the badger.

Behaviour: Memory

The design of the *Badger* memories was based on use of the optimal pathfinding A* search algorithm in Toger, et al, (2018). The A* search algorithm can find optimal solutions for path searching in grids of Nodes using heuristics. My version of the A* was written in Netlogo from a description in 'generic' coding language in Lague (2021) and is outlined in Figure 4.

The *Badgers* did not follow the ideal pathways perfectly, but had their CRSS movements guided by waypoint *Nodes* to discovered Food-patches. When a *Badger* found a Meal, it added the *Food-Patch* to its own list of located Food-Patches. After returning to their *Setts* at the end of a night, the *Badgers* would 'dream' and use the A* algorithm to create an ideal route between each *Food-Patch* on their list. This ideal route would be mapped on the grid of *Nodes* on a 30m x 30m grid, shown in

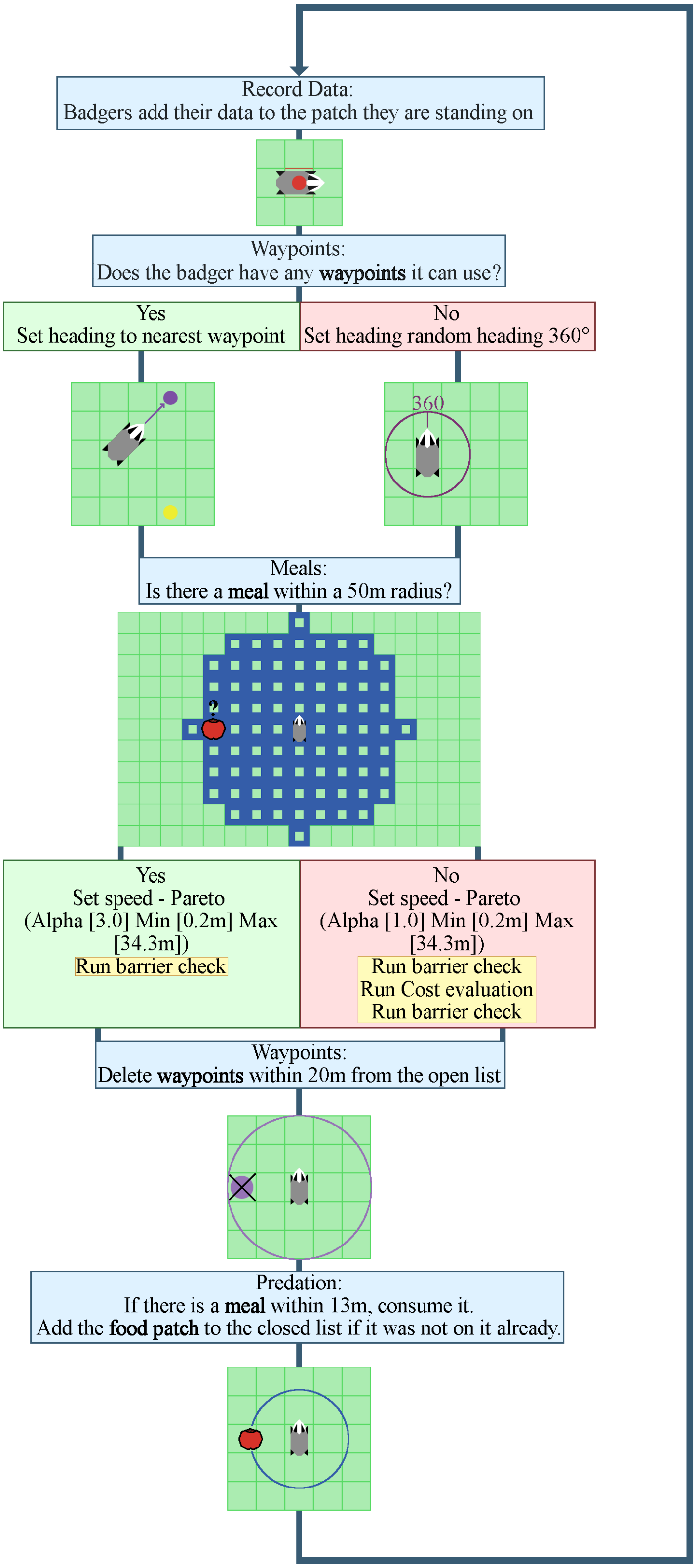

Figure 1: Flow Diagram of the *Badger* behaviour loop. *Badger* agents move with speed and heading on a raster grid of patches. *Waypoints* are a list nodes stored by badgers that they use to return to the *Food*-*Patches* that they previously found *Meals*. Speed is taken from a Pareto distribution with different **μ** levels depending on the proximity to food. The Barrier check and Cost Evaluation are shown in Figure 3. This loop will run 300 times each night so as to simulate a foraging *badger*.

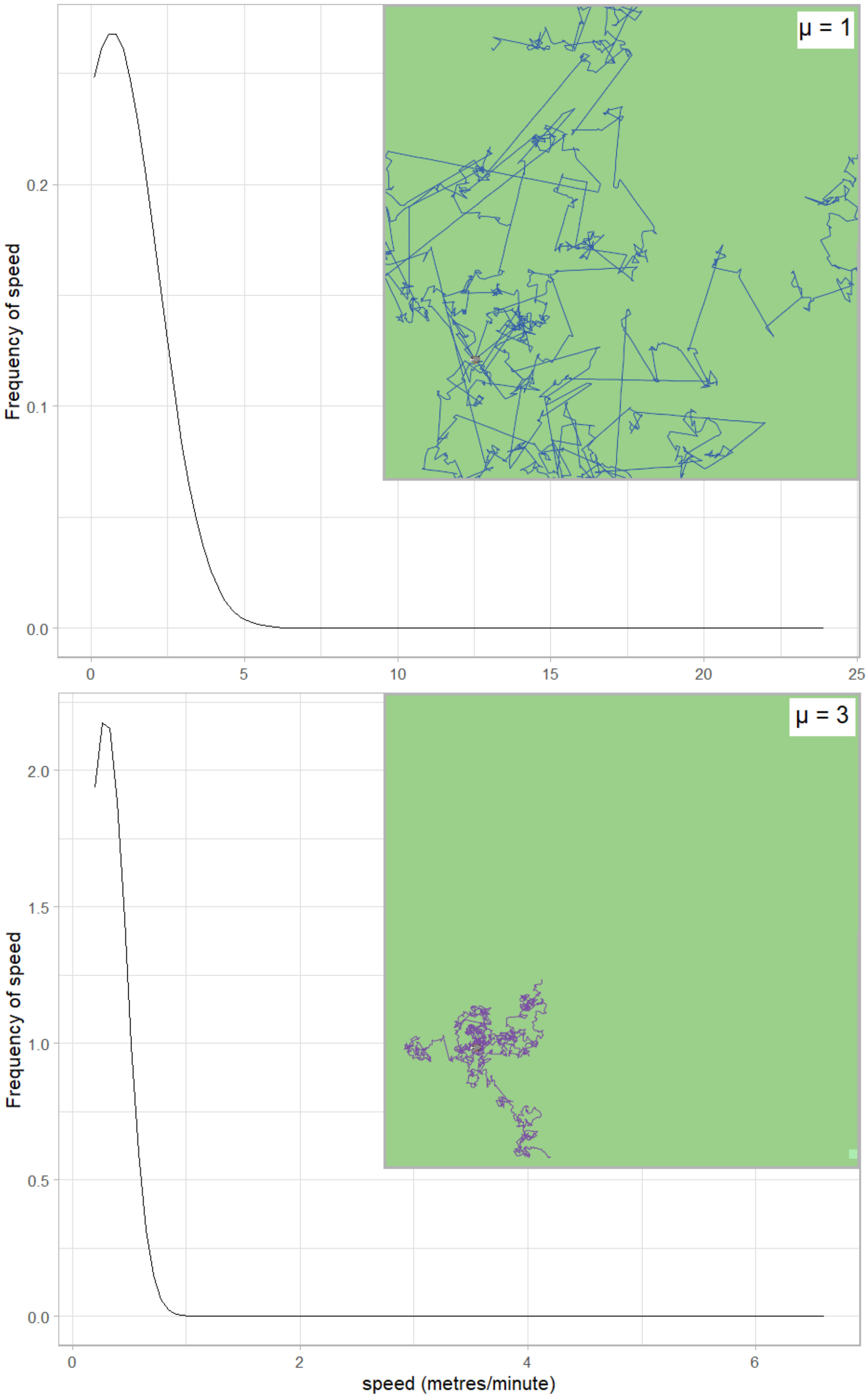

Figure 2: Graph and Image of Netlogo interface showing the different speeds of badgers based on two different Pareto distributions, **μ** = 1 (Top) where longer step lengths give badger larger movements and **μ** = 3 (Bottom) where shorter step lengths give badger smaller movements

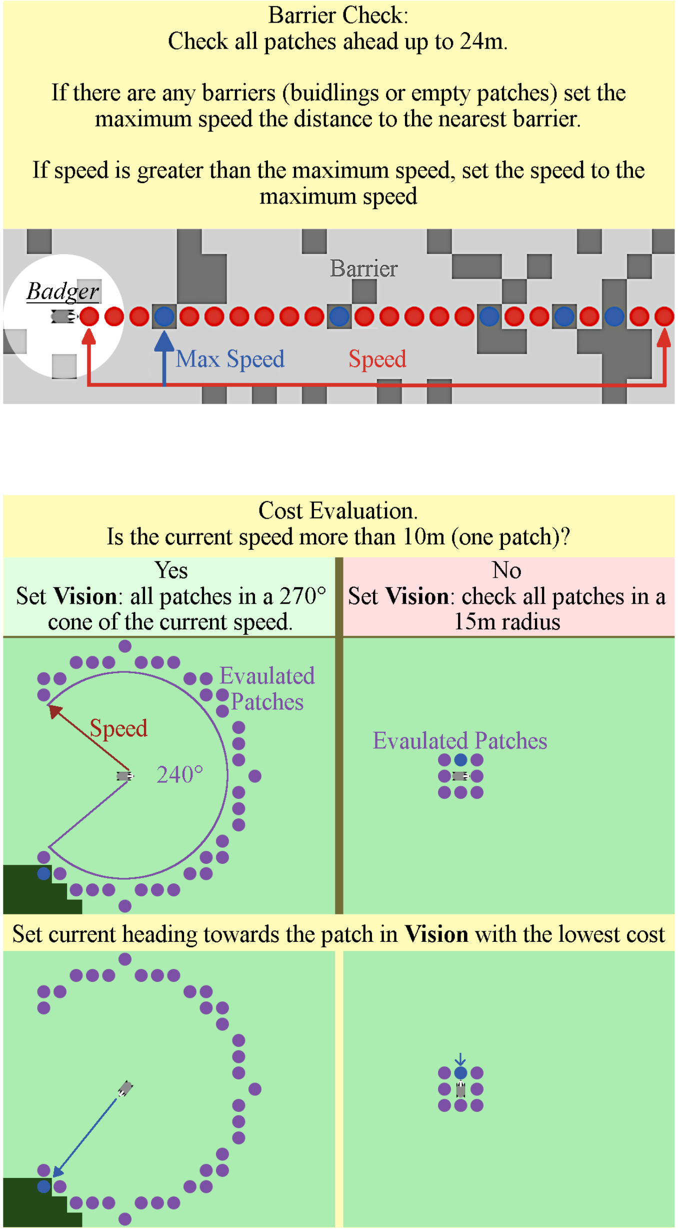

Figure 3: Diagrams of Barrier check and Cost evaluation functions used in *Badger* movement behaviour. The Barrier function is used to stop *Badgers* moving through buildings by capping their speed to the distance to the nearest barrier in front of them. The Cost evaluation function will change badgers headings towards patches with lowest cost. At slower speeds this is the 8 patches that surround them, and at faster speeds it is the patches in a 240° arc with a radius of their speed. If there are multiple patches with low a cost available, then one is chosen at random.

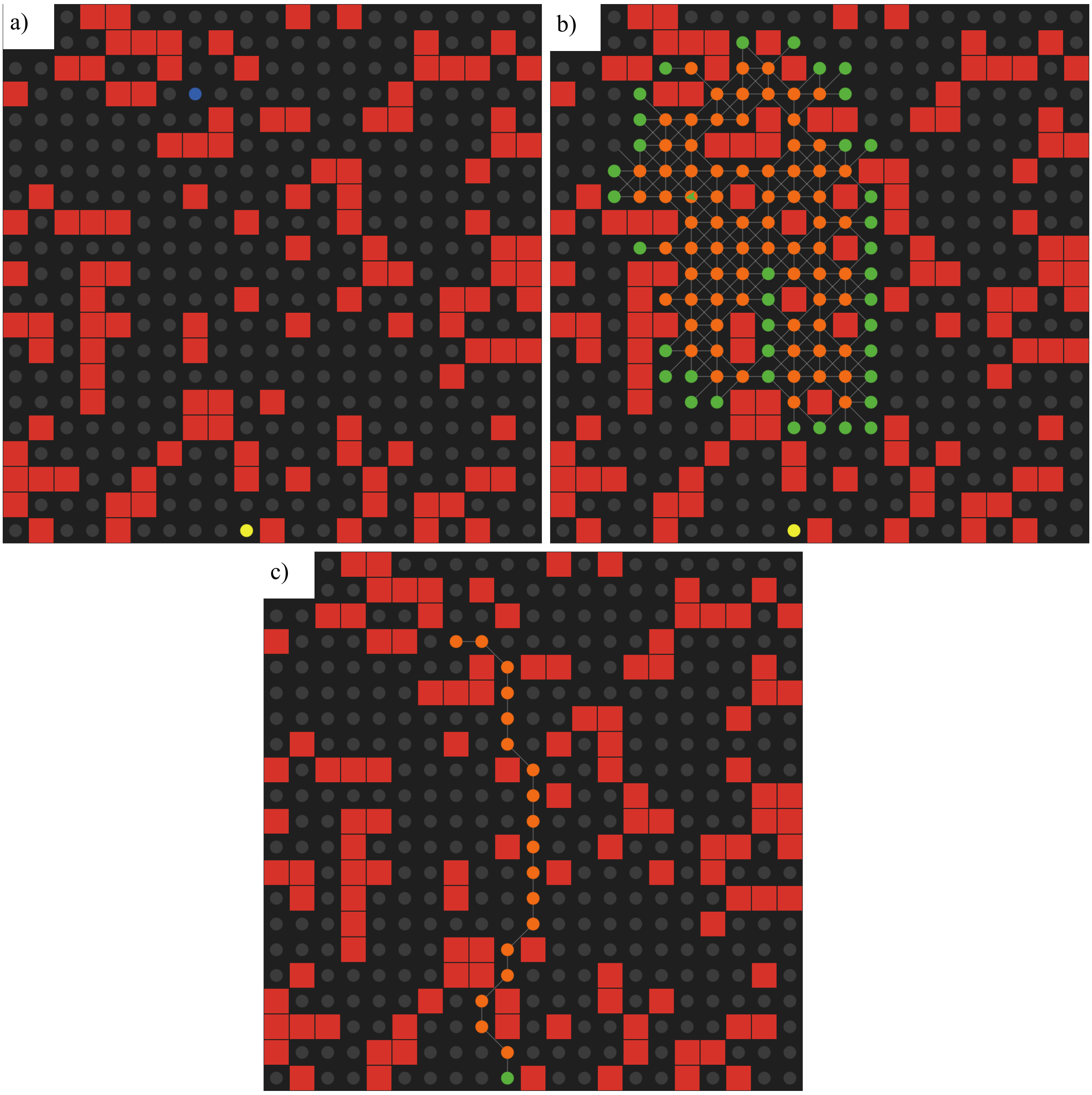

Figure 4: Images of a Netlogo interface for my version of the A* algorithm, which finds the ideal route from a starting *Node* (blue) to a target node (yellow) in a grid of *Node* (circles) with a maze of barriers (squares).

A) The *Nodes* are setup, with a target and start *Node*. *Nodes* can be either **open** (green), **closed** (orange), or **unvisited** (grey). They can also have 'parent' *Nodes* (light grey lines).

B) A current *Node* is selected, which is the open node with the lowest f-cost. The f-cost is the h-cost (distance to target node) added to the g-cost (length of route to the start node via each connected parent node). At the beginning of the function the current *Node* is the starting *Node* . The 8 neighbouring *Nodes* of the current *Node* are then evaluated unless they are **closed**. The g-cost of each neighbour *Node* is then calculated, and if it is less than the *Nodes* original g-cost, or the *Node* is unvisited, then this neighbouring *Node* is updated. Once a new current *Node* is chosen the process will start again and repeat until the current *Node* is the target *Node* .

C) The chain of parent *Node* from the target to the start *Node* will then make up the ideal pathway.

Figure 5. The route would start by creating a path to the *Food-Patch* nearest the Sett, then then to its nearest Food-Patch, and then the next for each consecutive *Food-Patch* until every *Food-Patch* had been routed as shown in Figure 5.

Once the ideal routes had been completed, they were available to the *Badger* as a list of waypoints which would guide the *Badgers*' random movements. Waypoint *Nodes* were recorded by each *Badger* as a list and would be deleted when *Badger* came within 20m. This meant *Badgers* would then move through each waypoint Node until they ran out, at which point they moved with the default CRSS. This waypoint based memory system allowed the *Badgers* to retain a core movement based on the CRSS, but be guided by their memories to *Food-Patches* that they had visited which created individual movement patterns with specific home ranges as shown in Figure 6.

Behaviour: Cost Evaluation

Cost evaluation was needed in order to program specific habitat preferences in the *Badgers* so that 3 model scenarios could be tested: Null, Test and Inverse. Null had no preferences, Test preferred Woodland and Scattered Trees and inverse preferred Grassland and Built-up. This cost needed to be able to work for both the step-by-step CRSS and the routes being used in the *Badger* memories.

Firstly, patches were allocated cost numbers based on the habitat preferences I wanted to test. This ranged from a cost of 1.00 to a maximum of 1.06. This cost was then used to multiply to h-cost of *Nodes*. At a cost of 1.0 the h-cost would be the exact distance to the target. At a cost of 1.06 the h-cost would be multiplied enough that the A* algorithm would begin to completely avoid using that node when it created the ideal route.

For the CRSS, the *Badger* would first set a random turning angle and set its speed. It would then assess the cost of every patch in a 240° cone and select the one that had the lowest cost to set at its new heading. If the speed was less than 10m it would assess the 4 neighbouring patches, as at this distance the 240° cone would not pick up any patches, and this part of the *Badger* movement was logistically important in preventing them from crossing barriers. The barrier check function would also need to be run before the cost evaluation to prevent a Netlogo runtime error. The barrier check would also run after cost evaluation, to check for barriers on the new heading.

Because the cost evaluation was done after the initial random 360° heading, it still generated a similar fractal pattern characteristic as a default CRSS. The cost evaluation was only run when the *Badgers* had not detected any Meals. This system of evaluating patches always chose the patch with the lowest cost, so the actual number itself did directly alter which patch it chose. If grassland was set to a high cost of 1.01 and woodland to 1.00, the outcome would be the same as if grassland was set to 1.06 and woodland 1.05. However, the memory algorithm would produce different paths, with different waypoints because the numbers affected the *Nodes* h-cost.

Behaviour: Biological Principles in Model design

The model was designed using inferences and assumptions based in aspects of badger behavioural ecology found in the literature. The CRSS was chosen as a core movement because it is similar to a very wide range of foraging animals including a member of the mustelid family (Haskell, 1997). The CRSS also seemed plausible based on a badger's behavioural ecology, as their diets have patchy distributions (Revilla and Palomares, 2002). A study by Mellgren and Roper (1986) showed that badgers could detect *Food-Patches* and alter their movement speeds to search within them.

The barriers to movement were added to Built-up areas because buildings, walls and fences are physical barriers to animal movement. This had implications for camera trap methodology as it could cause a channelling effect where animals are forced to go down specifics routes.

The addition of memory was based on the conservative nightly movements of badgers within their home ranges (Davidon et al, 2009), and evidence that that they frequently leave their setts in the same direction each night (Cresswell and Harris, 1988). This strongly implied that they have a consistent nightly routine. This would likely include a route between *Food-Patches*, as Mellgren and Roper (1986) indicated that badgers were effective at remembering the area and location of *Food-Patches* using landmarks. Because of this I decided that a 'Food-Patch' memory would be a good way to program the badgers to have conserved home ranges. This was based on a study of simulated

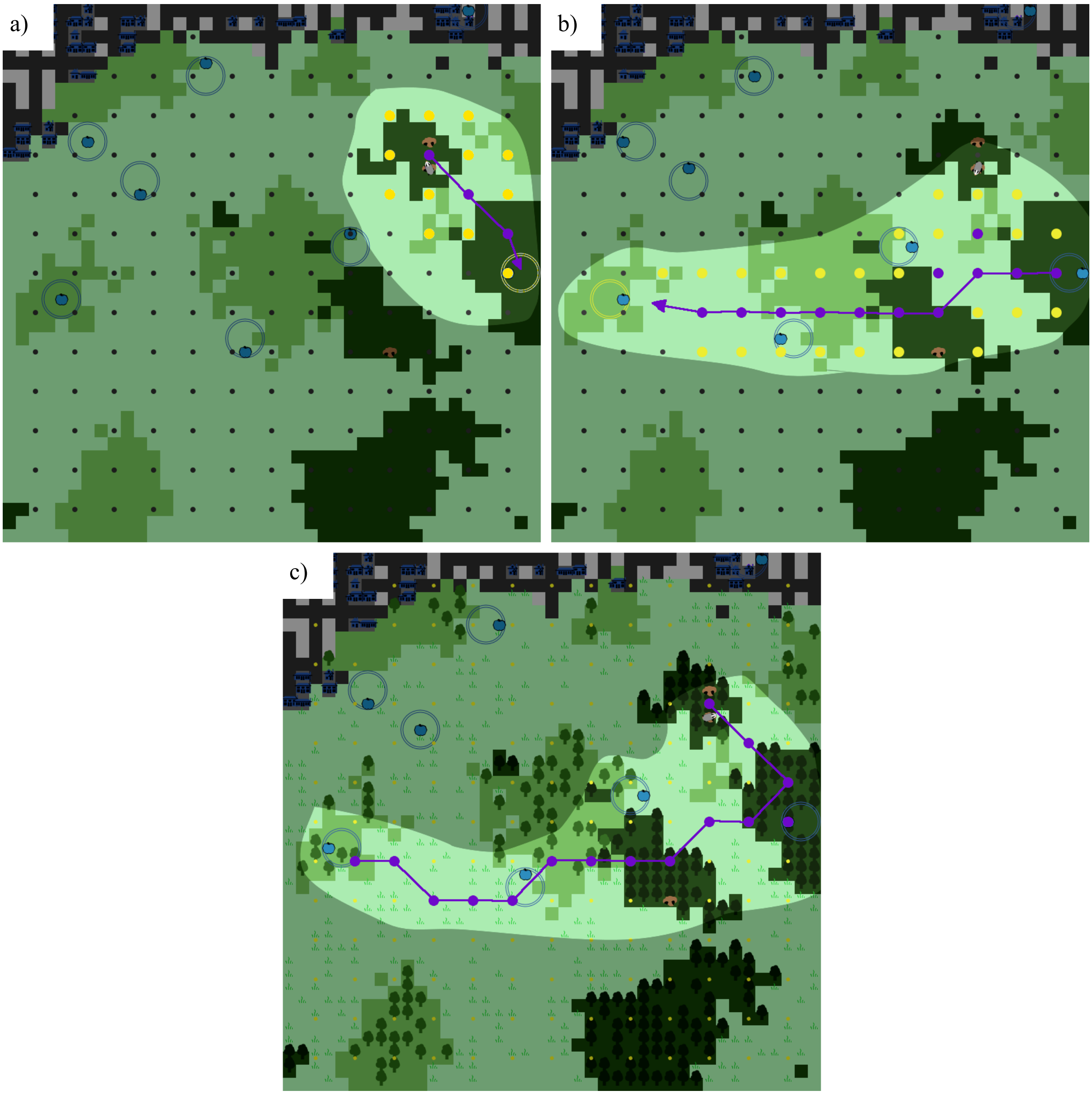

Figure 5: Diagram Images from a Netlogo interface showing the A* algorithm finding a ideal memory path for a _Badger_. _Nodes_ are circles, with closed nodes in purple. _Food-patches_ are blue circles with blue apple shaped _Meal_ inside. A) A* finds a route from the _Sett_ to the nearest known food patch. B) A* finds a route to each consecutive nearest _Food-patch_. C) a path of waypoints is created for the _Badger_ to follow.

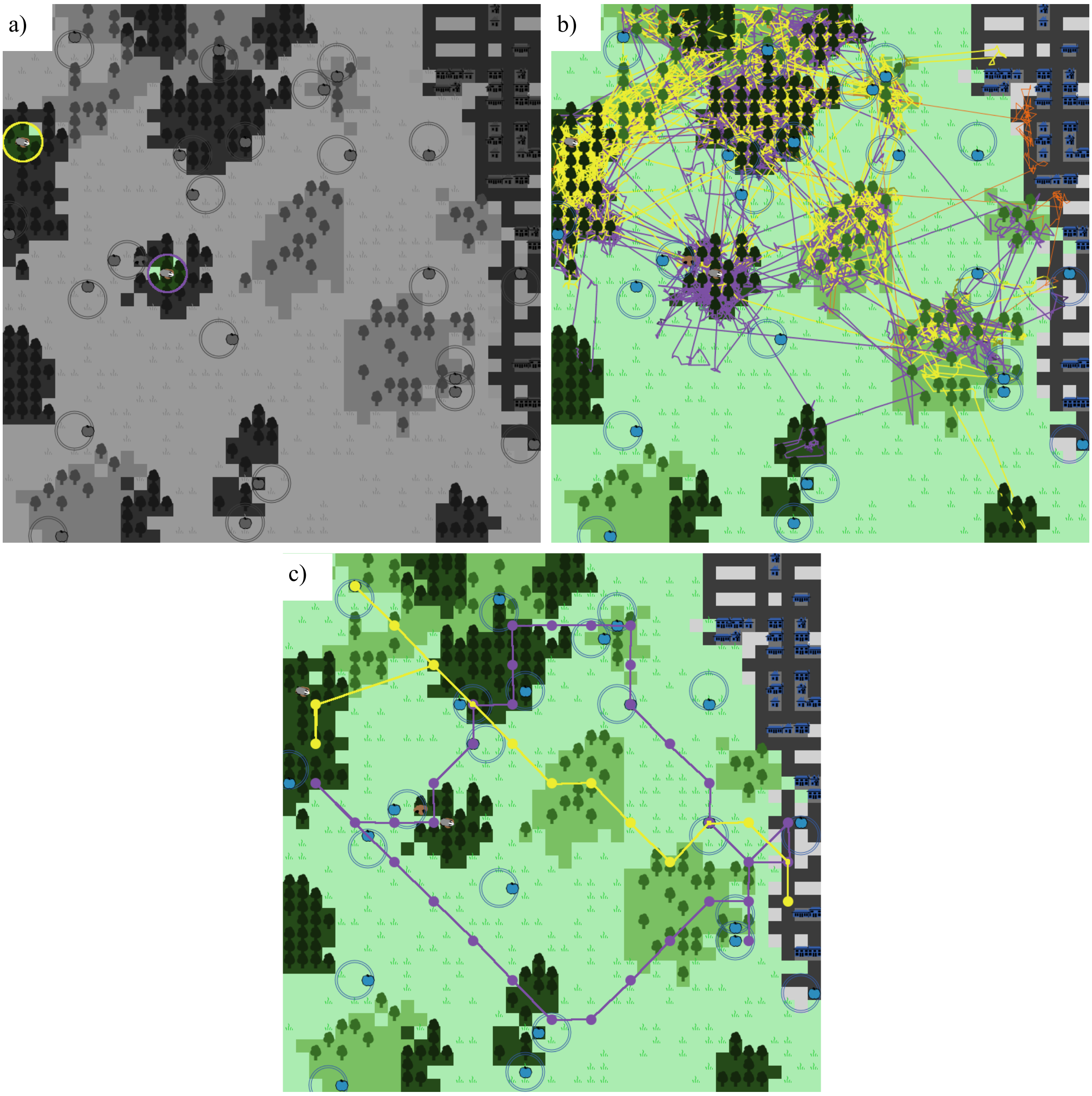

Figure 6: Diagram Images from a Netlogo interface showing movements of badgers over a simulation for two badgers, one purple and one yellow. Waypoint Nodes are circles. Food-patches are blue circles with blue apple shaped Meal inside. Paths of Badgers are lines with the same colour as the Badger (yellow/purple), unless the Badger is moving without waypoints, in which case it is orange.

A) Initial placement of Badgers in their setts. B) The Badgers nightly movements after 14 consecutive nights. C) The paths of memory Nodes used to guide the Badgers CRSS movements between Food-Patches.

foraging by Riotte-Lambert (2016) which showed that memories of locations of *Food-Patches* formation home ranges.

For constructing the memory paths, the 'Nearest neighbour' approach was chosen as the order of routing each *Food-Patch* as it was the simplest solution to the notorious 'travelling salesmen' problem. This was also based on a study by Anderson (1983) which indicated that it was more effective for a foraging animal than planning routes 2 or 3 steps ahead. The angle of vision for the Cost Evaluation was chosen on the basis that badgers likely have a similar field of vision as dogs (Miller, 2001).

Simulations

The first simulation was intended as a test of the original methodology, which equated to 25 cameras on a 150m grid. I ran 20 simulations, each one with a different randomly generated environment, but using the same 20 seeds (random number generators). The number 20 was chosen as 1 in 20 is the random chance of a false positive results for the $p < 0.05$ statistical threshold used in the statistical test.

For the initial camera trap methodology, 3 different scenarios of model were run. The first was a null model where the *Badgers* had no programmed habitat preference. The second was a test model where grassland was given a cost of 1.06, woodland a cost of 1.00, scattered trees a cost of 1.00 and built-up areas a cost of 1.03. The third was an inverse model, where woodland cost was 1.06, scattered trees 1.03, built-up areas 1.01 and grassland 1.00.

The second series of simulations investigated variations of camera trap methodologies. This was traps on 300m grid and 130m grid, a 28-night run time and a 7-night run, randomly placed cameras and nested cameras. nested cameras are placed in areas of potential high activity which in this case is on *Food-Patches*.

Statistical analysis

The original statistical analysis in Mallinson (2021) was a negative binomial generalised linear mixed model with frequency of *Badger* contacts as the response variable, habitat as one of the explanatory variables, trapping effort as an offset variable and survey location as a random factor. My simulations were analysed with a negative binomial generalised linear model (nbGLM), which included habitat classification as an explanatory variable as the others did not exist in my simulation. I also did not include trapping effort as an offset variable as all the cameras in the simulation had the same trapping effort.

Each version of my ABM ran 20 simulations, which produced a reference data set and camera survey data set. Each data set from each simulation was analysed with the nbGLM. The nbGLM generates Incidence Rate Ratios (IRR) which are how much the nbGLM predicts *Badger* activity increases in that habitat when the overall activity increases by one. IRR values < 1 indicate *Badger* activity increases slower compared to the overall population (negative relationship), and >1 indicate activity increases faster (positive relationship).

By comparing the IRRs of the nbGLM analysis of camera data to the nbGLM analysis of the reference data I can infer a % error rate. This is the count results in the camera data that are inconsistent with the reference data, divided by the total number of tests (number of terms multiplied by number of simulations). The nbGLMs for the reference data had no P-values as the frequency of replications renders them meaningless (see review in White et al, 2014).

Results

Badger activity in Reference data

Analysis of the activity data for the Test ABM simulations, shown as in Figure 8A, were consistent with the preferences that were programmed. The results for the Test model indicated that *Badgers*' activity has a strong positive relationship with Woodland and Scattered Trees, no relationship with Built-up Areas, and a small positive relationship with Grassland. This mostly aligns with the results of original camera trap analysis in Figure 7, apart from Grassland which did not show a strong negative relationship. The variation of incidence rate ratios between simulations was minimal indicating the model has good stochasticity.

The activity shown in the Null model simulations showed no relationships with the habitats, as shown in Figure 8B, with the exception of Grassland which showed a very strong positive relationship. There was a notable degree of variation between simulations for the urban habitat. This trend was reversed if distance to sett was added as a offset variable, shown in Figure 10 in the appendix The activity in the Inverse model, shown in Figure 8C, showed a strong negative relationship for all habitats, including built-up, and a strong positive relationship with Grassland. This is curious as built -up had been set to the lowest cost.

Original Camera Trap Methodology

Compared to relationships shown in the reference data, the original camera data performed relatively well. For the positive relationship with Woodland and Scattered Trees, only the 1/ 20 simulations were not significant, and there was one significant relationship with built-up. However, the weak positive relationship with Grassland was only detected in 9 of 20 simulations. This gives the overall error rate of 18% (14 errors / (20 simulations * 4 Terms)).

The cameras performed much better with the Null mode, with an error rate of 5% (4/80), where 4 simulations showed an incorrect significant relationship with Woodland. The camera data performed worst on the Inverse model, with the correct relationships only being detected in 31% of simulations (25/80). For Built-up areas there was an incorrect positive relationship for 20% of simulations. Overall, this means the design from the original sampling method showed a total error rate of 18% (43/240) across the 20 simulations for 3 models.

Variations of Camera Trap Methodology

For the Test model, there were 6 different variations on the original analysis, shown in Figure 9. Increasing the trapping effort to 28 days improved the error rate to 11% (9/80), whilst reducing the trapping effort to 7days greatly increased error rate to 29% (23/80). Increasing camera trap density to 41 cameras on a 130m grid gave same the error rate of 18% (28/80). Decreasing density to 9 cameras on a 300m grid caused a sharp increase in error rate to 35% (28/80). Exchanging the grid arrangement to random trap placement also increased error rate to 26% (21/80), whilst the 'nested' setup performing the worst with an 34% error rate (27/80).

Modifications to original methods

The same 20 seeds of random numbers were used for the 20 simulations except for the 41 camera ABM in Figure 9C as this needed simulation 7 and 11 rerun on different seeds. The Nested nbGLM had the Group ID of each triplet of cameras added as a fixed effect.

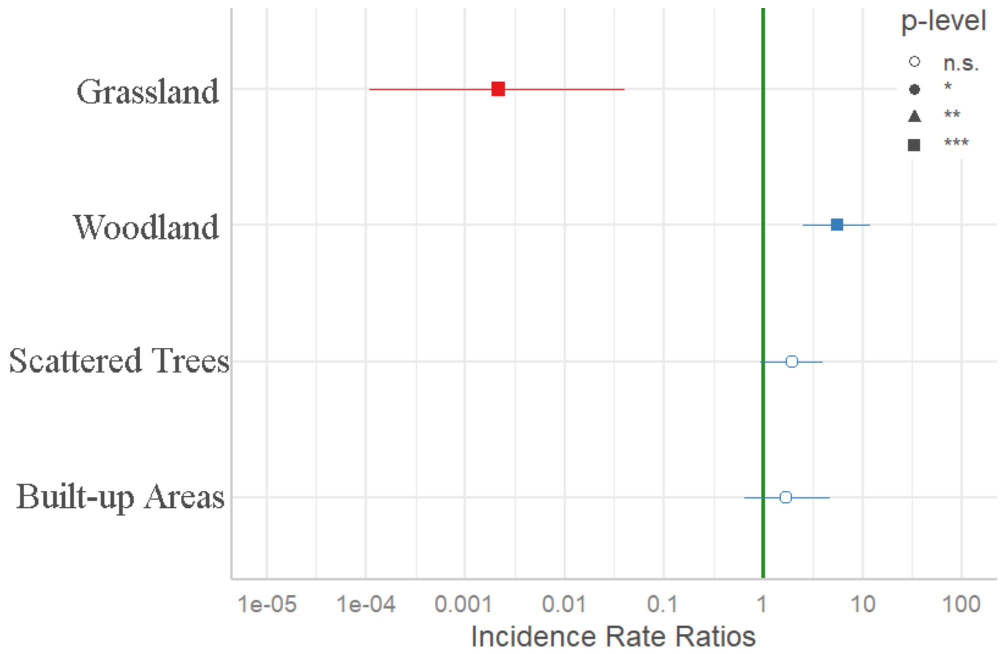

Figure 7: Incidence rate ratio response plots of Negative Binomial Generalised Linear Mixed Models, run on the original camera trap data in Mallinson (2021). Grassland was the intercept. Horizonal lines show 95% Confidence Intervals. Point Shape indicated significance. Vertical green line is the "neutral" line of IRR value of 1, IRR > 1 is a positive relationship, IRR< 1 is negative. Grassland showed a Negative relationship with badger activity, and woodland showed a positive relationship with activity. Scattered trees was near significant (p = 0.08), and was significant in the Home park models, so can also be considered a positive relationship. Note that this plot does not show the other explanatory variables that were present in this model.

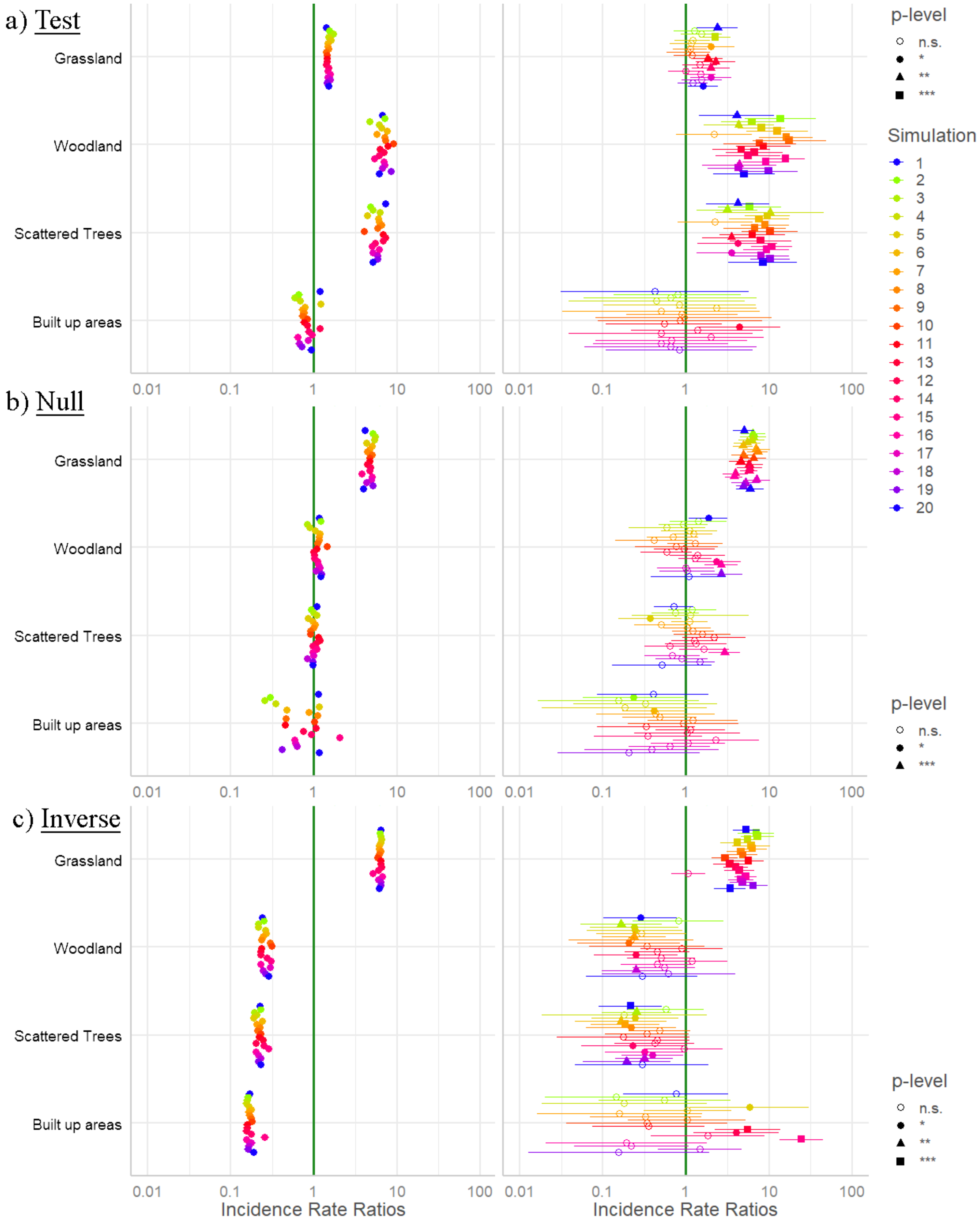

Figure 8: Incidence Rate Ratio response plots of Negative Binomial Generalised Linear Models run on reference (left) and camera trap (right) output data, from 20 simulations, across 3 versions of ABM. Badger Activity is the response variable and habitat classification as the explanatory variable. Grassland was the intercept. Note p-level symbol only refers to camera trap data. Horizonal lines show 95% Confidence Intervals. Vertical green line is the "neutral" line of IRR value of 1, IRR > 1 is a positive relationship, IRR< 1 is negative.

A) Test version: reference data shows a positive relationship with Grassland, Woodland & Scattered Trees, which the Camera data detected with an error rate of 18% (14 errors / (4 terms x 20 simulations))

B) Null version: reference data shows a strong positive relationship for Grassland and high variation for built-up. Camera data detected this with an error rate of 5% (4/80).

C) Inverse version: reference data shows positive relationship with Grassland and negative relationship for all other habitats. Cameras data mostly detected this, but with a high error rate of 28% (23/80) including 4 reversed relationships for Built-up.

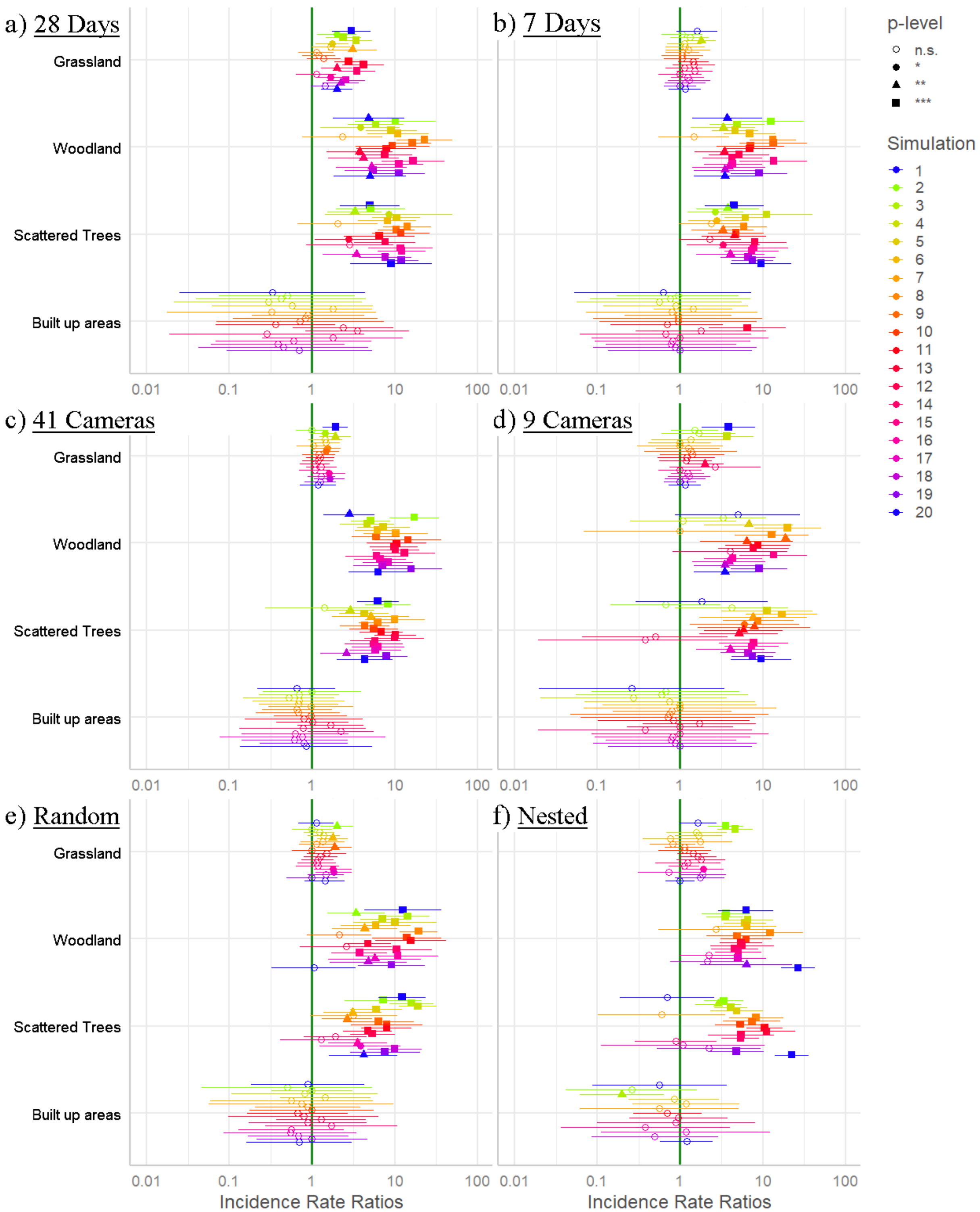

Figure 9: Incidence rate ratio response plots of Negative Binomial Generalised Linear Models run on camera trap (right) data sets from 20 simulations, for 6 variations of methodology. Badger Activity is the response variable and habitat classification as the explanatory variable, Grassland was the intercept. Vertical green line is the “neutral” line of IRR value of 1, IRR > 1 is a positive relationship, IRR< 1 is negative.

A) Increase Trapping effort to 28-days : had a lower error rate 11% (9 errors / (4 terms * 20 simulations)) compared to the default error rate of 18%
B) 7-Day trapping effort: had a higher error rate of 29% (23/80).
C) 41-Cameras on 130m Grid: had the same error rate of 18% (14/80)
D) 9-Cameras on 300m Grid: had a much higher error rate of 35% (28/80)
E) Randomly Placed Cameras, rather than on a grid: had a increased error rate of 26% (21/80)
F) A Nested setup of 3 cameras placed near a food patch, using the camera triple Group ID as a fixed effect: had the worst error rate of 34% (27/80)

Discussion

My ABM demonstrated that the methodology of camera traps analysed with generalised linear models may not be sufficiently effective at detecting trends under the design used in Mallinson (2021). The standard confidence interval for a type I error is 0.95, or 5% chance of the patten being there by chance (Schervish, 1996). When the sampling method was run on the virtual data across 20 simulations, it gave a type II error for 18% of the results. Considering this simulation had cameras which were 100% effective, the results in Mallinson (2021) may be very ineffective at detecting patterns of spatial activity.

The original study indicated that a lack of a significant positive relationship with urban areas suggested that urban badgers were not foraging in these areas, unlike red foxes. Thus, it is possible that urban badgers were more restrained to parks as urban adaptors, rather than urban exploiters like the red fox. The positive but non-significant relationship with urban areas may be due to the sampling method being ineffective at detecting a patterns of badgers foraging in built up areas.

A caveat is that deciding what counts as an 'error' compared to the reference data was not clear cut. The relationships in the reference data had to be inferred without P-values. This means they had to be clearly defined from the green 'neutral' line. They would also have to show low enough stochasticity between simulations to indicate that it is clearly a trend. For the Test model, the positive relationship with Grassland in the reference data could be considered too weak to be used as a comparison, which shifts the Test model error rate to 5% (3/60), with 1 error for each term. Similarly, in the Null model the stochasticity was low for the built-up term. If Built-up is removed the error rate is lowered to 8% (5/60). However, these changes only had small effect, with a new error rate of 15.5% (31/100) rather than 18% (43/240).

In order to improve this error rate, the only notable modification that reduced error rate was increasing the sampling effort to 28 days. This specifically decreased the error rate in detecting the positive relationship with grassland, from 70% (12/20) to 30% (6/20). This is not a surprising find, as increasing the trapping effort would be the most effective way to increase the contrast in spatial activity. However, future versions of this simulation need to account for the fact that real camera traps are not perfect (Swann, Kawanishi & Palmer, 2011). This would likely change what methodological alterations are effective at improving accuracy. In particular, the nested arrangement, which had the lowest accuracy, could prove useful when cameras are not precise at detecting badgers. This is important as increasing trapping effort would likely be the most logistically difficult modification. Cameras generate significantly more data to process, and can be constrained by factors like battery life or camera SD cards becoming full.

Overall, the simulated camera traps have demonstrated that Agent Based Models can be used to trial this type of sampling technique. Particularly, models indicate that their current setup may ineffective at detecting existing movement patterns. Further work is needed on what variations of the methodology can improve the accuracy. However, the flexibility of the programme makes it viable to virtually simulate any study design. This initial model has laid out a clear potential using ABM to run pilot studies on ecology of urban badgers. Furthermore, it can also be applied ecological fieldwork as a whole, as the ABM technique is highly versatile and can be used to understand the error rates of a virtually any study design.

ABM performance

The Test model was intended to be a reproduction of the badger behaviour scenarios seen in the camera trap study by Mallinson (2021). Here, the Incidence rate ratio response plots of the Test model reference data analysis in Figure 8A appear relatively consistent to the response plots of the real-world data Figure 7. The one major difference is that the relationship with Grassland was strongly negative in the original model, but was slightly positive in my simulations. This is curious as the Grassland had the highest cost of 1.06, which means the ***Badgers*** should have been selecting any other habitat patch when they ran their Cost evaluation loop. Combined with the Null model's strong positive relationship with Grassland, it can be concluded that there was some default preference to Grassland in my model.

The cause of this is unclear but is likely an interaction of the Badger's movement with the general size of the habitat. An initial bias that I investigated was the proximity to ***Setts*** as the area around the

Sett had by default a very high rate of activity. However, adding *Sett* proximity as an offset variable caused a reverse effect where Grassland had a strong negative relationship with activity (Figure 10 in appendix). This means that there was also an interaction with the behaviour, but what aspect has not been established. It did not appear to be caused by *Badgers*' memory, as disabling memory did not remove the positive relationship. It was also not caused by the context-specific nature of the CRSS as disabling *Food-Patches* did not remove the relationship either. Neither was it an artifact of the Pareto speed distribution as the relationship was still there when *Badgers* speed was fixed at 50m/min.

The variation in the IRR's for Built-up in the Null model (Figure 8B) is also curious. By default, *Badgers* might spend more time in a habitat by chance, as the first few *Food-Patches* they encounter would be added to the memory first and then visited over and over again. Because of the barrier checking function, the *Badgers* move slower in the urban habitat. This means that if by chance a larger portion of *Badgers* found urban *Food-Patches* then this would translate as high activity because it takes longer for them to navigate in and out.

Overall, the mode showed enough stochasticity in the movement trends between simulations that it could still be used to evaluate camera trap survey. The analysis was demonstrative of how effective the simulated surveys are even if the trends are not highly representative of true badger movements.

Future Model Development

The primary focus for further development of the model should be on tuning the model to match the trends seen in the real data. This would start with an investigation of the cause of the relationships with Grassland, and the navigation problem for Built-up areas. The memory function also needs work as the *Badgers* showed a large degree of overlap in their home ranges. If these can be addressed, then there is potential for this model to be expanded to add the other significant terms in Mallinson (2021) in order to complete the analysis of the studies methodology.

To address movement in Built-up areas, one tested solution was Navigational Loop. This would continually change the *Badgers* heading until there was no barrier in front of them. This prevented the *Badgers* getting stuck moving slowly in corners, allowing them to move through the Built-up area at speeds closer to the other habitats. The issue was the headings were not random so were not compatible with the CRSS. The Navigational Loop did work well with a prototype Correlated Random Walk. The CRSS was originally chosen because it was generic and didn't need telemetry data for headings and step lengths. However, if this data were to be available, then it can be extrapolated using the techniques to create a more accurate CRW version of my model.

The CRW could also function better with the memory and cost evaluation systems. Because headings in a CRW do not have to be random they can be more tailored to biases. For cost evaluation, the *Badger* can bias a heading to the proportionally lower part of their field of view, rather setting the heading towards a random low-cost patch. This could utilize a more continuous 'cost landscape' that funnels *Badgers* along gradient lines, allowing more specific routes to be developed. These routes could then be used to set linear/non-linear habitat in the model and work well in tandem with the A* waypoint system.

To adjust the A* memory system, a mechanism is needed by which *Badgers* can drop frequently empty *Food-Patches* from their memory. This is needed so that indirect competition causes more specific *Badger* home ranges. When patches are being frequently raided by other *Badgers*, they will be found empty by those that reach it slower, causing those individuals to drop the *Food-Patches*. Over a number of nights, this would cause the *Badgers* to build their own routes.

With these improvements, the model has potential to answer a greater range of methodological questions. For instance, how an edge effect could makes a habitat preference less clear, as a more fragmented habitat increases the encounter rate of new habitats. If the Cost Evaluation has a chance of the badger randomly chooses a less favourable habitat, then more encounters make it more likely they will spend time in less favourable habitats. This could dilute the spatial activity, making the patterns of habitat less clear and harder to detect. This effect would be stronger if the badgers also had a preferences for other habitat when they bordered a favourable habitat. This would be a important question to investigate, as different parks could easily vary in the fragmentation of their habitats.

A similar bias that the model could test for would be channelling effects. Because dense habitats channel animals down linear paths (Sollmann, 2018), the spatial activity detected by camera traps can be more erratic depending on whether they are placed next to one of these routes. This could be a particularly strong effect within Built-up areas with their walled streets. This was a particular problem for the models design as the *Badgers* in the simulation could actually get stuck in the maze of the Built-up areas.

Furthermore, the model could be converted to run on a recreation of the study area by converting habitat raster layers into Netlogo patches. This would allow the model to take on a function to aid in understanding the foraging patterns of badgers under different scenarios. In context of the urban exploitation investigated in Mallinson (2021), this would involve programming the other factors investigated. By running simulations with different behavioural preferences for these factors, the results of the real world studies can be better understood by seeing which simulated scenario they resemble. As the Urban badgers would continue to be investigated, this model could be improved in accuracy and adapted for new questions as ever evolving tool.

Conclusion

The aim of this study was to evaluate how effective a camera trap methodology was at detecting the spatial ecology of badgers when compared to a complete reference data set. The results indicate that the methods were less effective than a standard 95% confidence interval, and that increasing trapping effort is the most effective alteration to methodology. Future iterations of this model would need logistical improvements, and could then look at testing more variations design with more environmental factors. As this model is improved, its ability to put real data context by comparing different scenarios would make it an invaluable tool for the study of these urban badgers.

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Appendix

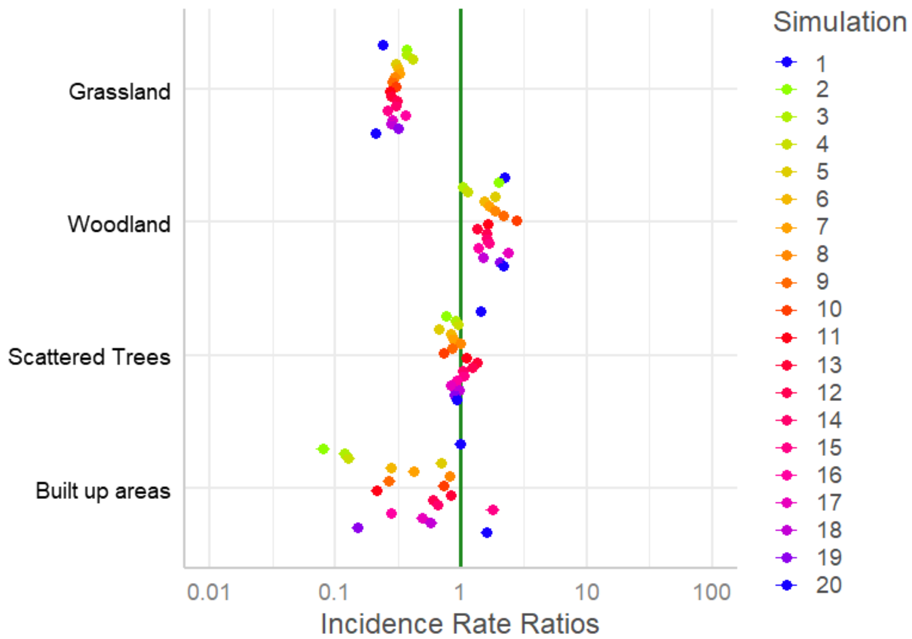

Figure 10: Incidence Rate Ratio response plots of Negative Binomial Generalised Linear Model run on reference data, from 20 simulations. Badger Activity is the response variable and habitat classification as the explanatory variable, with the addition of proximity to the nearest *Sett* as a offset variable. Grassland was the intercept. Horizonal lines show 95% Confidence Intervals. Vertical green line is the “neutral” line of IRR value of 1, IRR > 1 is a positive relationship, IRR< 1 is negative. Grassland shows a negative relationship with badger activity, whilst woodland shows a weak positive relationship.