Modelling current and future Lyme Disease risk in urban greenspaces: an agent-based approach

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Summary

Green infrastructure (GI) is an important promoter of urban biodiversity. However, improper GI planning can lead to negative outcomes (disservices) such as the increased transmission risk of Lyme Disease (LD) to humans. We describe an agent-based approach to model LD risk under current and future GI scenarios. We model the interaction of humans, ticks, and deer within GI in order to estimate LD risk to humans under different landscape scenarios. This will provide new insight into LD risk and enable policy makers to better understand how to plan GI to maximise its benefits to people and the planet.

KEYWORDS: Agent based modelling, green infrastructure, spatial pathology, urban planning

1. Introduction and background

Biodiversity is an important regulator of ecosystem services (functions that provide positive outcomes for people and the planet) and disservices (functions that provide negative outcomes). To promote positive outcomes in urban areas we need to manage services and disservices (Labib et al., 2021). One approach is to create networks of planned semi-natural spaces i.e., green infrastructure (GI). However, planning GI can difficult. Debates such as whether a singular large habitat or several small (SLOSS) habitats is better for biodiversity are ongoing and raises questions about the optimal size, shape, and layout of GI (Fahrig, 2020).

Here, we focus on one disservice: the transmission of pests, pathogens, and diseases, specifically *Lyme borreliosis* i.e., Lyme disease (LD). LD is a bacterial infection transmitted to humans through the bite of an infected tick. GI provides corridors for tick hosts to move into urban areas, creates urban refugia to hosts and ticks, and provides new opportunities for interaction between people and infected ticks (Steinbrink et al., 2022).

LD transmission risk refers to either acarological risk (the density of infected ticks (DIN)), or LD prevalence in humans (Steinbrink et al., 2022). LD risk is commonly estimated using two approaches: statistical modelling of LD risk (e.g., DIN or prevalence in humans) and predictor variables (such as temperature, land cover); or mathematical models, which simulate vector-host-pathogen-transmission cycles (Norman et al., 2016). However, both types of models are deterministic and embed assumptions about population level tick, host, and human behaviour and their interactions with each other and the environment. It is therefore difficult to predict how LD risk may change under alternate landscape scenarios.

Agent-based models (ABMs, also known as individual-based models), offer a promising alternative approach to estimating LD risk. ABMs enable population level patterns and interactions to be observed and understood by simulating individual population members (Grimm and Railsback, 2005). ABMs remove problematic assumptions about population level behaviours and enable dynamic between-agent (ticks, hosts, humans) and agent-environment interactions to be observed, helping us to understand population-scale responses to changes in environment. ABMs enable us to understand how current LD risk occurs (Arifin et al., 2015) and how changes in the area, type, or distribution of GI changes LD risk.

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Here, we apply an ABM to understand current LD risk within GI in Glasgow, UK and how different GI planning scenarios may change LD risk. Using field observations and secondary empirical data, we develop an ABM to replicate typical tick, Roe deer and human movement and interaction of the three species and answer the following research questions:

1. How does LD risk vary spatially and temporally in Glasgow?
2. How does GI size, shape, and layout change LD risk in Glasgow?

2. Methods

2.1 Model development

The ABM (Figure 1) is designed to model tick, deer and human interactions within GI spaces and transmission of LD over 6 years (x2 the average tick life span). Deer move freely through the model whereas humans only exist within GI spaces. Ticks can also move throughout the model but only when attached to a host. The model consists of four agents: ticks, Roe deer (adult and juvenile), and humans. Other tick hosts (rodents, insectivores, birds) are not modelled as agents to minimise computational demand but are considered within tick behaviour. Spatial distributions of deer and ticks are based on Spring/Summer 2022 field surveys and humans are seeded at the entrances of GI. Ticks interact with other agents by attaching to them, feeding on them, and then dropping off.

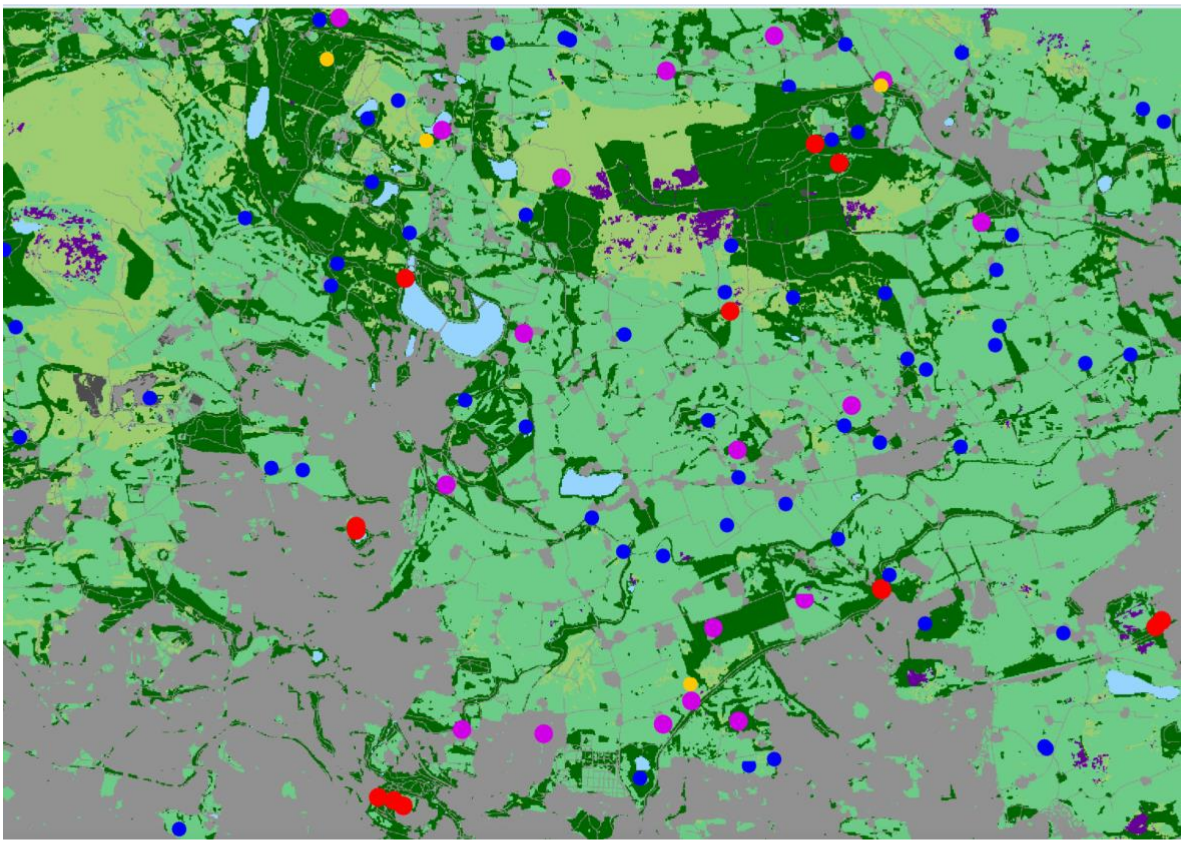

Figure 1 The ABM model. Adult deer are displayed as pink circles, juvenile deer as orange circles, ticks as blue circles and humans as red circles.

Deer behaviour is based on an ABM developed by Topping et al. (2003). The ABM uses secondary empirical data to parameterise deer behaviour and control changes in behaviour (Jepsen and Topping, 2004). Deer are split into two agent types: Adult deer (1+ years) and juvenile deer (<1 year) to simplify the transition from juvenile to adult deer.

Tick behaviour is described in figure 2 and uses secondary empirical data (Li et al., 2019) and domain knowledge from specialists in tick phenology, behaviour, and disease. To model other tick hosts (rodents, insectivores, birds), probability distributions are used to describe the likelihood of attachment, transport distance and transmission risk from host to tick (from secondary empirical data). Initial tick infection rate is estimated from laboratory tests of field collected ticks for the *Borrelia* pathogen. Climate data is used to determine tick activity and mortality.

Modelling human behaviour is highly complex and large amounts of observational data are required to realistically model human behaviour. Humans are therefore only modelled within GI spaces where data on their behaviour will be collected. The risk a human will contract LD is based upon estimations in other western European countries e.g. (Markowicz et al., 2021). Climate data is used to influence human behaviour (e.g., more people during warm, dry weather).

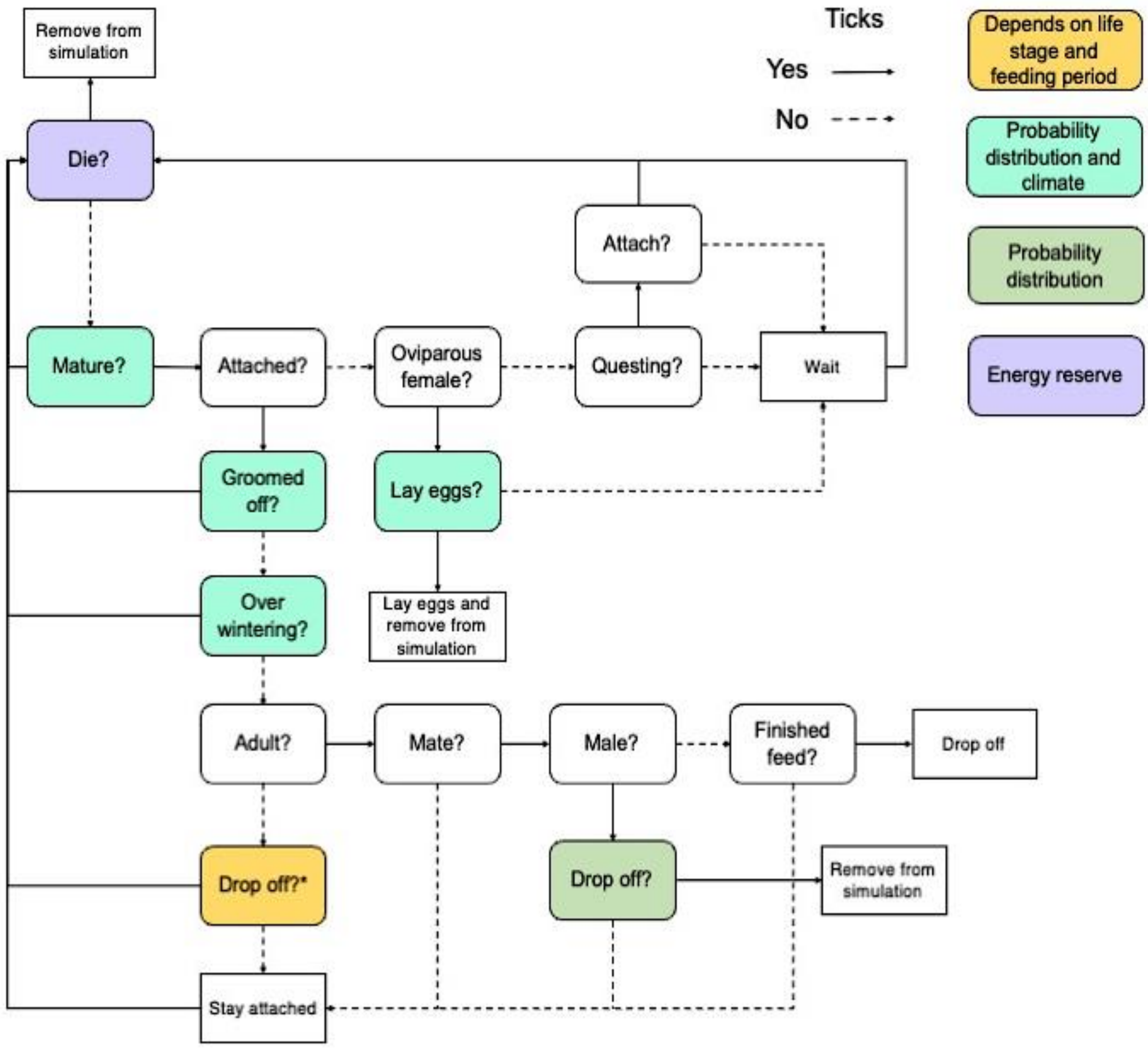

Figure 2 Flow chart demonstrating tick behaviour.

2.2 Study area

Our research is part of a larger project investigating GI in 15 UK towns and cities. Here, we use Glasgow as our case study following field confirmation of Roe deer and tick presence in most surveyed sites (Figure 3). Due to their size, cities were surveyed using a transect from the centre of the city to its edge, which increased in width with distance from the city centre forming a 'wedge'. GI sites within each wedge were selected to capture a gradient of GI from urban to rural settings. Our model covers an area of 250 km^2 and contains all Glasgow wedge sites.

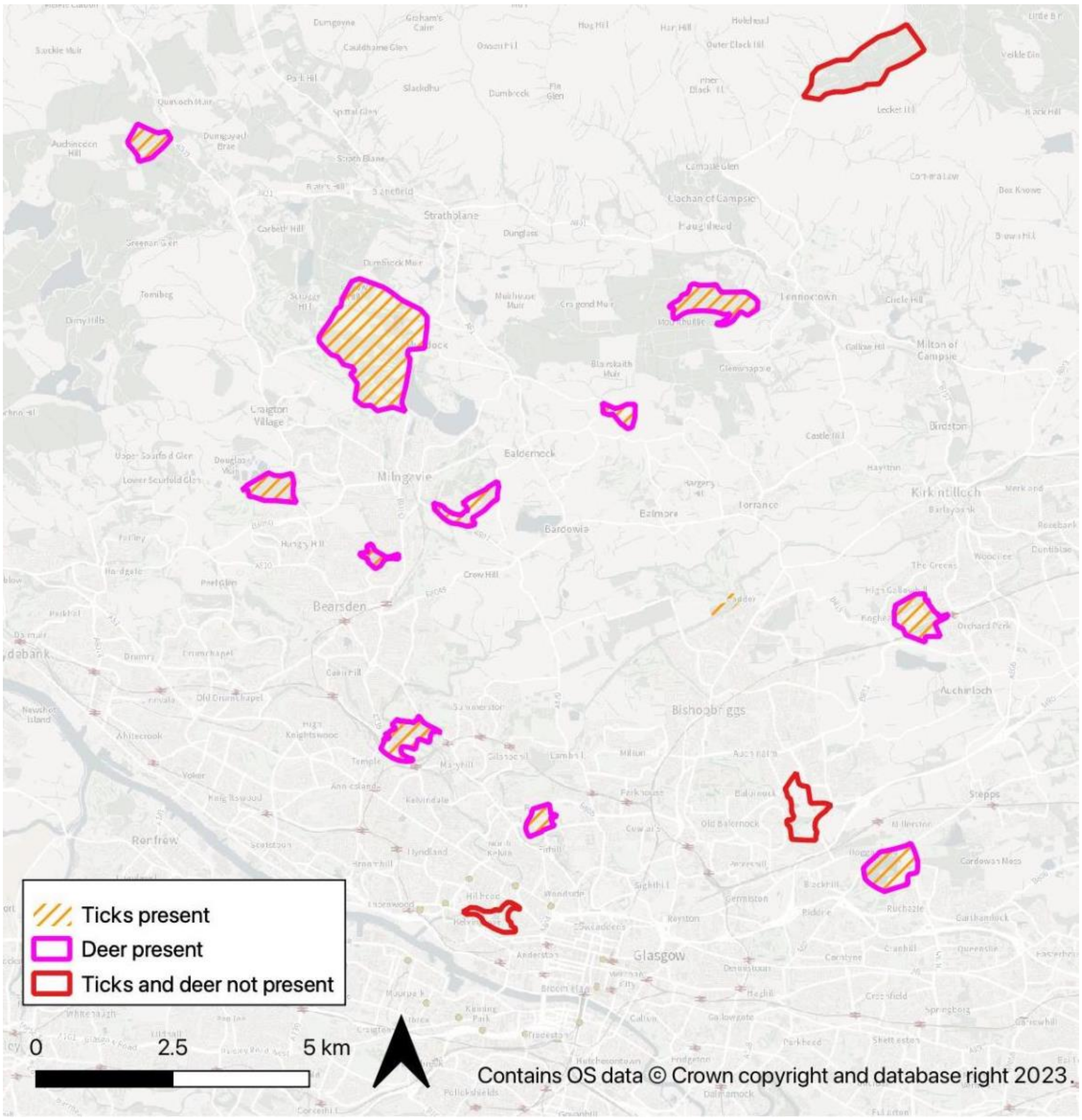

Figure 3 Glasgow city sites and confirmation of tick/deer presence.

3. Model results and scenario testing

To quantify LD risk, surfaces of the number of infected humans, DIN, density of nymphs, density of deer, and number of tick attachments to other LD competent and non-competent hosts will be output at daily intervals. Outputs will be aggregated to three-monthly averages to quantify seasonal variations. As the model is stochastic, Monte Carlo Simulation will be used to establish averages and their associated uncertainties (Evans, 2011). Model results will be compared against reported cases of LD in

Glasgow city as a preliminary indicator of model performance.

Following the first model run using baseline conditions (current GI layout), the model will be re-run with a series of new GI layouts. The GI layouts will follow a gradient where the number of GI increases and their size decreases to reflect the opposing sides of the SLOSS debate. LD risk surfaces will be produced for each scenario to demonstrate which GI layouts increase LD risk and which decrease LD risk.

4. Conclusion

Model development and analysis are still ongoing at the time of writing. Scenario results described in section 3 alongside a more detailed description of model development will be included in the accompanying oral presentation. The scenario results are planned to be incorporated into a web-based tool that can be used by urban planners to inform future GI planning. Our ABM provides new insights into the disservices that can arise from GI creation and provides policy makers with a tool to better understand how to plan GI to maximise its benefits to people and the planet.

5. Acknowledgements

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7. Biographies

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Jonathan Huck is a Senior Lecturer in Geographical Information Science in the Department of Geography at the University of Manchester. He is interested in the application of maps, GIS and emergent technologies to geographical problems, particularly in the areas of health, conflict and the environment.