Challenges for ABM in Applied Urban Modelling

Nick Malleson, Alison Heppenstall and Ed Manley

AUM Symposium, 29th June – 1st July 2022
University of Cambridge

Computers, Environment and Urban Systems
Volume 32, Issue 6, November 2008, Pages 417-430

Key challenges in agent-based modelling for geo-spatial simulation

Andrew Crooks, Christian Castle, Michael Batty

Show more

GeoInformatica (2019) 23:169–199
https://doi.org/10.1007/s10707-018-00340-z

CrossMark

Crossing the chasm: a 'tube-map' for agent-based social simulation of policy scenarios in spatially-distributed systems

J. Gareth Polhill[1] · Jiaqi Ge[1] · Matthew P. Hare[1] · Keith B. Matthews[1] · Alessandro Gimona[1] · Douglas Salt[1] · Jagadeesh Yeluripati[1]

Editorial: Meeting Grand Challenges in Agent-Based Models

Li An[1], Volker Grimm[2,3], Billie L. Turner II[4]

[1]Center for Complex Human-Environment Systems, Department of Geography San Diego State University, Storm Hall 303C, San Diego, CA, United States
[2]Department of Ecological Modelling, Helmholtz Centre for Environmental Research - UFZ, Permoserstr. 15, 04318 Leipzig, Germany
[3]University of Potsdam, Potsdam, Germany
[4]School of Geographical Sciences and Urban Planning, College of Liberal Arts and Sciences, Arizona State University, PO Box 875302, Tempe, AZ 85287-5302, United States
Correspondence should be addressed to lan@mail.sdsu.edu

Journal of Artificial Societies and Social Simulation 23(1) 13, 2020
Doi: 10.18564/jasss.4012 Url: http://jasss.soc.surrey.ac.uk/23/1/13.html

Received: 16-03-2019 Accepted: 05-11-2019 Published: 31-01-2020

Methodological Issues of Spatial Agent-Based Models

Steven Manson[1], Li An[2], Keith C. Clarke[3], Alison Heppenstall[4], Jennifer Koch[5], Brittany Krzyzanowski[1], Fraser Morgan[6], David O'Sullivan[7], Bryan C. Runck[8], Eric Shook[1], Leigh Tesfatsion[9]

[1]Department of Geography, Environment, and Society, University of Minnesota, 267, 19th Ave S, Minneapolis, MN 55455, United States
[2]PKU-SDSU Complex Human-Environment Systems Center and Department of Geography, San Diego State University, 5500 Campanile Dr, San Diego, CA 92182, United States
[3]Department of Geography, University of California Santa Barbara, 1720 Ellison Hall, Santa Barbara, CA 93106, United States
[4]School of Geography, University of Leeds, Leeds LS2 9JT, United Kingdom
[5]Department of Geography and Environmental Sustainability, The University of Oklahoma, 100 E Boyd St., Norman, OK 73019, United States
[6]Landscape Policy and Governance Manaaki Whenua — Landcare Research, Private Bag 92170, Auckland Mail Centre, Auckland 1142, New Zealand
[7]School of Geography Environment and Earth Sciences, Victoria University of Wellington, Wellington City 6012, New Zealand

Geographical Analysis (2021) **53**, 76–91

Special Issue

Future Developments in Geographical Agent-Based Models: Challenges and Opportunities

Alison Heppenstall[1,2], Andrew Crooks[3], Nick Malleson[1,2], Ed Manley[1,2], Jiaqi Ge[1], Michael Batty[4]

[1]School of Geography, University of Leeds, Leeds, U.K., [2]Alan Turing Institute, The British Library, London, U.K., [3]Department of Computational and Data Sciences and Department of Geography and Geoinformation Science, George Mason University, Fairfax, VA USA, [4]Centre for Advanced Spatial Analysis (CASA), University College London, London, U.K.

J Land Use Sci. 2016; 11(2): 177–187. PMID: 27158257
Published online 2015 Apr 13. doi: 10.1080/1747423X.2015.1030463

Strategic directions for agent-based modeling: avoiding the YAAWN syndrome

David O'Sullivan,[a,*] Tom Evans,[b] Steven Manson,[c] Sara Metcalf,[d] Arika Ligmann-Zielinska,[e] and Chris Bone[f]

Author information Copyright and License information Disclaimer

Presentation Overview

- Rule initialisation and agent behaviour
- Visualisation
- Data
- Calibration / validation and uncertainty
- Computational
- Digital Twins
- (Examples throughout…)

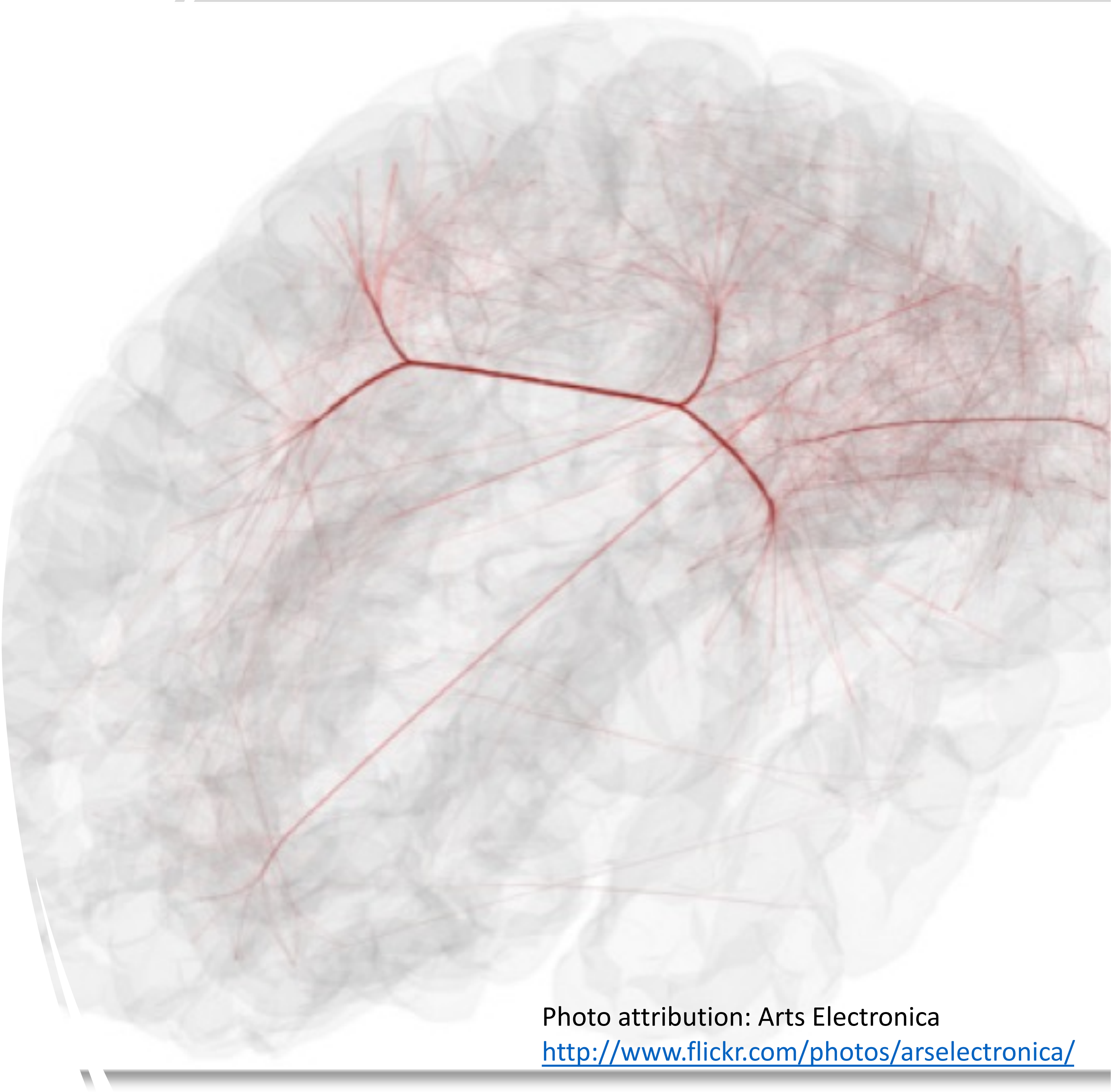


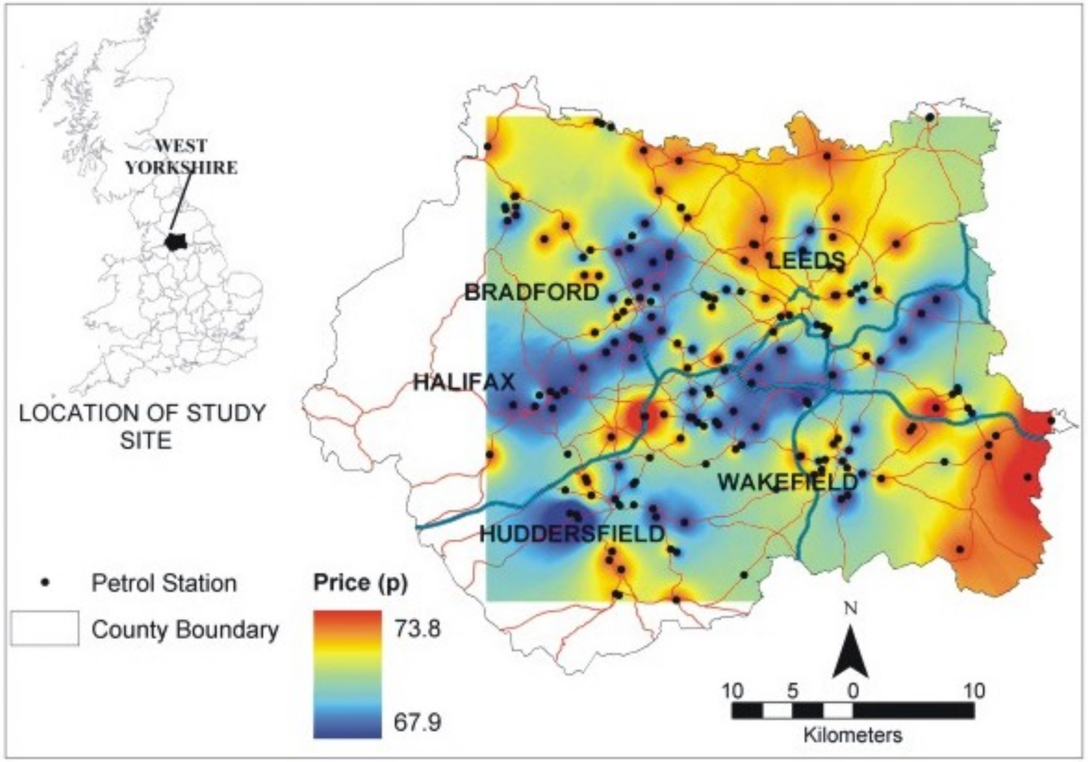
Photo attribution: Arts Electronica
http://www.flickr.com/photos/arselectronica/

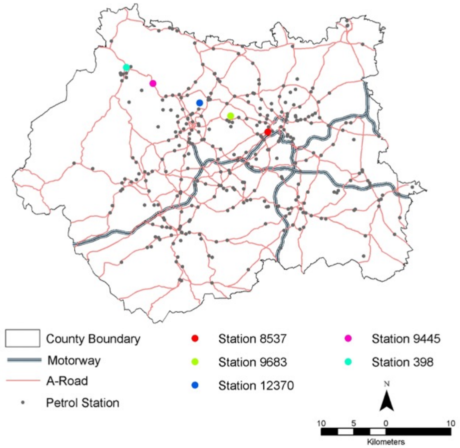
Rule initialisation and agent behaviour

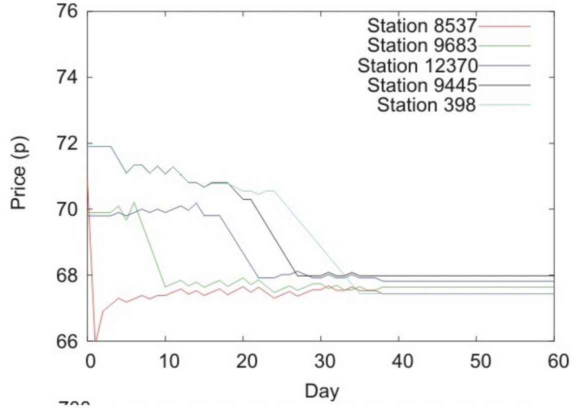
Rule initialisation and agent behaviour

- Opportunities for agents to 'learn' how to behave, based on rewards
- Deep Reinforcement Learning and other generative approaches enable production of rulesets that mimic humans
- Learning in 3D spaces allows agents to 'experience' cities like we do
- However – models very slow/difficult to calibrate, and may lead to unrealistic and unconstrained behaviours
- Inverse Generative Social Science

Visualisation

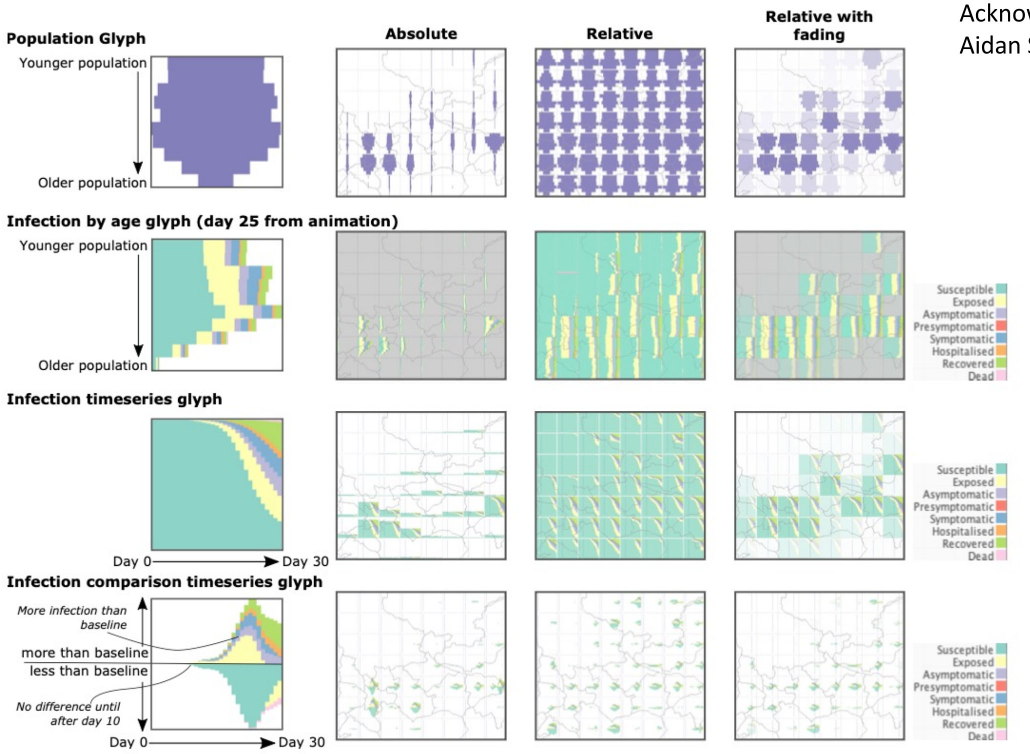


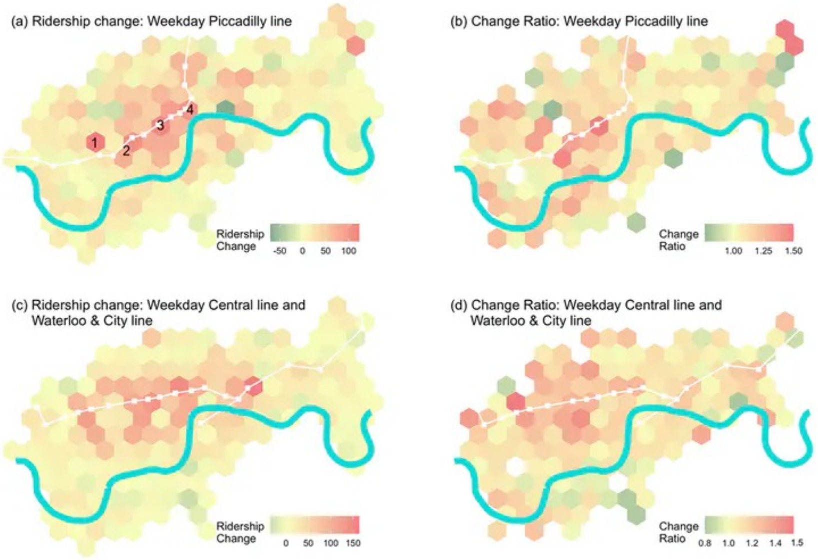




Heppenstall et al (2006); https://www.jasss.org/9/3/2.html

Acknowledgement:
Aidan Slingsby





Yuanxuan Yang et al. (2022). *Journal of Transport Geography*.

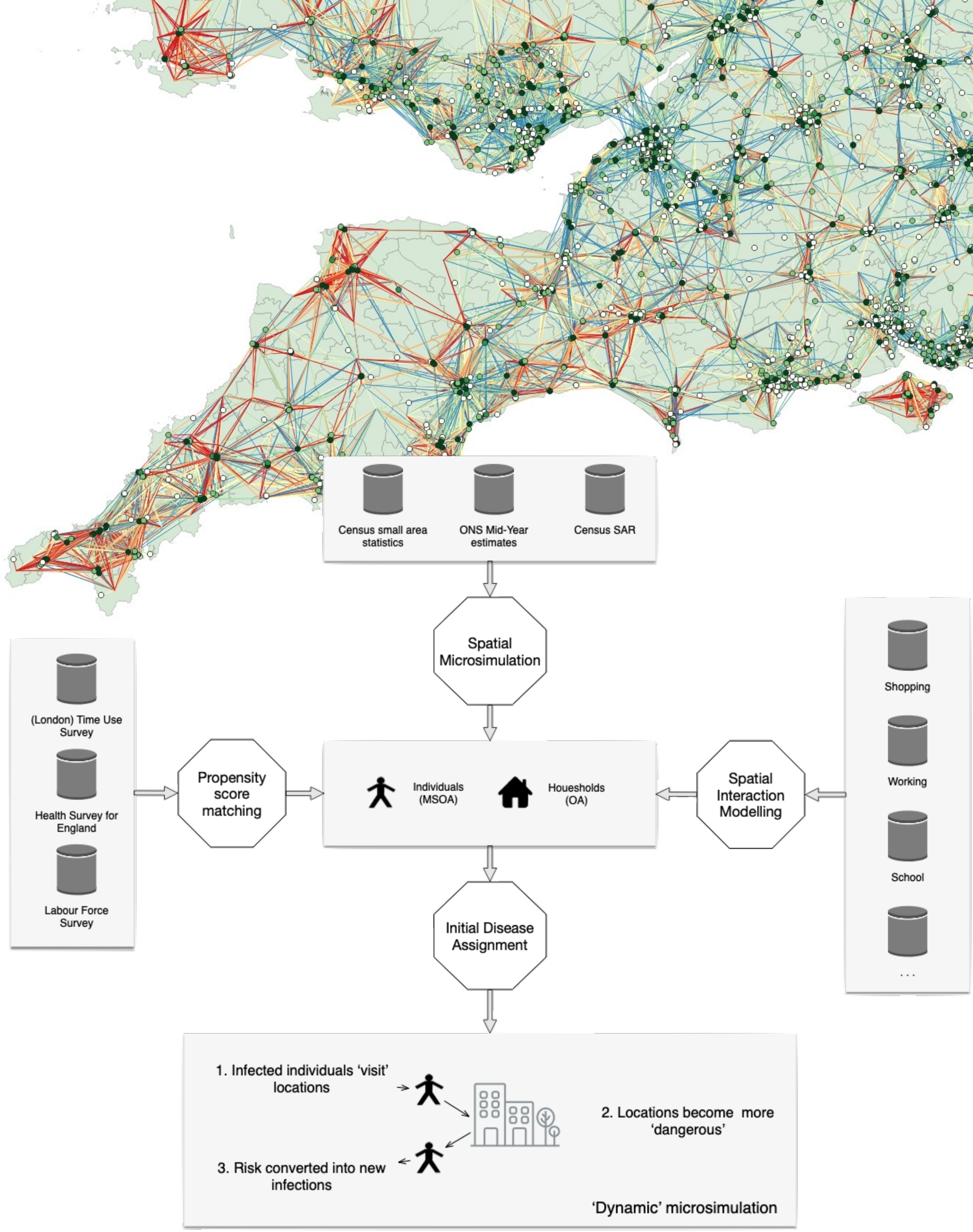
Data

Data

- ABMs are typically very rich (high spatio-temporal resolution)
- But data are often much coarser (usually highly aggregated)
- Difficulties:
    - Pattern Oriented Modelling (POM: Grimm et al., 2005)
    - Identifiability

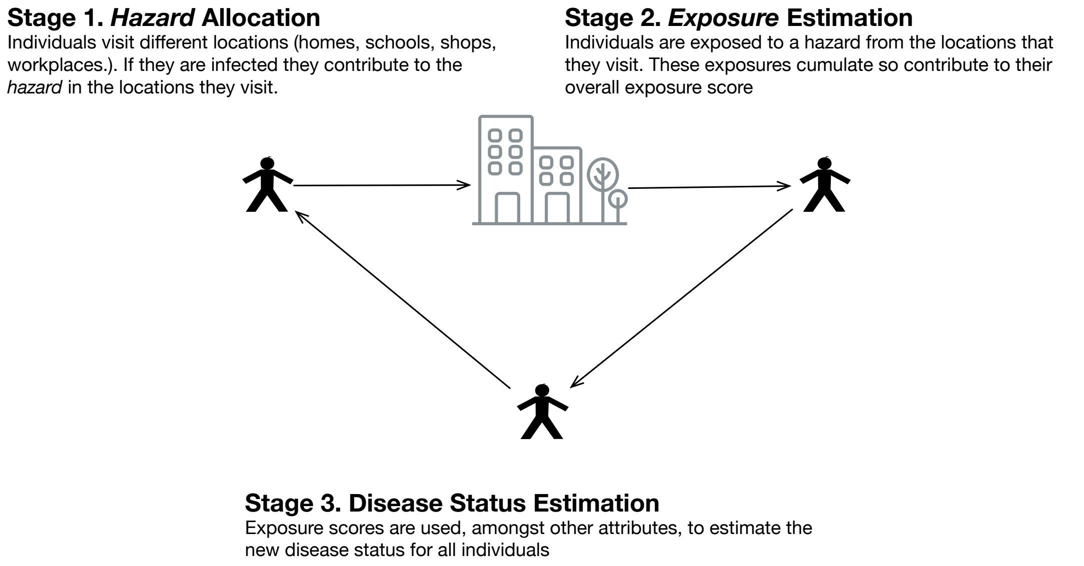
Example: Dynamic Model for Epidemics (DyME)

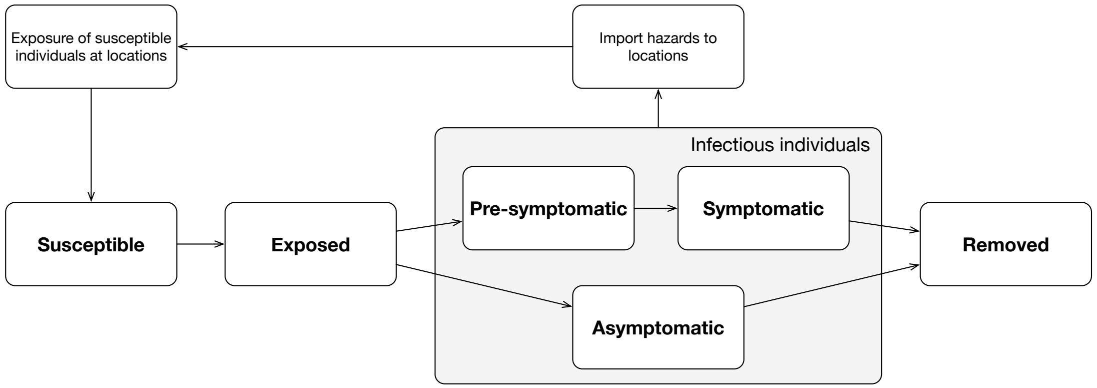
- Spooner et al. (2021)
- Part of the Royal Society Rapid Assistance in Modelling the Pandemic (RAMP) call
- COVID transmission model including dynamic spatial microsimulation, spatial interaction model, data linkage, ….
- Represents all individuals in a study area with activities: *home, shopping, working, schooling*
- Daily timestep



Dynamic Model for Epidemics (DyME)

- Incredible detailed model!
- Only data available for validation: COVID cases and hospital deaths
- Only quantify a tiny part of the transmission dynamics
- Modelling was the easy part …
- No ‘solution’, but better use of the available data might help ….



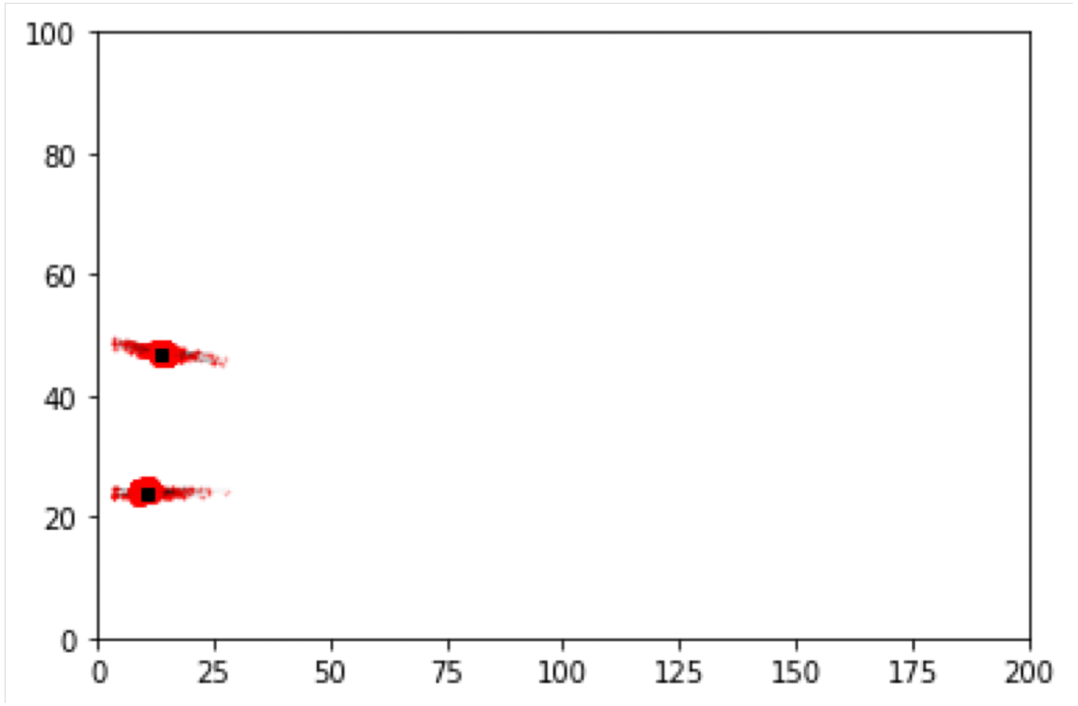


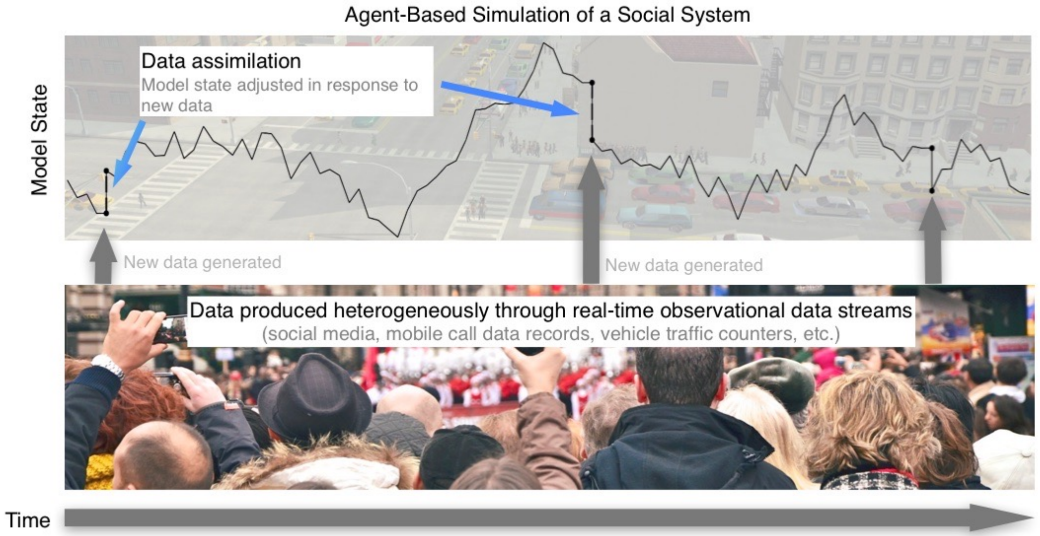
Data Assimilation for Agent-Based Models

- We know that models will diverge from reality
  - Uncertainty in parameters, input data, model structure, etc.
  - Natural stochasticity
- How to keep models and reality aligned?
- Data Assimilation
  - Used in meteorology and hydrology to bring models closer to reality.
  - Try to improve estimates of the true system state by combining observations and estimates of the system state (the model)
- https://dust.leeds.ac.uk/

Data Assimilation for Agent-Based Models

- DUST project: experimenting with various data assimilation algorithms
  - (Ensemble / Unscented) Kalman Filter
  - Particle Filter
  - Quantum Field Theory
- Work towards large-scale, real-time urban ABMs
- For more information: https://urban-analytics.github.io/dust/publications.html

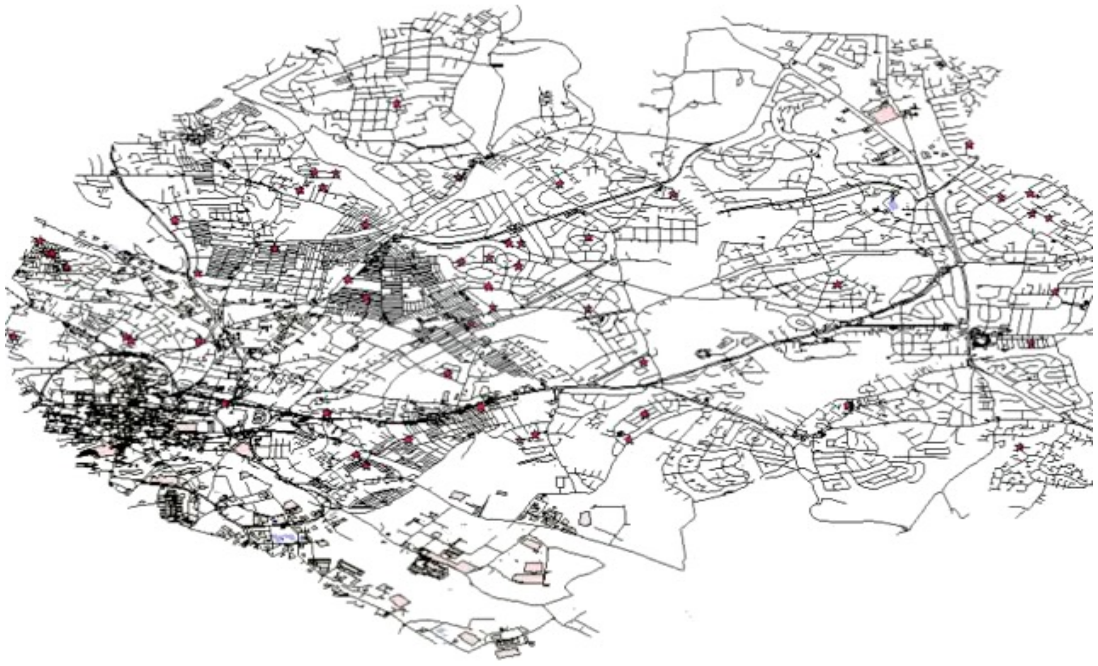


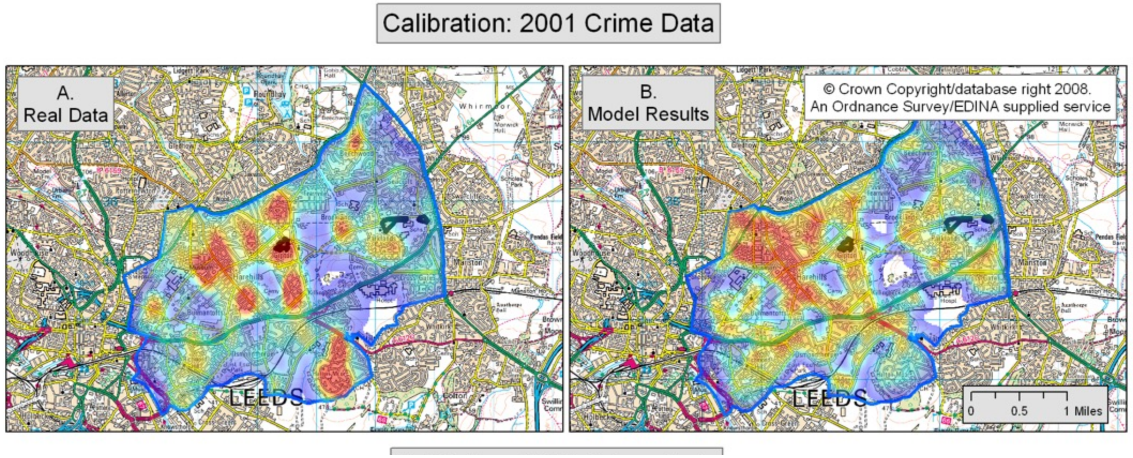


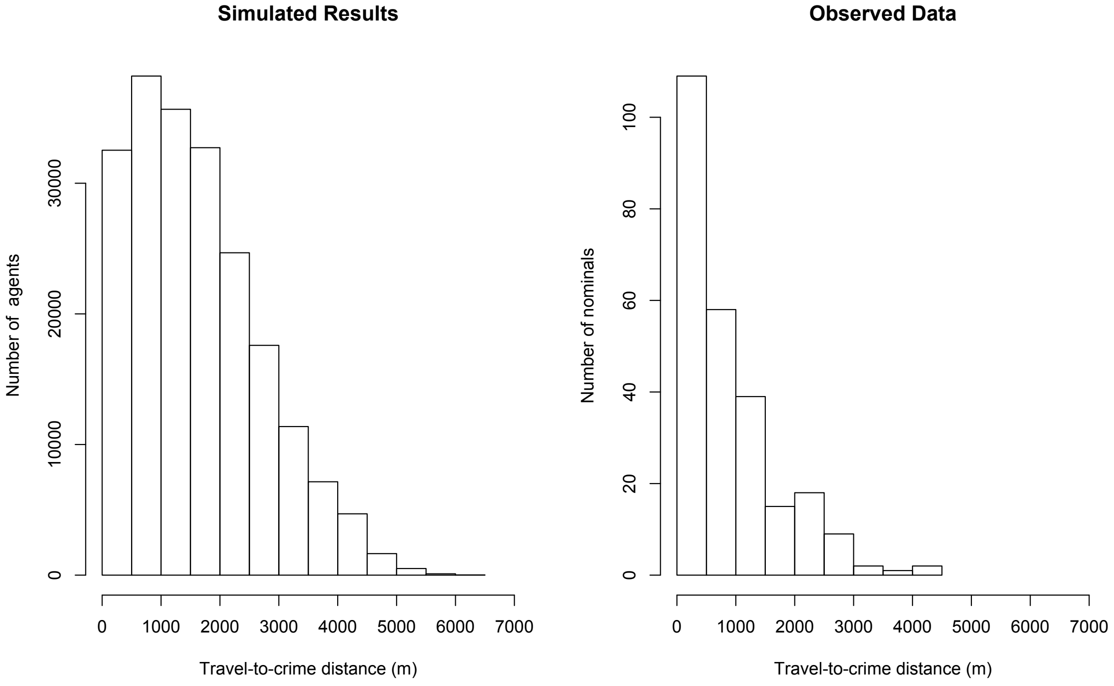
Calibration / validation and uncertainty

Calibration, Validation, and Uncertainty

- Ongoing challenges for ABM (An et al., 2021)
    - Difficult to evaluate model at multiple scales
    - Limited data
    - Computationally expensive to run large numbers of models (a pre-requisite for many methods)







Malleson, N., L. See, A. Evans, and A. Heppenstall (2012). Implementing comprehensive offender behaviour in a realistic agent-based model of burglary. SIMULATION 88(1) 50-71

Calibration, Validation, and Uncertainty

- McCulloch (2022)
- Draw on **Uncertainty Quantification** for more **efficient calibration** and for quantifying **understanding uncertainty:**
- History Matching to quantify uncertainties and rule out implausible parameter ranges
- Approximate Bayesian Computation to find suitable parameter distributions

JASSS
THE JOURNAL OF ARTIFICIAL SOCIETIES AND SOCIAL SIMULATION

JASSS is an interdisciplinary journal for the exploration and understanding of social processes by means of computer simulation

ENHANCED BY Google

Homepage | Journal information | Journal statistics | Journal Content | Contact us

Home > 25 (2), 1

Calibrating Agent-Based Models Using Uncertainty Quantification Methods

Josie McCulloch[a], Jiaqi Ge[a], Jonathan A. Ward[b], Alison Heppenstall[c], J. Gareth Polhill[d] and Nick Malleson[e]

[a]University of Leeds, United Kingdom; [b]School of Mathematics, University of Leeds, United Kingdom; [c]University of Glasgow, United Kingdom; [d]The James Hutton Institute, United Kingdom; [e]School of Geography, University of Leeds, United Kingdom

Other articles by these authors

Journal of Artificial Societies and Social Simulation **25** (2) 1
<https://www.jasss.org/25/2/1.html>
DOI: 10.18564/jasss.4791 Save citation...

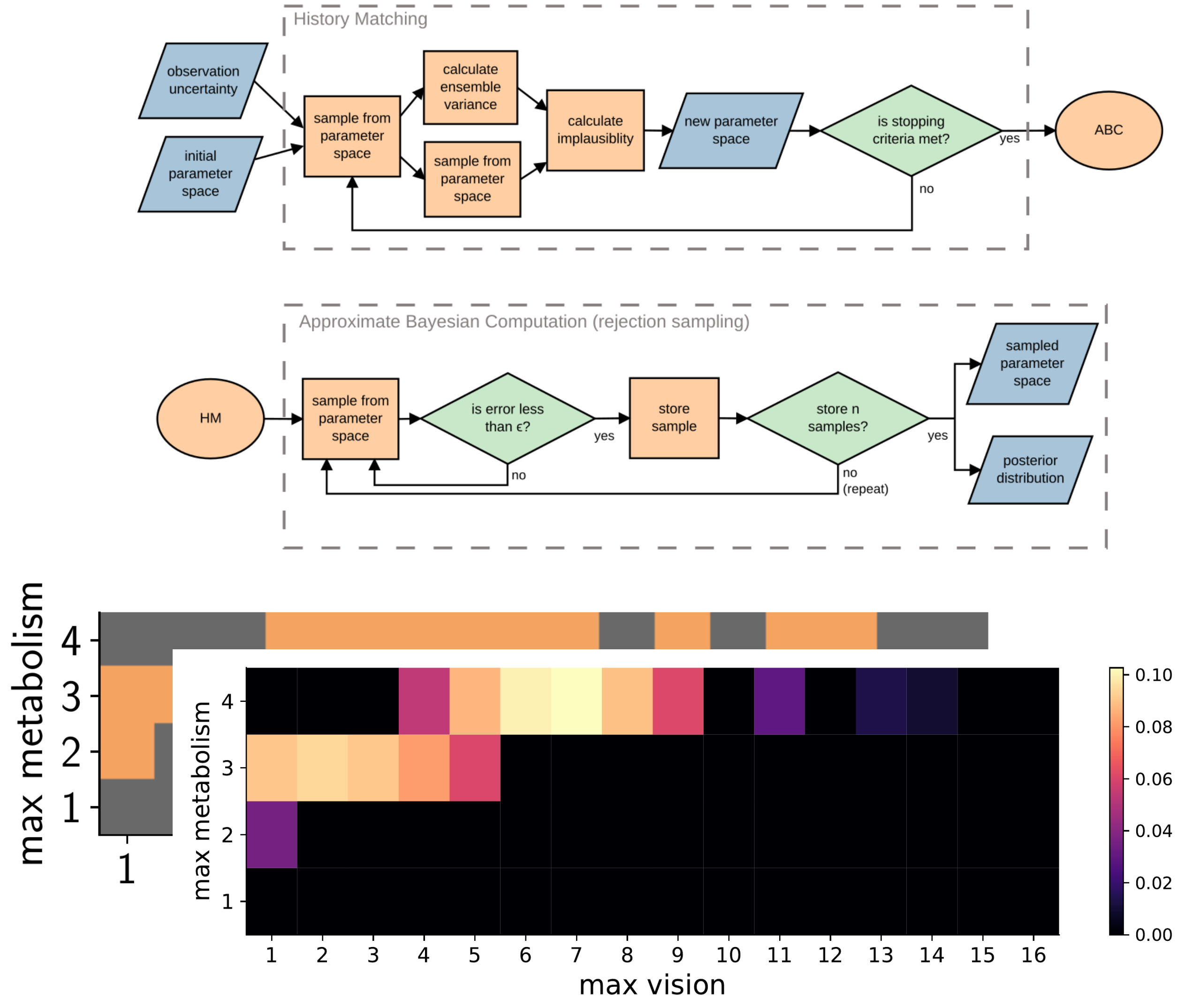
Received: 19-May-2021 Accepted: 29-Jan-2022 Published: 31-Mar-2022

Abstract

Agent-based models (ABMs) can be found across a number of diverse application areas ranging from simulating consumer behaviour to infectious disease modelling. Part of their popularity is due to their ability to simulate individual behaviours and decisions over space and time. However, whilst there are plentiful examples within the academic literature, these models are only beginning to make an impact within policy areas. Whilst frameworks such as NetLogo make the creation of ABMs relatively easy, a number of key methodological issues, including the quantification of uncertainty, remain. In this paper we draw on state-of-the-art approaches from the fields of uncertainty quantification and model optimisation to describe a novel framework for the calibration of ABMs using History Matching and Approximate Bayesian Computation. The utility of the framework is demonstrated on three example models of increasing complexity: (i) Sugarscape to illustrate the approach on a toy example; (ii) a model of the movement of birds to explore the efficacy of our framework and compare it to alternative calibration approaches and; (iii) the RISC model of farmer decision making to demonstrate its value in a real application. The results highlight the efficiency and accuracy with which this approach can be used to calibrate ABMs. This method can readily be applied to local or national-scale ABMs, such as those linked to the creation or tailoring of key policy decisions.

Calibration, Validation, and Uncertainty

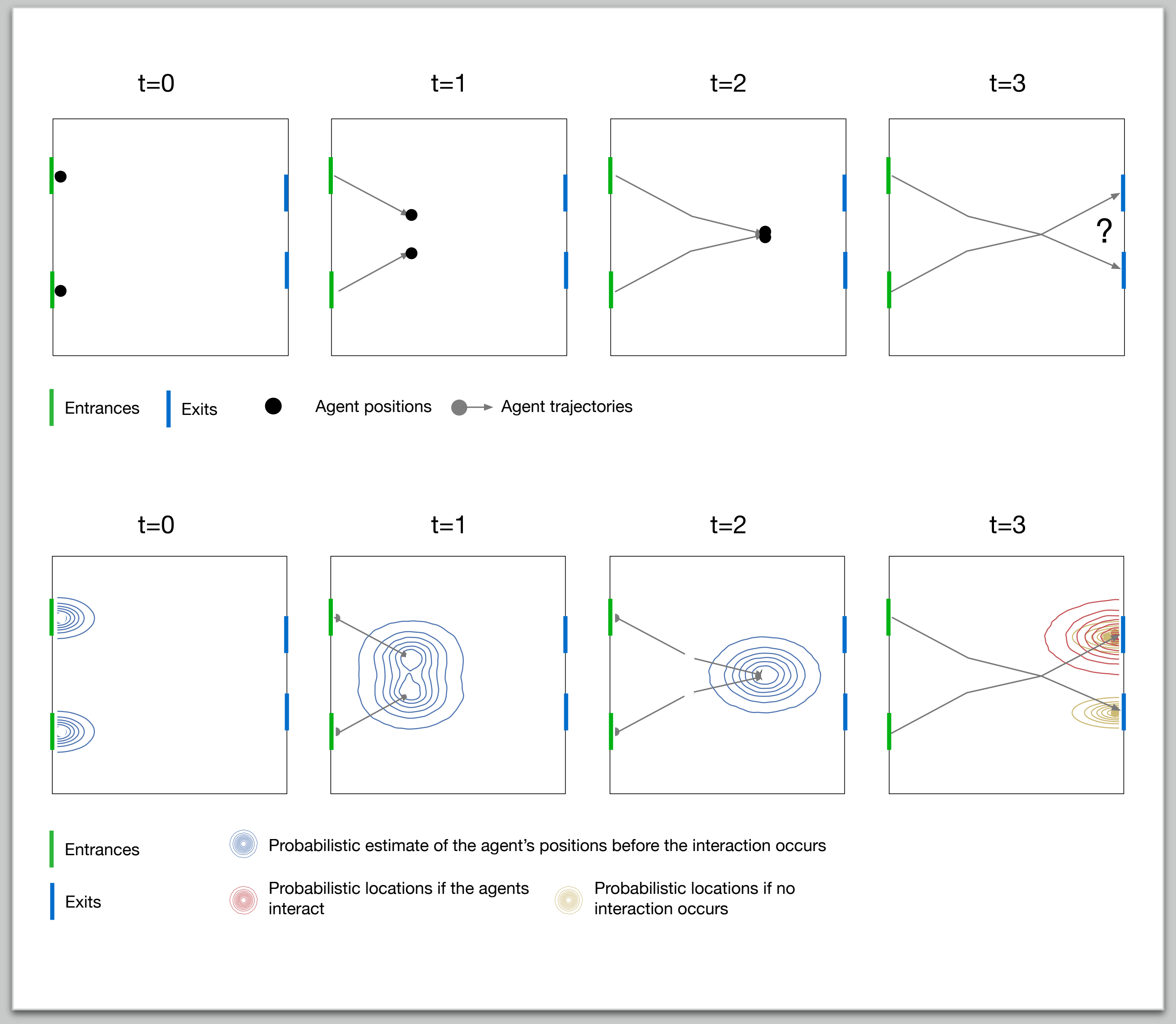
1. Define parameter space to be explored
2. Quantify uncertainties:
    - Model discrepancy (how well the model outcomes reflect the data)
    - Ensemble variance (how much the model varies with the same parameter values)
    - Observation uncertainty
3. Run History Matching to identify implausible parameter regions
4. Run Approximate Bayesian Computation, using uniform priors from HM



Source: McCulloch (2022): https://www.jasss.org/25/2/1.html

(An aside) Probabilistic Agent-Based Modelling

- Rather than running an ABM thousands or millions of times to explore its uncertainties, can we treat agents as fundamentally probabilistic?
- Instead of representing agents as points, represent them as probability distributions.
- Loads of questions about how this would work and what would happen, but might be worth exploring…



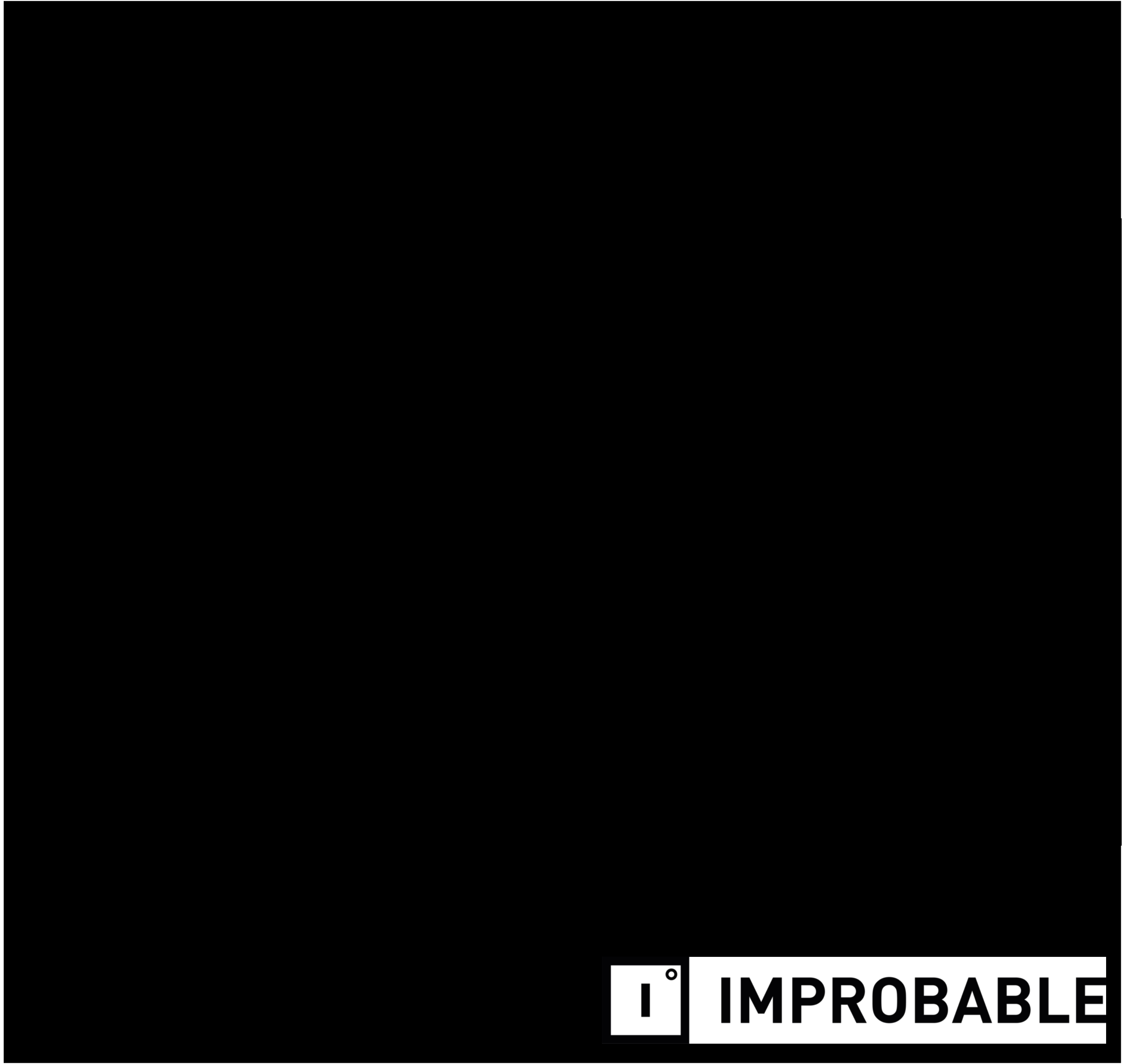
Computational Issues

Computational Issues

- ABMs are typically computationally expensive
- This prevents the use of more advanced methods (need 1000s+ model runs)
- Big computers can help
- But maybe if modelers were better at programming …

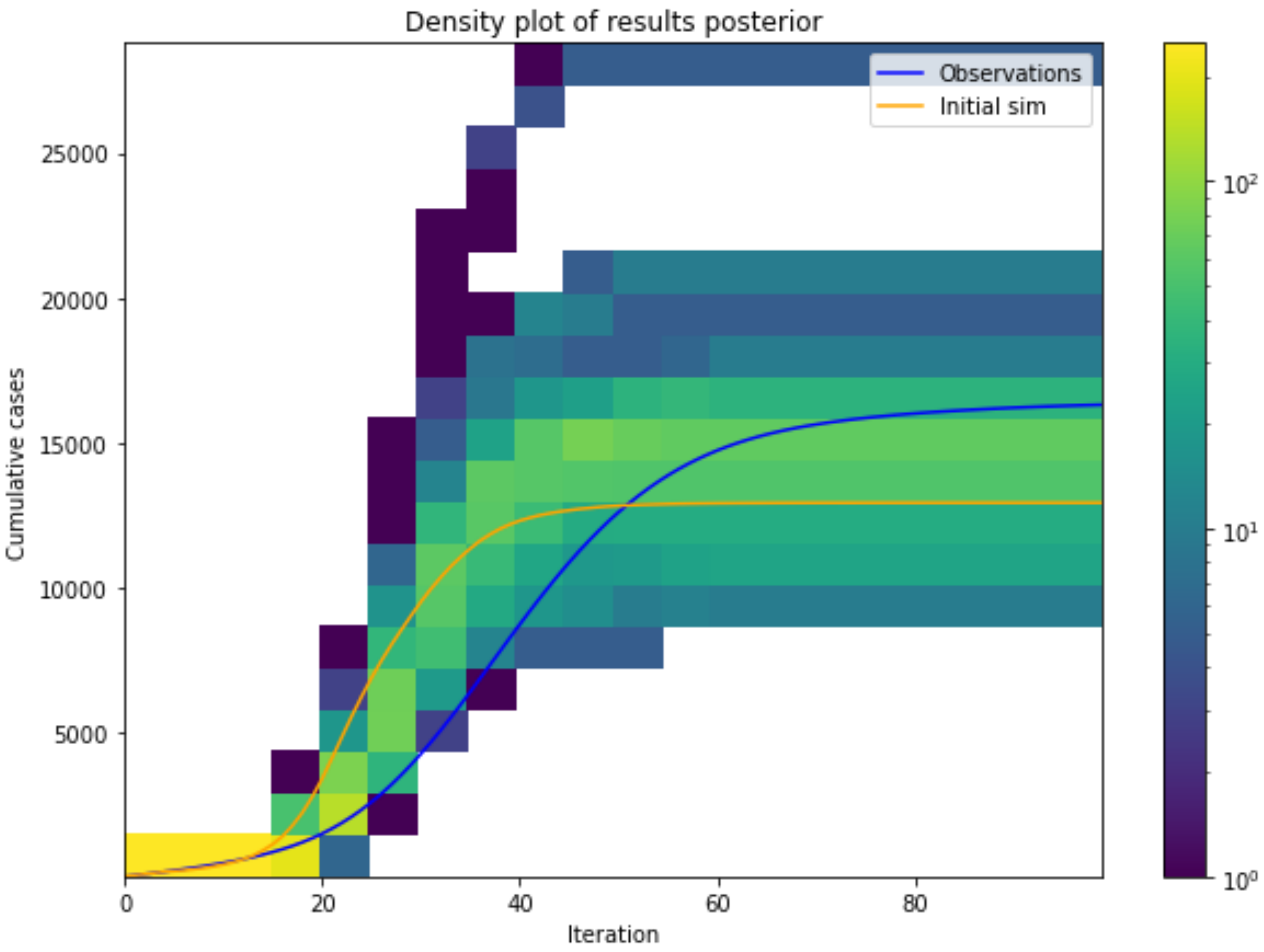
DyME Python and OpenCL

- Dynamic Model for Epidemics (DyME) applied to Devon
  - ~800,000 individuals
- Lots of interactions
- Python/R implementation:
  - 2 hours
- Rewritten by Improbable using OpenCL (python and C):
  - 5 seconds!
  - Opens new & exciting opportunities for model inference etc.



DyME Python and OpenCL

- Further benefits of fast model: Approximate Bayesian Computation
- Parameter inference
- Uncertainty in parameter estimates and (future) model predictions



Digital Twins

Digital Twins

- Significant interest from government (and industry / academia) in digital twins
- Pieces coming together (SIPHER, DyME, QUANT, GALLANT…)
- Problems:
  - Data (and multi-level validation)
  - Compute
  - Sharing and linking models
  - Ensuring they are equitable

Summary

- Rule initialisation and agent behaviour
- Visualisation
- Data
- Calibration / validation and uncertainty
- Computational
- Digital Twins

Save the date: GIScience 2023

- We are delighted to announce that the **2023 GIScience conference** will be held at the **University of Leeds, UK**, from **Wed 13th - Friday 15th September 2023**

References

- An, L., Grimm, V., Sullivan, A., Turner II, B.L., Malleson, N., Heppenstall, A., Vincenot, C., Robinson, D., Ye, X., Liu, J., Lindkvist, E., Tang, W., 2021. Challenges, tasks, and opportunities in modeling agent-based complex systems. Ecological Modelling 457, 109685. https://doi.org/10.1016/j.ecolmodel.2021.109685
- Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.-H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. Science 310, 987–991. https://doi.org/10.1126/science.1116681
- Malleson, N., K. Minors, Le-Minh Kieu , J. A. Ward , A. West and A. Heppenstall (2020) Simulating Crowds in Real Time with Agent-Based Modelling and a Particle Filter. Journal of Artificial Societies and Social Simulation (JASSS) 23 (3). https://doi.org/10.18564/jasss.4266
- McCulloch, J., Ge, J., Ward, J.A., Heppenstall, A., Polhill, J.G., Malleson, N., 2022. Calibrating agent-based models using uncertainty quantification methods. Journal of Artificial Societies and Social Simulation 25, 1. https://doi.org/10.18564/jasss.4791
- Spooner, F., Abrams, J.F., Morrissey, K., Shaddick, G., Batty, M., Milton, R., Dennett, A., Lomax, N., Malleson, N., Nelissen, N., Coleman, A., Nur, J., Jin, Y., Greig, R., Shenton, C., Birkin, M., 2021. A dynamic microsimulation model for epidemics. Social Science & Medicine 291, 114461. https://doi.org/10.1016/j.socscimed.2021.114461

Challenges for ABM in Applied Urban Modelling

Nick Malleson, Alison Heppenstall and Ed Manley

AUM Symposium, 29th June – 1st July 2022

University of Cambridge