

Challenges and opportunities of using ABMs for simulating social systems

Alison Heppenstall and Gary Polhill





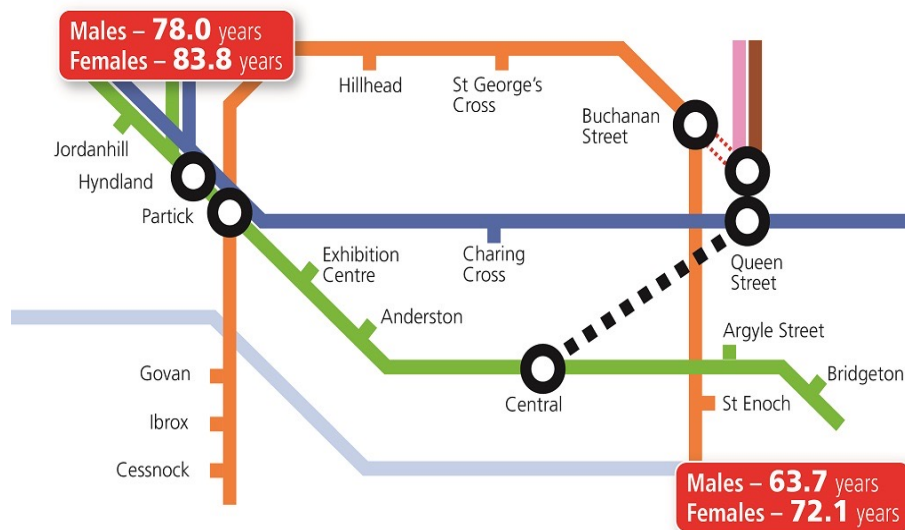
Outline

- Modelling context
- Causality
- Behaviour
- Example: Health
- Exascale
- Summary





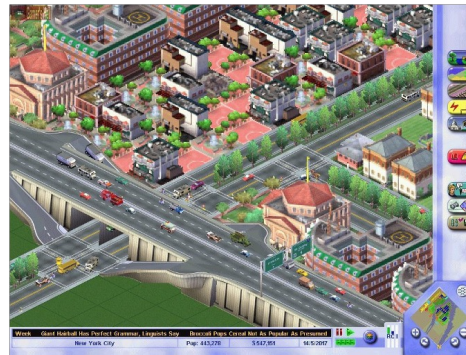
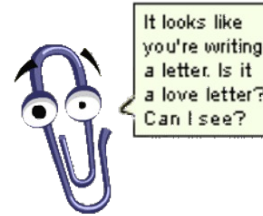
What are the impacts of sustainability policies on inequalities?



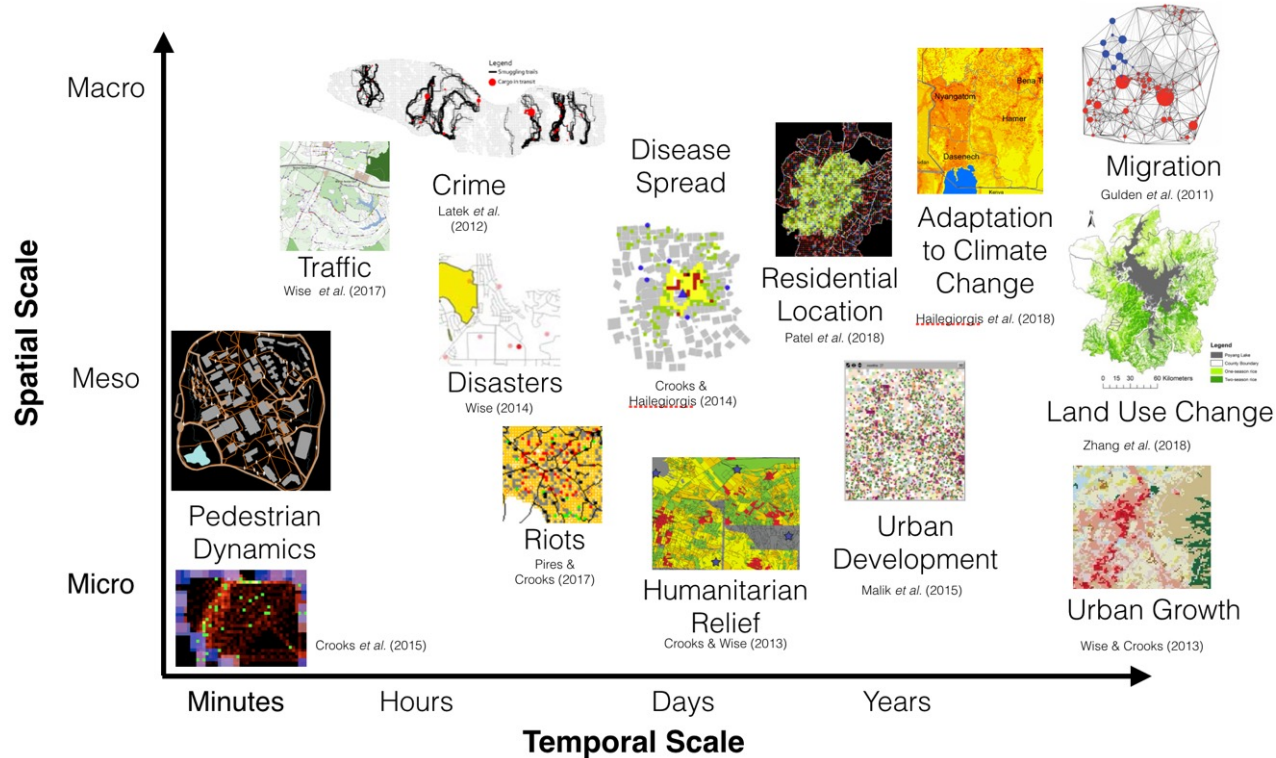
Glasgow subway: Public Health Scotland

Agent-based modelling (ABM)

- Autonomous, heterogeneous, interacting agents
- Represent individuals or groups
- Situated in a virtual environment



Types of problems



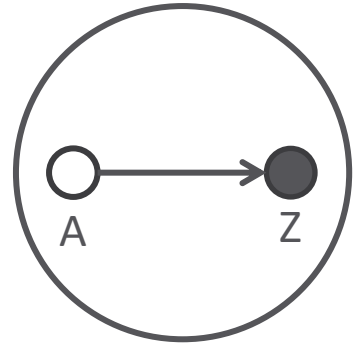
Why ABM?



- ABM being used for wide range applications
 - Integrate diverse knowledge and data
 - Simulate dynamics from intervention scenarios
 - Unintended consequences
 - Need to understand the relationships in the real data: the cause and effects (challenging in this area)
- MacKay (2008): Complex systems as “intricate graph of causal links”
 - Graphs are cyclic, creating feedback loops
 - All nodes members of at least one loop – agents cannot optimize without infinite recursion
 - No node directly influences every other node
 - No agent can undertake an action guaranteed to generate a consequent state of the whole system

Simple causation

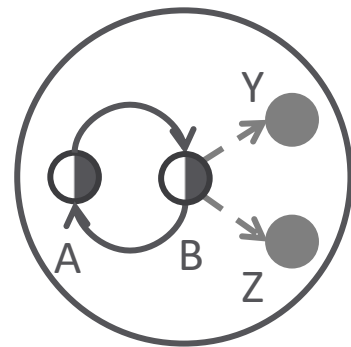
- Causation is a temporal relationship between pairs of events
 - Effects can have *necessary* causes
 - The occurrence of the effect means the cause must have happened
 - and *Sufficient* causes
 - If the causes occur then the effect will happen
- Simple causation
 - No external influence on the system
 - An event of class A (empty circle) always leads to an event of class Z (filled circle)



Complications

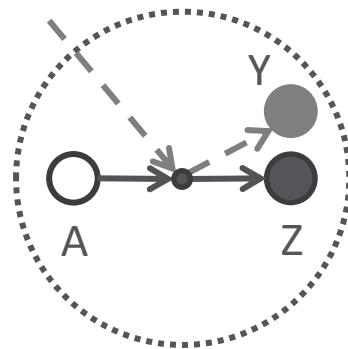
■ Reinforcement

- Event classes A and B reinforce each other
- Precise details of system states lead to qualitatively different resulting event classes Y and Z



■ Openness

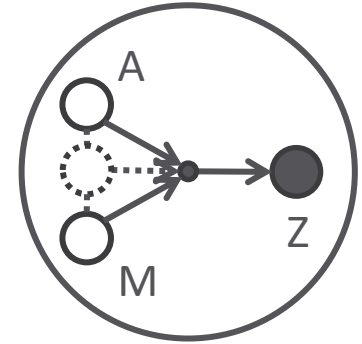
- Complex systems have permeable boundaries (Turner et al. 2018)
- External influences lead to event classes other than Z given necessary and sufficient conditions A



Complications

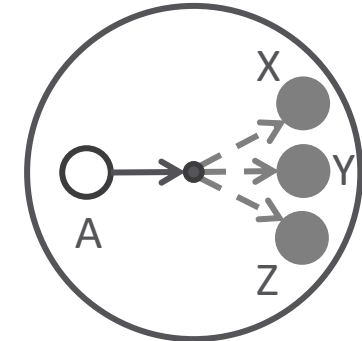
■ Multidimensionality

- Events of multiple classes A, B, ..., M are needed to bring about Z
- Harder to isolate these, and harder to make them happen together in order to achieve Z



■ Multiple asynchronous, autonomous actors

- Events of class A can lead to multiple classes of event X, Y, Z, ...
- Order in which asynchronous actors operate influences outcome
- Usually managed by social norms and institutions



Causation and ABMs



- ABMs integrate many models of causation
 - Generative (micro-macro)
 - But also:
 - Counterfactual causation
 - Law-like causation
 - Probabilistic causation
 - And macro-micro interventions

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<https://doi.org/10.1080/13645579.2022.2049510>

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Sensemaking of causality in agent-based models

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ABSTRACT

Even though agent-based modelling is seen as committing to a mechanistic, generative type of causation, the methodology allows for representing many other types of causal explanations. Agent-based models are capable of *integrating* diverse causal relationships into coherent causal mechanisms. They mirror the crucial, multi-level component of emergent phenomena and recognize the important role of single-level causes without limiting the scope of the offered explanation. Implementing various types of causal relationships to complement the generative causation offers insight into *how* a multi-level phenomenon happens and allows for building more complete causal explanations. The capacity to work with multiple approaches to causality is crucial when tackling the complex problems of the modern world.

KEYWORDS

Causality; agent-based modelling; complexity

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

Andrew Crooks¹, Christian Castle², Michael Batty³

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



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

J. Gareth Polhill¹, Jiaqi Ge¹, Matthew P. Hare¹, Keith B. Matthews¹,
Alessandro Gimona¹, Douglas Salt¹, Jagadeesh Yeluripati¹



Editorial: Meeting Grand Challenges in Agent-Based Models

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

Methodological Issues of Spatial Agent-Based Models

Steven Manson¹, Li An², Keith C. Clarke³, Alison Heppenstall⁴,
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Geographical Analysis (2021) 53, 76–91

Special Issue

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

Alison Heppenstall^{1,2}, Andrew Crooks³, Nick Malleson^{1,2},
Ed Manley^{1,2}, Jiaqi Ge¹, Michael Batty⁴

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

[J Land Use Sci. 2016; 11\(2\): 177–187.](#)

Published online 2015 Apr 13. doi: [10.1080/1747423X.2015.1030463](https://doi.org/10.1080/1747423X.2015.1030463)

PMID: [27158257](https://pubmed.ncbi.nlm.nih.gov/27158257/)

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

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Appeal of ABM: Modelling Human Behaviour

- Human – rational animals? Predictable?
- Does the data contain the right processes?
- Many many behavioural frameworks – which one?



Ecological Economics
Volume 131, January 2017, Pages 21-35



Analysis

A framework for mapping and comparing behavioural theories in models of social-ecological systems

Maja Schlüter ^{a,*,} Andres Baeza ^{b, c,} Gunnar Dressler ^{d,} Karin Frank ^{d,} Jürgen Groeneveld ^{d, e,} Wander Jager ^{f,} Marco A. Janssen ^{c,} Ryan R.J. McAllister ^{g,} Birgit Müller ^{d,} Kirill Orach ^{a,} Nina Schwarz ^{h,} Nanda Wijermans ^a

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Environmental Modelling & Software
Volume 48, October 2013, Pages 37-48



Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol

Birgit Müller ^{a,*,} Friedrich Bohn ^{a,} Gunnar Dreßler ^{a,} Jürgen Groeneveld ^{a, f,} Christian Klassert ^{c,} Romina Martin ^{a,} Maja Schlüter ^{d, e,} Jule Schulze ^{a, b,} Hanna Weise ^{a,} Nina Schwarz ^b

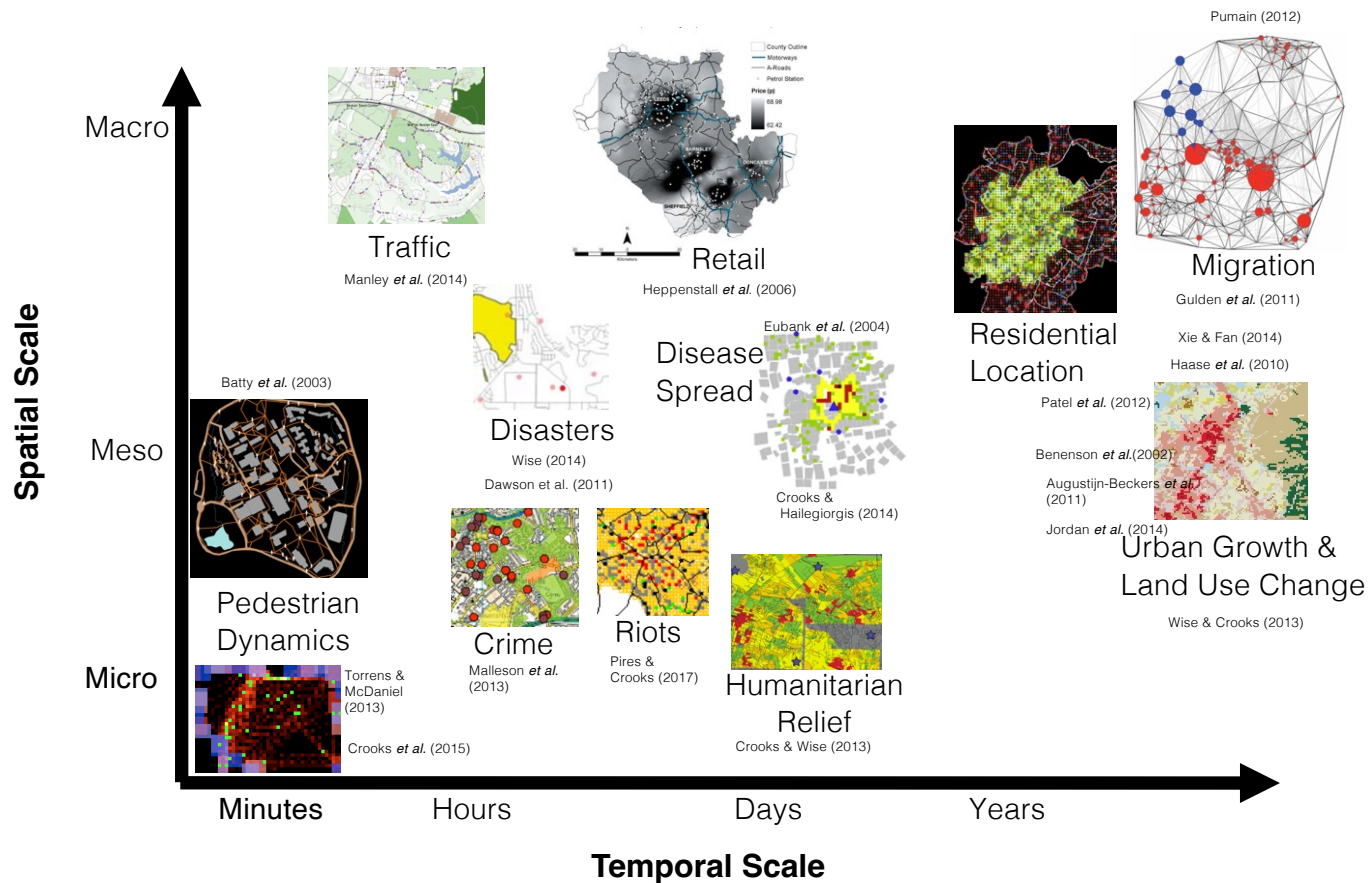
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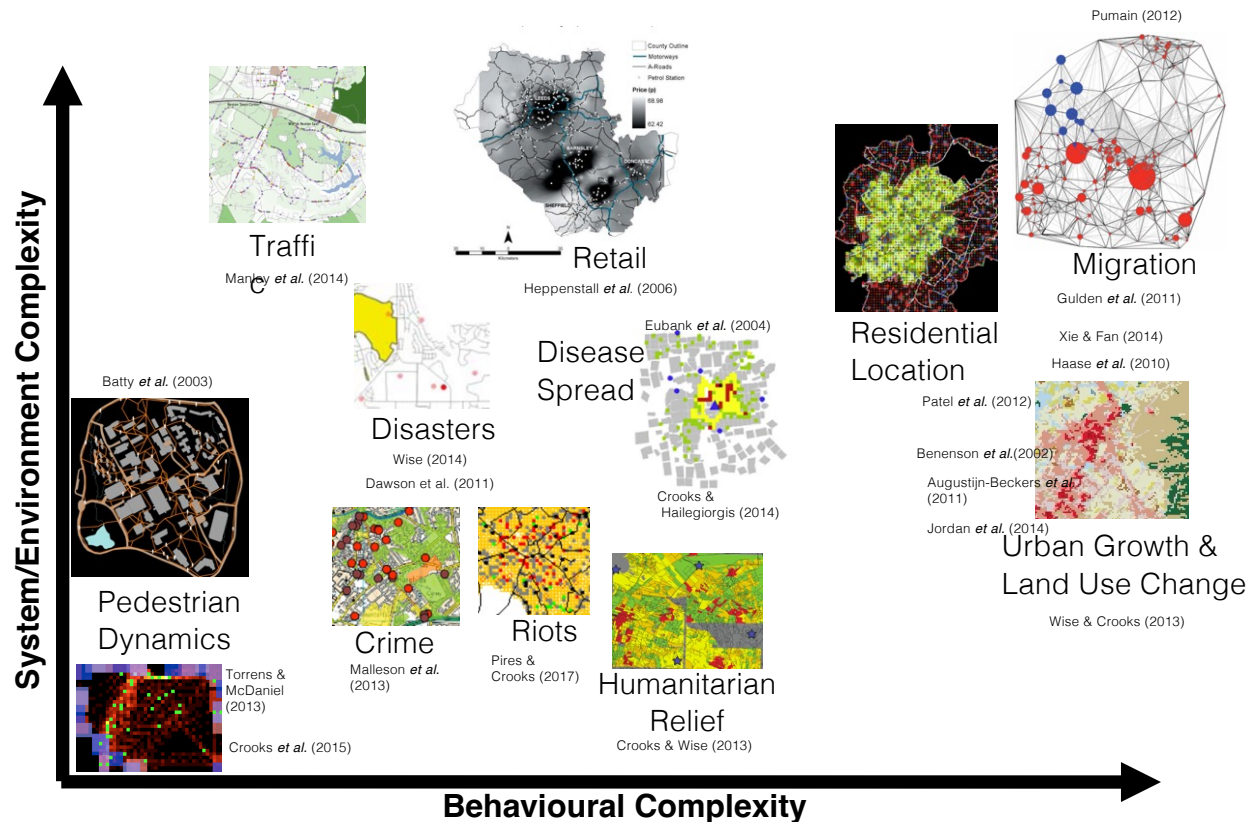
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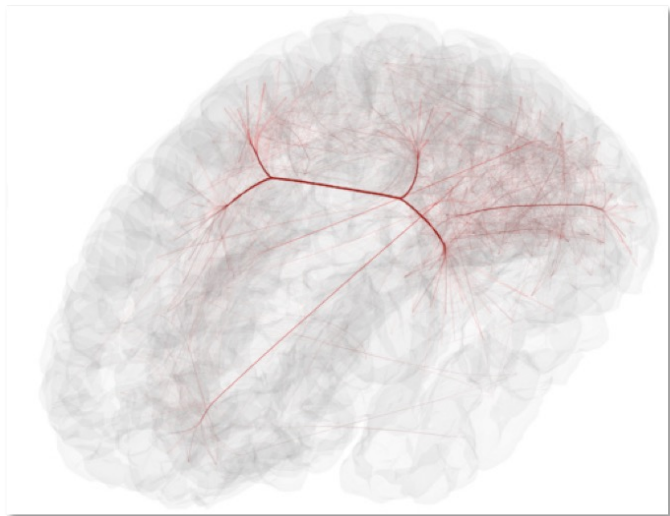
Geographical Applications



Geographical Applications



Appeal of ABM: Modelling Human behaviour

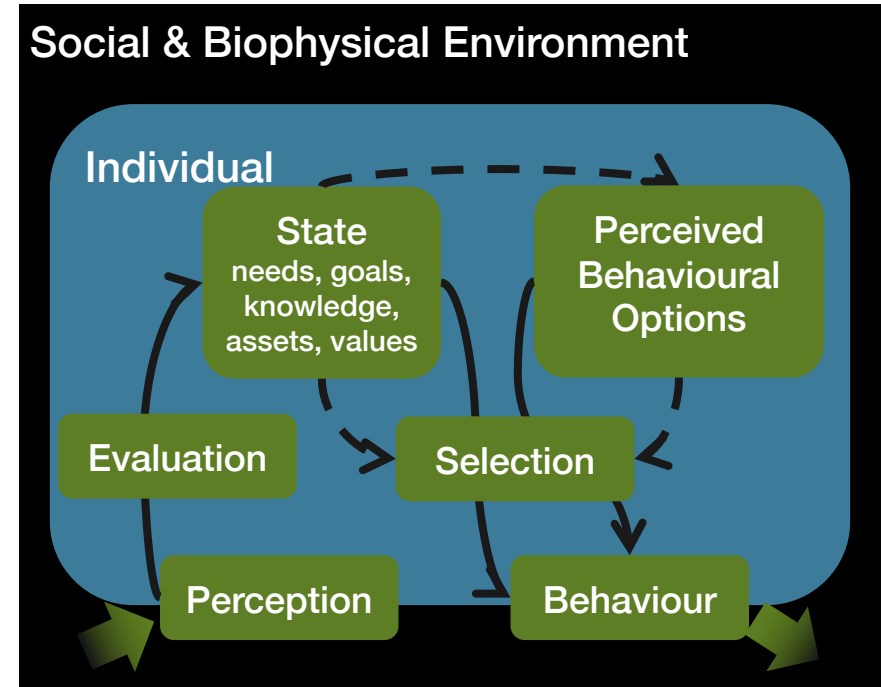


Quiz

- Choose a number between 1 and 4
- What percentage of people do you think chose:
 - 1?
 - 2?
 - 3?
 - 4?

Schlüter et al. (2017): MoHuB

- Framework for thinking about decision-making in ABMs of SES
 - What does the agent perceive?
 - How does the agent evaluate their significance?
 - What aspects of the agent's state drive the options to choose from?
 - How does the agent choose?
 - What is the effect of the choice?



Various options for simulating the choice

- Heuristics
 - e.g. from interview data
- Decision trees
 - e.g. learned from questionnaire data
- Optimization
 - A surprising number of ABMs use utility maximization!
- Formalizing social theories
 - e.g. CONSUMAT (Jager 2000; see right):
 - Needs (Max-Neef 1992), Behavioural control (Ajzen & Madden 1986), Theory of planned behaviour (Ajzen 1991), Social Learning (Bandura 1977), Social comparison (Festinger 1964)
 - Social theories are not software specifications!
 - (Muelder & Filatova 2018)
- Cognitive
 - e.g. Case-Based Reasoning, Belief-Desires-Intentions
- Adaptive
 - e.g. Evolutionary, Learning (including neural nets)

Context of decision

Satisfaction of needs

High

Low

Uncertainty

High

Do what
most others
do

Do what
others most
like me do

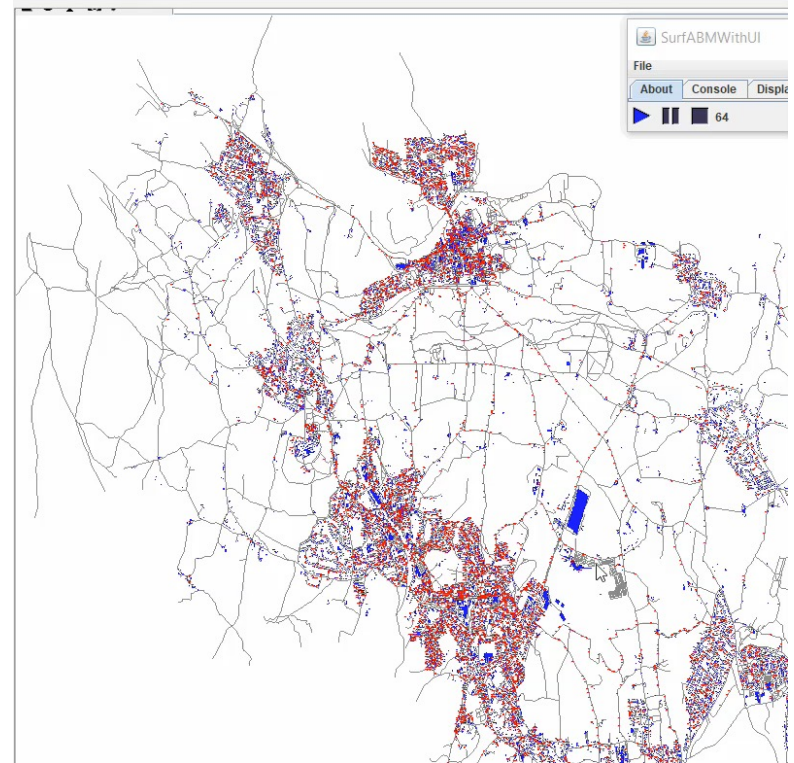
Low

Habit

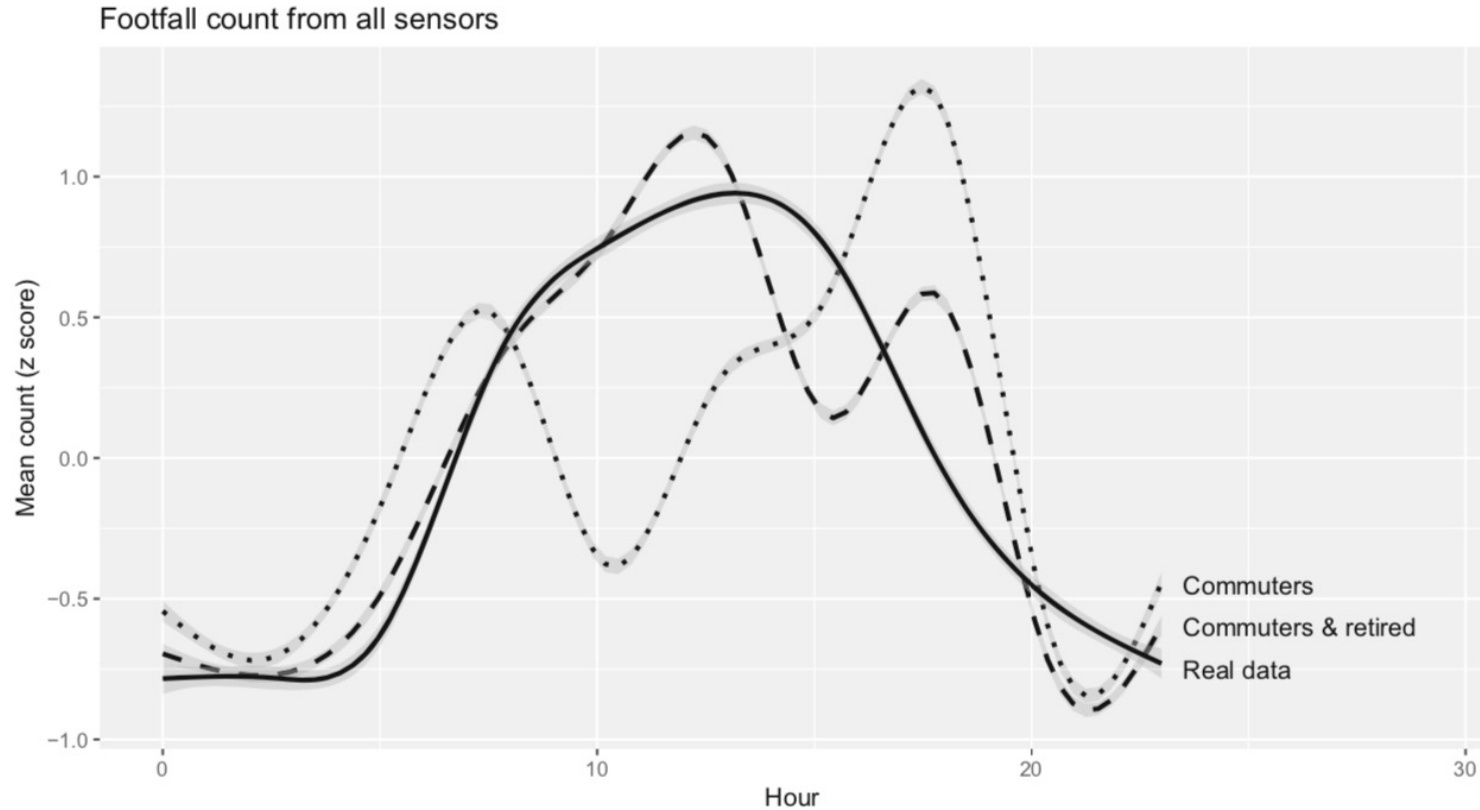
Optimize

Simulating pedestrian movement

- Can we use data sources to create an accurate picture of how people move around (behave) an urban space?
 - Use Census to create population
 - Use Time/Work survey to put in basic behaviour (commuting)
 - Put them in houses and watch them go
 - Calibrate against sensor information



Crols, T. and Malleson, N. (2019) Quantifying the ambient population using hourly population footfall data and an agent-based model of daily mobility. *GeoInformatica*, 23: 201-220

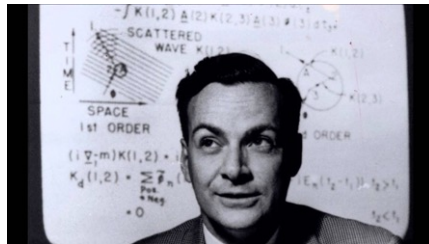


Crols, T. and Malleson, N. (2019) Quantifying the ambient population using hourly population footfall data and an agent-based model of daily mobility. *GeoInformatica*, 23: 201-220

Can we get behaviour right?

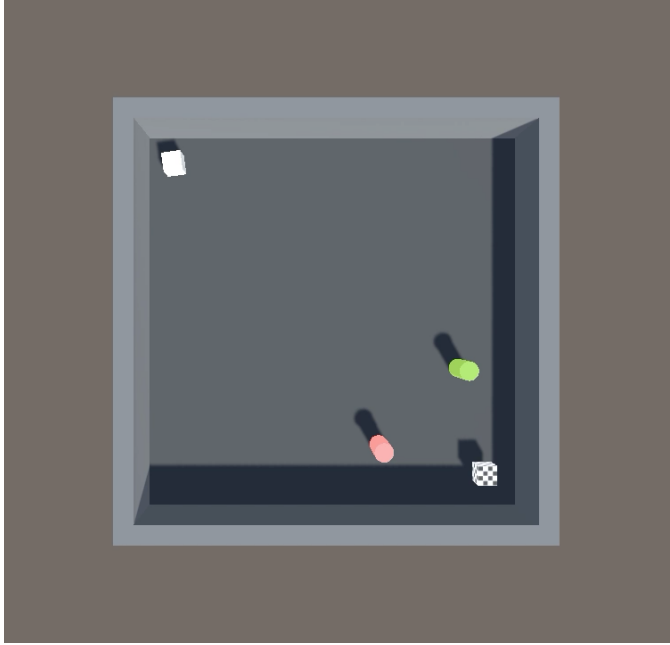


- Behavioural rules often drawn from historical data
- Need rich, individual-level data
 - Contain all events/experiences, results of feedback
 - How extract behavioural rules from qualitative data?
 - Assumptions (rationale, knowledge...)



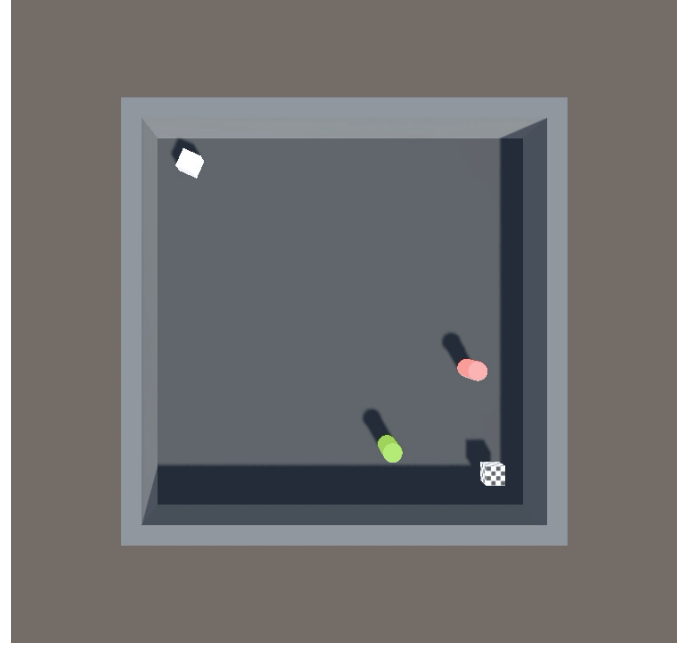
“Imagine how much harder physics would be if electrons had feelings!”

Acknowledgement: Ed Manley



Trained Navigating Agent

Using perspective visual inputs to navigate
Landmarks help guide way to target



Confused Agent

Landmarks switched
Finding target difficult for agent

Olmez, S., **Heppenstall, A.**, Birks, D. (2023) Investigating the emergence of complex behaviours in an agent-based model using reinforcement learning. *In Review*



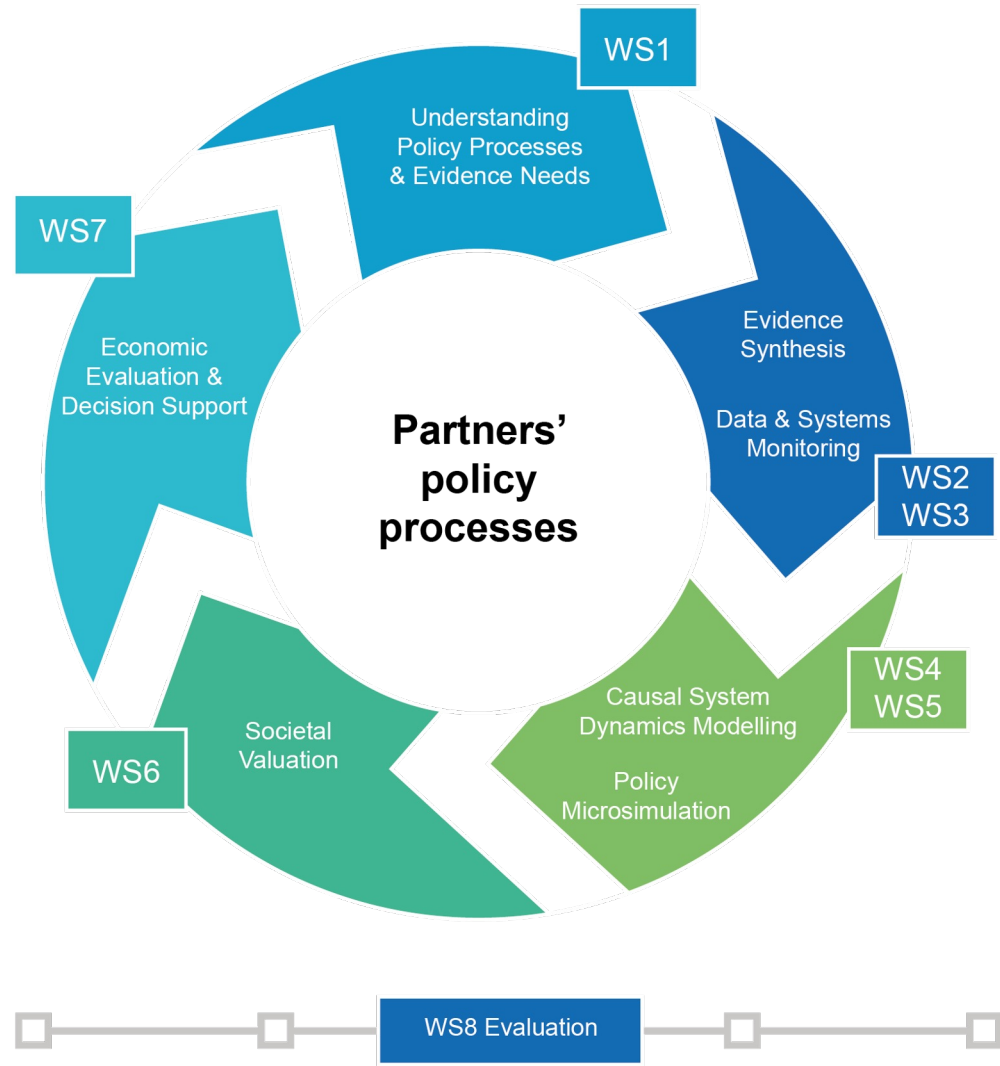
Systems science
In Public Health and
Health Economics Research



Working together to tackle health inequalities
and improve the health of the public

The SIPHER Wheel

Eight integrated workstrands



Synthetic populations

A synthetic population dataset for estimating small area health and socio-economic outcomes in Great Britain

Guoqiang Wu^{1*}, Alison Heppenstall^{1,2}, Petra Meier³, Robin Purshouse⁴, Nik Lomax^{1,2}

August 31, 2021

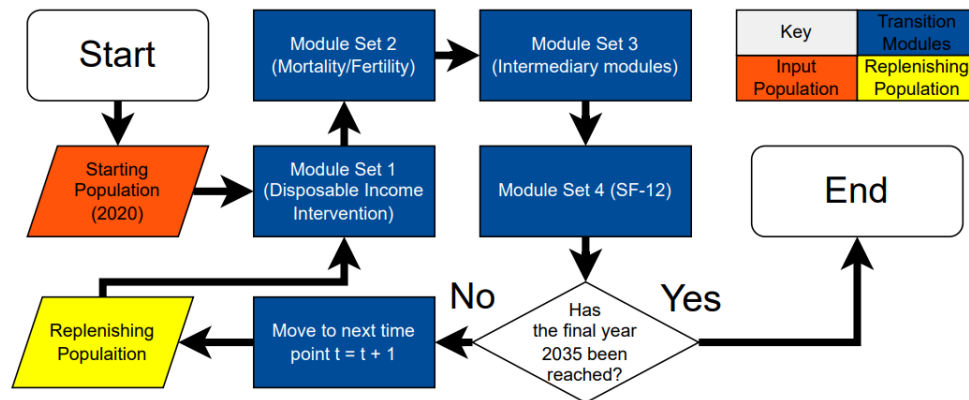
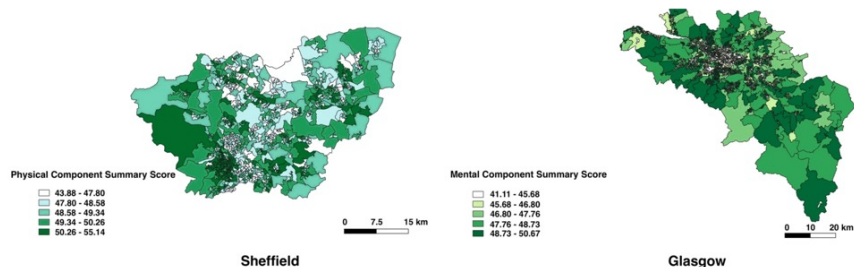
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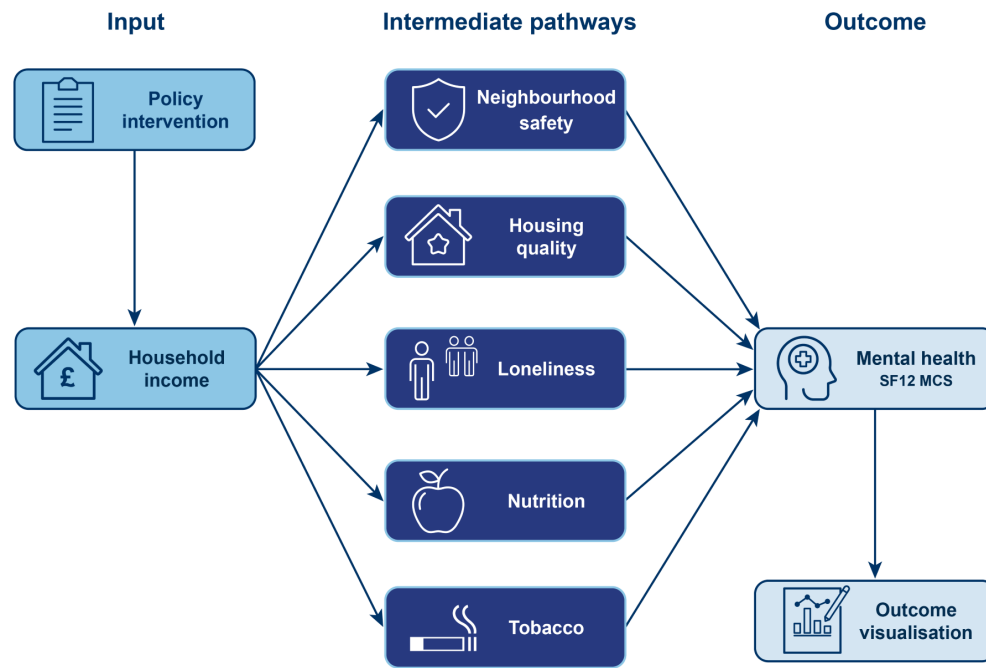
4. Department of Automatic Control and Systems Engineering, University of Sheffield, Portobello Street, Sheffield, S1 3JD, UK

* corresponding author (g.wu@leeds.ac.uk)

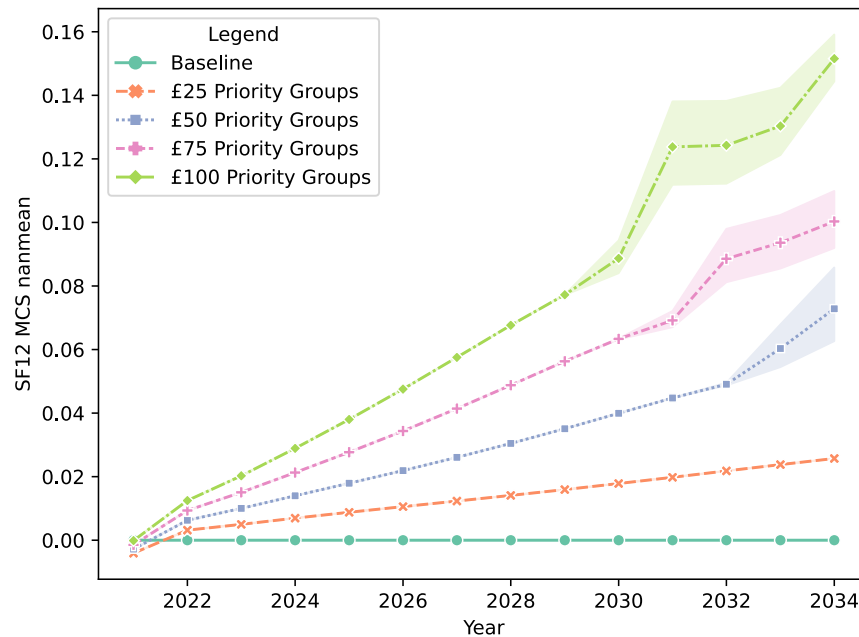
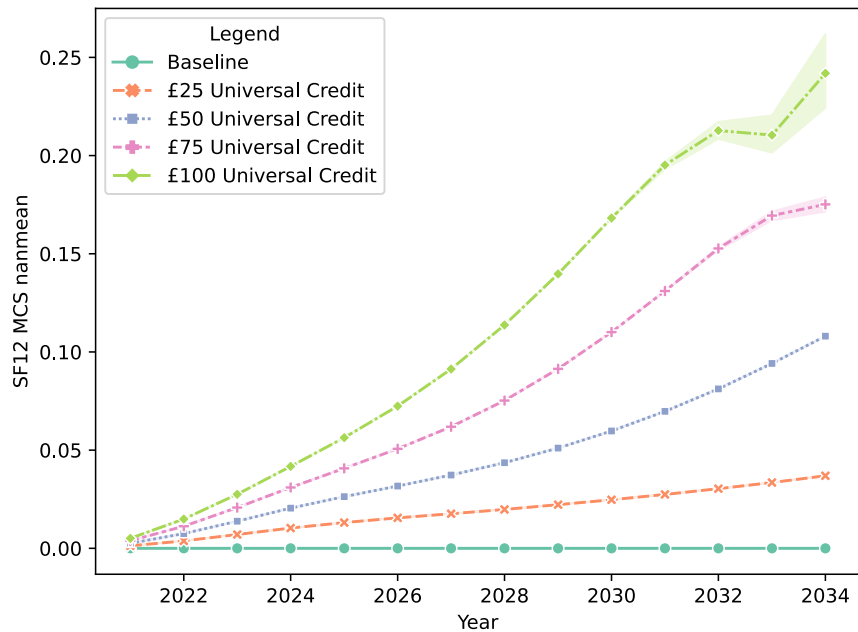


Dynamic microsimulation

- Run policy scenarios
 - Effects of 'cost of living' crisis
 - Universal credit uplift
- Assess impact on Mental Health (SF12)



Universal credit uplift



Move towards urban digital twins

- Recent significant interest from government (and industry / academia)
- Pieces coming together (SIPHER, DyME, QUANT, GALLANT...)
- Can we make inclusive DTs that can help decision-makers?
- Number of challenges still to overcome.



Some urban authorities are developing digital copies of cities, as portrayed in this artist's impression.

Make more digital twins

Virtual models boost smart manufacturing by simulating decisions and optimization, from design to operations, explain **Fei Tao** and **Qinglin Qi**.

Digital twins — precise, virtual copies of machines or systems — are revolutionizing industry. Driven by data

information on its materials and structure, while the manufacturers keep data on how the vehicle is produced and garages retain

What is exascale computing?



- Exascale computing entails 10^{18} floating-point operations per second (flops)
 - Your laptop $\sim 10^9$ flops
 - exascale = a billion laptops
 - A small cluster $\sim 10^{12}$ flops
 - exascale = a million small clusters
 - A large cluster/cloud $\sim 10^{15}$ flops
 - exascale = a thousand clouds
- Flops roughly equal to instructions per second

Example



- ~20,000 runs
- 76 CPU days of computing time
 - 4G ips CPUs
- 3×10^{16} CPU instructions
- 1.5 days on 200 CPUs
- 0.3s at exascale



Environmental Modelling & Software

Volume 45, July 2013, Pages 74-91



Nonlinearities in biodiversity incentive schemes: A study using an integrated agent-based and metacommunity model ☆

J. Gary Polhill  , Alessandro Gimona, Nicholas M. Gotts

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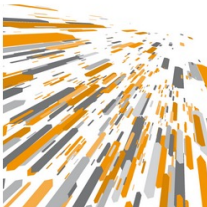
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<https://doi.org/10.1016/j.envsoft.2012.11.011> ↗

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Exascale computers around the world

- Frontier (Oak Ridge, Tennessee, USA)
 - 602,268 CPU cores (AMD); 8,335,360 GPU cores (Radeon)
 - 1.1 exaflop capability May 2022
 - 21MW of power needed!
- Second fastest (Fugaku) on top500.org has ~0.5 exaflop performance
 - 30MW; 7.6M cores
- Chinese believed already to have two as of 2021
 - <https://www.datacenterdynamics.com/en/news/china-may-already-have-two-exascale-supercomputers/>
 - Not official, but if true, it would have been the first country to achieve exascale computing capability
- UK planning one
- Ditto EU (in Germany – JUPITER)






TOP500 LIST



25
YEARS
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NEWSLETTER
SIGN UP

- 1 **Frontier** - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE
- 2 **Supercomputer Fugaku** - Supercomputer Fugaku, A64FX 48C 2.2GHz, Tofu interconnect D, Fujitsu
- 3 **LUMI** - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE

The ExAMPLER project



- 18 month project started 1 June 2023
 - Polhill et al. (2023)
- Exploring the potential of exascale computing for ABSS
 - ... with appropriate institutional and software support ...
- Bringing the social sciences into the conversation about exascale computing
- Gap analysis approach
 - How ready is the ABSS community to take advantage of exascale?
 - What needs to be done to get the ABSS community using exascale?

Doing ABSS differently?



- How might exascale ABSS drive workflows for designing, building and using ABSSs?
- What does ABSS look like in ten years' time?
 - What software are we using?
 - What computers are we using?
 - What methods/workflows are we using?
 - Who are we working with?
 - Who are we working for?
 - What can we do that we can't do now?

Final thoughts



- ABM has multiple uses / purposes:
 - understanding how the system works
 - explaining how phenomena can occur
 - ‘prediction’...? (Debatable)
 - See Elsenbroich & Polhill (2023); Polhill et al. (2021)
 - integrating knowledge, data, and modes of causation
- Other challenges:
 - Model initialisation
 - Calibration and validation

Opportunities

- Creating inclusive, robust DTs
- Rapid evidence-based work with policymakers
 - Understand likely impact of interventions
 - Unintended consequences





Acknowledgements

Mike Batty, Corinna Elsenbroich, Petra Meier, Richard Milton,
Doug Salt, Nik Lomax, Ricardo Colasanti, Matt Hare



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