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Editorial

Comparative Approaches for Innovation in Agent-Based Modelling of Landscape Change

James D. A. Millington [1,*] and John Wainwright [2,*]

[1] Department of Geography, King's College London, Strand Campus, London WC2R 2LS, UK
[2] Department of Geography, University of Durham, Durham DH1 3LE, UK
* Correspondence: james.millington@kcl.ac.uk (J.D.A.M.); john.wainwright@durham.ac.uk (J.W.)

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In this Special Issue on "Agent-Based Modelling and Landscape Change" we aimed to bring together articles that showcase innovative uses of agent-based models (ABMs) for investigating and explaining landscape change and dynamics. The resulting 10 articles demonstrate the diverse range of processes and landscapes that ABMs are currently used to examine, including: land-use decision making in agricultural landscapes; soil erosion in semi-arid environments; forest change in mountainous landscapes; trade in 1st Century BC southern France; social adaptations of herders in northern Mongolia; and malaria epidemiology in Kenya. The articles (Ding *et al.* 2015 [1], Olabasi *et al.* 2015 [2], Morgan *et al.* 2015 [3], Badmos *et al.* 2015 [4], Barton *et al.* 2015 [5], Johnson 2015 [6], Brändle *et al.* 2015 [7], Crabtree 2015 [8], Clark and Crabtree 2015 [9] and Arifan 2015 [10]) draw on a range of modelling approaches, but one common theme among several of the papers is the use of comparative approaches. Here, we discuss how comparative approaches offer opportunities for future innovation in modelling landscape change, particularly for addressing the challenge of understanding the role of human activity in the Anthropocene.

The issue of comparison in ABMs is not new to the studies in this Special Issue and has been advocated and pursued over many years. Axtell *et al.* (1996) [11] were among the earliest to investigate the alignment of computational models, or 'docking' as they suggested it might be abbreviated. Docking entailed comparing an ABM to another model (whether ABM or otherwise) of the same system to see if the models could reproduce similar results, thereby enabling critical experimentation and the determination of whether one model was better than another, or if one was a special case of the other (*i.e.*, could be subsumed). Since then, model-to-model analysis has continued (e.g., Hales *et al.* 2003 [12], Rouchier *et al.* 2008 [13]), although the rate of comparison has not kept pace with number of ABMs being developed. Robust comparison of models, to the point of trying to 'break' them (*i.e.*, identifying at what point modelled mechanisms are no longer useful for explaining observations), is needed to ensure credible and efficient scientific progress in computational modelling (Thiele and Grimm 2015 [14]). Beyond examining how well different models fit the same set of empirical data, model comparison can aim to reproduce others' models from scratch in new computer code (e.g., Janssen 2009 [15]) or extend analysis including by exploring the sensitivity of model parameters in greater detail (e.g., Miodownik *et al.* 2010 [16], Seagren 2015 [17]). In contrast, articles in this Special Issue examine variations in agent-based representation, from an entire absence of agent representation, through comparing heterogeneous *vs.* aggregated representation of human activity, to alternative means of parameterizing individual agent behaviour.

For example, to investigate the effect of agricultural practices on the formation of deeply incised valley formations in semi-arid Mediterranean landscapes, Barton *et al.* (2015) [5] 'turned off' the human land-use component of their hybrid ABM-cellular model. By using the same model with humans represented versus not, this approach aims to understand the influence of human activity on landscape change (e.g., as discussed by Wainwright and Millington 2010 [18]). Through this experimental use of their model, Barton *et al.* showed that the non-ABM component of their model that represents climate and natural vegetation change is able to capture broad-scale (climate-driven) vegetation-change impacts on gulley incision. Including the agent-based representation of human activity shows how finer-scale, localized vegetation change can have similar effects without climate change. Thus, this example shows how drivers of landscape change acting over different scales may need to be represented through fundamentally different modelling approaches.

Brändle *et al.* (2015) [7] compared agent-based versus aggregated models of agricultural change in a contemporary mountain landscape in Switzerland, examining the trade-offs between model types for considering different temporal extents of simulation. They found that their ABM, based on recent behavioural data, was able to simulate landscape change over short and medium durations better than an aggregated model assuming land optimization, while maintaining equivalent sensitivity to broader socio-economic drivers. The trade-offs identified are between the greater demand for more detailed information about (farming) actor behaviour and decision-making by the agent-based model (making transferability of the model to other landscapes difficult) versus the more realistic spatially explicit simulation of land abandonment over the short and medium term due to better representation of diversity in decision-making. However, over longer simulated durations the advantages of an agent-based approach are less obvious and the results remind us that the choice of modelling approach depends on the questions being investigated and relative advantages of the available approaches.

In a third example from the Special Issue, Morgan *et al.* (2015) [3] compared three different approaches for estimating the likelihood of land-use conversion by agricultural agents in New Zealand: (i) no difference between agents in likelihood (*i.e.*, assumes universally rational, profit-maximisation agents); (ii) the social and geographic network of agents influences likelihood (*i.e.*, representing influence of endorsement and imitation alongside economic considerations), and (iii) empirical estimation of likelihood based on an individual agent's attributes (including age, education, land holdings, *etc*.). The different approaches reflect differing perspectives and traditions in how human activity has been investigated by economists compared to geographers. Results showed that at some broader units of aggregation (catchment level) there was little appreciable difference in simulated land uses between the approaches, whereas at finer units differences were evident.

The Brändle *et al.* (2015, [7]) and Morgan *et al.* (2015, [3]) examples are as good as currently exist for demonstrating how assumptions about agent heterogeneity are comparable to existing accepted modelling approaches. Comparisons such as these, and which investigate how and when ABMs are better for improving understanding than other modelling types, will enable demonstrations of how ABM are useful and robust for understanding change into the future. However, they also highlight that differences in modelling approaches are not fully resolved and that the choice of modelling approach will depend on the scientific and policy questions being asked. Currently, the primary influence on modelling approach seems to be the scales and organizational levels at which answers are required. For example, although ABMs may be designed to provide greater representational fidelity (e.g., fine detail at the level of individuals) implementing such models often comes with costs of development (time and data), use (computational resources) and transferability (between landscapes). In some instances the benefits of developing an ABM may ultimately not outweigh the costs, particularly if there is limited heterogeneity in the decision-making context of actors or limited interaction effects between agents (e.g., O'Sullivan *et al.* 2012, [19]).

Taking an alternative perspective, in the Special Issue, Johnson (2015, [6]) explores using an ABM as a mediator or "interested amateur" in the process of policy making. If constructed independently of the policy context (*i.e.*, not co-constructed with stakeholders), using the model and its output in discussions forces a focus on assumptions but in an impersonal way, not directed at any particular person. The comparisons here are between the way in which the model represents the world, how the policy maker understands the world to be structured, and between expected and unexpected outcomes as shown by the model. Johnson argues that for this approach to work there needs to be a degree of transparency about how the model represents processes (e.g., of landscape change) such that it is not a black box, but also that a detailed model is an advantage because it provides more assumptions about which participants can debate and explore the consequences of. More generally then, Johnson sees ABMs as providing greater benefit than rational utility maximization approaches both because the latter are more 'removed from reality' (e.g., not all actors are perfectly rational) but also because their more simplified worldview (with few assumptions) inhibits discussion about structures and relationships in the real world and how they could change. Johnson found his own particular ABM useful for facilitating discussion about policy options for soil and water conservation in Ethiopia, but more general comparison of ABMs against other model types for policy discussion would be welcome.

In future, it seems likely that beyond comparing different types of model (ABM, regression-based models, systems dynamics models), combining ABM with other modelling types to produce innovative representations will become more prominent. For example, Verburg *et al.* (2015, [20]) argue that if modelling is to assist in designing sustainable solutions to the challenges of the Anthropocene, innovative model architectures that can represent human-environment interactions across many scales and levels of organisation will be needed. O'Sullivan *et al.* (2015, [21]) advocated hybrid forms of land-use modelling in which competing and complementary approaches (beyond ABM) are compared and combined in an iterative approach to improve understanding. O'Sullivan *et al.* (2015, [21]) suggest different 'levels' of hybridity, from comparing different modelling approaches to investigate the same substantive domain, through coupling different types of model to examine a single domain, to actually integrating modelling approaches so that there is no discernible point at which one model ends and another begins (e.g., agents that run regressions dynamically and internally as a proxy for individual decision-making).

Developing such innovative modelling hybridity in land-change science is particularly imperative given the recognition that landscape change can be influenced not only by local circumstances (neighbours' decisions, local environmental conditions) but also by decisions and processes that are far remote and operating at different scales and levels of organization (Liu *et al.* 2013, [22]). However, careful thought will need to go into operationalising hybrid model forms for investigating such systems. Although representing all individual actors in a globalized system of land use and food trade, for example, might theoretically be possible, it is not immediately clear that this would be desirable. For example, the heterogeneity of decision-making and/or interaction at one level of organization (e.g., individual farmers) may be so low as to make little difference to what decisions mean for other levels of organization (e.g., food commodity traders). In such cases if the goal is understanding global interactions, but it is at other levels of organization at which most uncertainty, heterogeneity or influence occur, then it may be appropriate to represent local land use decisions in an aggregated manner and focus individual-level representation at non-global levels or scales. Such considerations for how to structure future hybrid models are important if we are to ensure the hybrids do not become 'monster models'—ever more complicated models that are more and more difficult to evaluate. Such a situation is not an inevitable result of hybridization (nor advocated), but as usual important consideration needs to go into developing models that are fit for the desired purpose.

Pursuing innovative and hybrid modelling approaches through iterative approaches to scientific inquiry, as advocated by O'Sullivan *et al.* (2015, [21]), might be usefully facilitated through online platforms that encourage greater collaboration between modellers and engagement with policy- and decision-makers. One example might be an online a community-modelling initiative to act as a clearing house for models and best practice. Contemporary online resources such as openABM.org are valuable as a space to present individual models—complete with a peer-review process—but as structured they currently do little to encourage modellers to think about how they can combine or build upon one another's models. A platform that actively encourages and enables modellers to interact, combine and 'mash-up' their conceptualizations to find synergies and produce novel model architectures that overcome trade-offs between representational fidelity and development costs would be particularly valuable going forward. From the perspective of policy-development, an online space such as this might also host models for policy makers to interact with as "interested amateurs". By better enabling modellers to work together to robustly compare and combine their models, and to discuss with users to learn and improve models, advantages of hybridity might be more readily realised. In turn, the models produced should enable more insightful contributions to the comparative issues discussed above and ensure the continuation of innovative modelling for understanding landscape change, its causes and consequences for sustainability in the Anthropocene.

References

1. Ding, D.; Bennett, D.; Secchi, S. Investigating impacts of alternative crop market scenarios on land use change with an agent-based model. *Land* **2015**, *4*, 1110–1137. [CrossRef]
2. Olabisi, L.; Wang, R.; Ligmann-Zielinska, A. Why don't more farmers go organic? Using a stakeholder-informed exploratory agent-based model to represent the dynamics of farming practices in the philippines. *Land* **2015**, *4*, 979–1002. [CrossRef]
3. Morgan, F.; Brown, P.; Daigneault, A. Simulation *vs*. Definition: Differing approaches to setting probabilities for agent behaviour. *Land* **2015**, *4*, 914–937. [CrossRef]
4. Badmos, B.; Agodzo, S.; Villamor, G.; Odai, S. An approach for simulating soil loss from an agro-ecosystem using multi-agent simulation: A case study for semi-arid ghana. *Land* **2015**, *4*, 607–626. [CrossRef]
5. Barton, C.; Ullah, I.; Heimsath, A. How to make a barranco: Modeling erosion and land-use in mediterranean landscapes. *Land* **2015**, *4*, 578–606. [CrossRef]
6. Johnson, P. Agent-based models as "interested amateurs". *Land* **2015**, *4*, 281–299. [CrossRef]
7. Brändle, J.; Langendijk, G.; Peter, S.; Brunner, S.; Huber, R. Sensitivity analysis of a land-use change model with and without agents to assess land abandonment and long-term re-forestation in a swiss mountain region. *Land* **2015**, *4*, 475–512. [CrossRef]
8. Crabtree, S. Simulating littoral trade: Modeling the trade of wine in the bronze to iron age transition in southern france. *Land* **2016**, *5*, 5. [CrossRef]
9. Clark, J.; Crabtree, S. Examining social adaptations in a volatile landscape in northern mongolia via the agent-based model ger grouper. *Land* **2015**, *4*, 157–181. [CrossRef]
10. Arifin, S.; Arifin, R.; Pitts, D.; Rahman, M.; Nowreen, S.; Madey, G.; Collins, F. Landscape epidemiology modeling using an agent-based model and a geographic information system. *Land* **2015**, *4*, 378–412. [CrossRef]
11. Axtell, R.; Axelrod, R.; Epstein, J.M.; Cohen, M.D. Aligning simulation models: A case study and results. *Computational & Mathematical Organization Theory* **1996**, *1*, 123–141.
12. Hales, D.; Rouchier, J.; Edmonds, B. Model-to-model analysis. *J. Artif. Soc. Soc. Simul.* **2003**, *6*.
13. Rouchier, J.; Cioffi-Revilla, C.; Polhill, J.G.; Takadama, K. Progress in model-to-model analysis. *J. Artif. Soc. Soc. Simul.* **2008**, *11*.
14. Thiele, J.C.; Grimm, V. Replicating and breaking models: Good for you and good for ecology. *Oikos* **2015**, *124*, 691–696. [CrossRef]
15. Janssen, M.A. Understanding artificial anasazi. *J. Artif. Soc. Soc. Simul.* **2009**, *12*, A244–A260.
16. Miodownik, D.; Cartrite, B.; Bhavnani, R. Between replication and docking: "Adaptive agents, political institutions, and civic traditions" revisited. *J. Artif. Soc. Soc. Simul.* **2010**, *13*. [CrossRef]
17. Seagren, C.W. A replication and analysis of tiebout competition using an agent-based computational model. *Soc. Sci. Comput. Rev.* **2015**, *33*, 198–216. [CrossRef]
18. Wainwright, J.; Millington, J.D.A. Mind, the gap in landscape-evolution modelling. *Earth Surf. Proc. Land.* **2010**, *35*, 842–855. [CrossRef]
19. O'Sullivan, D.; Millington, J.; Perry, G.; Wainwright, J. Agent-based models—Because they're worth it? In *Agent-Based Models of Geographical Systems*; Heppenstall, J.A., Crooks, T.A., See, M.L., Batty, M., Eds.; Springer Netherlands: Dordrecht, The Netherlands, 2012; pp. 109–123.
20. Verburg, P.H.; Dearing, J.A.; Dyke, J.G.; Leeuw, S.V.D.; Seitzinger, S.; Steffen, W.; Syvitski, J. Methods and approaches to modelling the anthropocene. *Glob. Environ. Chang.* **2015**. [CrossRef]
21. O'Sullivan, D.; Evans, T.; Manson, S.; Metcalf, S.; Ligmann-Zielinska, A.; Bone, C. Strategic directions for agent-based modeling: Avoiding the yaawn syndrome. *J. Land Use Sci.* **2016**, *11*, 177–187. [CrossRef] [PubMed]
22. Liu, J.G.; Hull, V.; Batistella, M.; DeFries, R.; Dietz, T.; Fu, F.; Hertel, T.W.; Izaurralde, R.C.; Lambin, E.F.; Li, S.X.; *et al.* Framing sustainability in a telecoupled world. *Ecol. Soc.* **2013**, *18*. [CrossRef]