AgTech that doesn't cost the Earth: Creating sustainable, ethical and effective agricultural technology that enhances its social and ecological contexts

Alan Dorin[1*], Alexandra S. Penn[2] and Jesús M. Siqueiros[3]
[1] Computational and Collective Intelligence, Dept. of Data Science & AI, Faculty of Info. Tech., Monash University, Australia
[2] Centre for the Evaluation of Complexity Across the Nexus, Centre for Research in Social Simulation, Dept. of Sociology, University of Surrey, UK
[3] Unidad Académica del IIMAS en el Estado de Yucatán, IIMAS, UNAM, México
*alan.dorin@monash.edu

Abstract

To feed the growing human population we require increased food production and security, while using less land and causing less environmental damage. Significant changes in agriculture are needed to meet these demands. One widely touted solution is smart, AI-enhanced Agricultural Technology. In this article we argue that improved technology is insufficient to address the needs of many farmers, but that by taking a whole-of-system approach native to Artificial Life we can shift towards creating sustainable, ethical and effective AgTech. This can innovate industrial agriculture in developed nations and benefit small landholders from vulnerable communities, whilst reducing the environmental impacts of food production globally.

Introduction and background

The rapidly increasing human population demands more food, and more reliable food production, but significant changes in agricultural practices are needed to meet these demands under urban intensification, in an increasingly unpredictable climate, whilst reducing poverty, resource consumption and environmental damage [1, 2]. The majority of the world's farmers operate very small plots in developing nations [3]. Agricultural Technology (AgTech) can *potentially* reduce their poverty, increase their well-being and food security [4], and drive economic development [5], but it hasn't yet, and it won't, unless changes are made in how it is created, applied and socially integrated. "AgTech" encompasses electronics and algorithms for monitoring, managing and harvesting crops and livestock, agrochemicals and biotech for growing and breeding robust nutritious food, even processes for marketing and distributing food [6, 7]. The data-driven digital technological aspects of AgTech are being prominently disrupted and improved by Artificial Intelligence (AI) [8-10]. However, the impacts of AgTech on food security and poverty are exceedingly complex, context-specific, and have little to do with the technological components of the situation that AI addresses most directly [4, 11]. Consequently, increased data availability and naïve AgTech enhancements via AI miss key factors relating to trust, reliability and social integration required especially for adoption by small-holder and subsistence farmers [8, 11]. They can generate substantial environmental footprints when used by large scale industry that may be forced upon developing nations (although, see [12]). AI and data-enhanced AgTech is therefore no silver bullet. A new approach is needed to lessen social and technological division. Relevant factors that must be incorporated into AgTech research include cultural, social, political and economic concerns that determine the relationship between humans, food, and environment [13]. Improved technology is only one issue for sustainable and ethically feeding people (e.g. [14, 15]).

Here, we link ideas from within the field of Artificial Life (AL) to sustainable, ethical and effective AgTech. These ideas aren't unique to AL, some are explored in fields addressing agriculture's social and environmental aspects. However, the multi/inter/trans-disciplinarity of AL links these aspects *and* technology, and this is specific to the field. Below we classify and discuss AL's potential contributions to AgTech.

Why *should* Artificial Life focus on AgTech?

Artificial Life is a scientific research field that studies natural living phenomena (e.g. organisms, ecosystems, social systems) through research and experimentation with artificial processes, often synthesised in software [16, 17]. Through its concerns with dynamics, synthesis, interactions and complex adaptive systems, AL offers broad, powerful perspectives for AgTech beyond AI-enhanced smart technology (e.g. [10]) and attainment of quantifiable engineering goals. AL principles point AgTech towards ethical food production situated within a whole-of-system context. We classify its contributions as: (i) Understanding and perspective; (ii) Simulation and modelling; (iii) Design and innovation; (iv) Intervention. This categorisation is counter to our intuition as AL researchers that linearity is appropriate, but it is selected for alignment with product lifecycle stages: requirements solicitation, design, development and testing, manufacture, sales, deployment, and customer relationship management.

(i) Understanding and perspective. As noted above, a key point brought home by AL's attention to complex adaptive systems, is that AgTech operates within a hybrid social, economic, technological, agricultural, climatic, ecological, biological system. If overall system behaviour is poorly understood, technological intervention will be unpredictable and failure prone. AL, as a "systems thinking" native, explores cascades of causal effects of technology beyond a myopic focus, e.g. on profit or crop yield, to encompass users' changes of practice and thinking as they interact with AgTech within extended social and environmental feedback loops. An AL perspective implies transdisciplinary co-design and a requirement to understand AgTech's consequences for people, land and environment [13] by unravelling the system's hypothetical trajectories – even if this approach is not (yet) widely adopted within the field itself. This can be achieved via participatory modelling strategies (e.g. (Evolved) Double Diamond [18], Companion Modelling [19]) that link relevant simulations (see (ii) below), stakeholders and researchers in design processes to aid social learning and innovation and to generate new, sustainable and just social, technological, environmental processes.

(ii) Simulation and modelling. AL often adopts interactive computer models and simulations to acquire a preliminary understanding of complex adaptive system behaviour [17, 20]. Only when this has been achieved is it sensible to decide what real challenges should be addressed, what system components or processes are suited to intervention, and what tools are best for intervention. This last point is important because AgTech is only one potential element of food security. Other options include improved land management processes [21, 22] social technologies [23-25], even the avoidance or removal of counter-productive or toxic technology [26, 27].

AL's diverse simulation techniques (e.g. agent-based models, cellular automata, L-systems, network-models) have been applied to bee-pollination [28], land use [29], plant/herbivore interactions [30] and livestock movement [31]. Spatial ecological interactions, information exchange, trade and cooperation in social systems and technology innovation, also form relevant streams in AL simulation research [32-35]. Such approaches can shift AgTech to explore new ideas, promote engagement, and anticipate implementation outcomes.

(iii) Design and innovation. The design, development and sale of current AgTech falls largely within engineering and technology industries. Examples include data platforms, smart farm tractor control and coordination, UAVs, greenhouses, water / nutrient supply systems, monitoring tools, and robotics [8, fig.4]. If tech-focused design processes dominate, manufacturers may entice farmers into ongoing, potentially unsustainable, complex relationships of dependence, such as sowing crops engineered for resistance to glyphosate [36]. They are also likely to develop technology assuming farms aim for profit and increased yield, underlying assumptions that can further divide largescale industrial wealth from subsistence farming poverty [37]. AL simulations can explore how the design and diffusion of technology alters unfolding societal technological dependencies, economies and ecosystems [38].

In software industries *software-as-a-service* contracts with individual users may support companies to maintain products and customer satisfaction [39]. Iterative user experience surveys can help technology address customer requirements within changing application landscapes [40]. AgTech can potentially extend these approaches to sustain interactions between technology and local, dynamic, social and ecological environments after roll-out. However, the diversity of stakeholders, from rural subsistence farmers to multinational corporations, makes this a costly proposition since with it comes vast differences in literacy, digital connectivity and communication preferences or constraints. If these hurdles are not leapt, AgTech risks increasing social division by ignoring the voices of the majority of farmers, who operate plots of less than 2 ha. [3, 41], and forcing them into unsustainable practices. This eventually has ramifications felt by industrial agriculture through international cascades of environmental destruction, famine, war and mass migration (exacerbated by climate change) – scenarios that AL simulations can explore [42, 43]. The preferred scenario is an AgTech that doesn't impose a-contextual technology's limitations on local practices. By investing in co-design and flexible (perhaps simulation-informed) implementation at a local scale, industry facilitates the shift of farmers from users to "active agents" (a prominent AL topic) who learn as they design relevant, sustainable, culturally coherent agrisystems [44]. This ethical approach empowers farmers to appropriate technology on their terms, adds to its longevity and immeasurably improves its value [45].

(iv) Intervention. If stages (i-iii) lead a co-design team to agree on technological intervention, this doesn't imply a "set and forget" mentality will succeed. Beyond initial intervention too, the principles of complex systems guidance familiar to AL researchers suggest that the farmer must continue to participate [46, throughout] in continuous iterative monitoring and adaptation of the dynamical system with novel technology as an untried component. User engagement and empowerment are key to managing this responsibility. Even if the system is understood prior to intervention, no model can predict behaviour subject to as many external influences, feedback loops and degrees of freedom as technology situated within agriculture; an exemplar of complexity. We also expect adaptation and evolution, of both biological and social components to occur. Stakeholders must continually learn and renegotiate the role of AgTech within the agrisystem – the system must be tweaked interactively from inside, a requirement with which many AL researchers are familiar – if food security is to be achieved. AL could further contribute experience with evolving complex systems to developing new adaptive management processes and tools.

Conclusion

Embedding approaches (i-iv) into participatory adaptive management processes [46], enhanced by technology, with stakeholders as full partners, would be a revolutionary vision of people empowered by AgTech to adaptively manage and steer their complex agricultural systems. Artificial Life's approaches have the potential to establish the paradigms to achieve this. We challenge the community to embrace participatory approaches and combine them with our unique technological expertise to make this vision a practicable reality.

References

1. Tallis, H.M., et al., *An attainable global vision for conservation and human well-being.* Frontiers in Ecology and the Environment, 2018. 16(10): p. 563-570.
2. Vågsholm, I., N.S. Arzoomand, and S. Boqvist, *Food Security, Safety, and Sustainability—Getting the Trade-Offs Right.* Frontiers in Sustainable Food Systems, 2020. 4(16): p. 1-14.
3. Lowder, S.K., M.V. Sánchez, and R. Bertini, *Which farms feed the world and has farmland become more concentrated?* World Development, 2021. 142(105455).
4. DeJanvry, A. and E. Sadoulet, *World poverty and the role of agricultural technology: direct and indirect effects.* Journal of Development Studies, 2002. 38(4): p. 1-26.
5. Tripp, R., *Technology and Its Contribution to Pro-Poor Agricultural Development*. 2005, Agriculture and Natural Resources Team - UK Department for International Development. Available from: https://www.fao.org/sustainable-food-value-chains/library/details/en/c/267205/.
6. Watz, E., *Digital farming attracts cash to agtech startups.* Nature Biotechnology, 2017. 35: p. 397–398.
7. Murase, H., *Special issue on Artificial intelligence in agriculture.* Computers and Electronics in Agriculture, 2000. 29(1-2): p. 1-178.
8. Southwood, R. and K. Wong, *Building a Data Ecosystem for Food Security and Sustainability in AgTech V3.0*. 2021, International Center for Tropical Agriculture (CIAT) / CGIAR: Cali, Colombia. p. 1-35. Available from: https://hdl.handle.net/10568/111666.
9. Spanaki, K., et al., *Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research.* Annals of Operations Research, 2022. 308: p. 491-524.
10. Smith, M.J., *Getting value from artificial intelligence in agriculture.* Animal Production Science, 2018. 60(1): p. 46-54.
11. Victor Galaz, et al., *Artificial intelligence, systemic risks, and sustainability.* Technology in Society, 2021. 67: p. 101741.
12. Hasegawa, T., et al., *Risk of increased food insecurity under stringent global climate change mitigation policy.* Nature Climate Change, 2018. 8(8): p. 699-703.
13. Marin, A., A. Ely, and P.v. Zwanenberg, *Co-design with aligned and non-aligned knowledge partners: implications for research and coproduction of sustainable food systems.* Current Opinion in Environmental Sustainability, 2016. 20: p. 93-98.
14. Marco V. Sánchez Cantillo, et al., *The State of Food and Agriculture 2019: Moving forward on food loss and waste reduction*, in *The State of Food and Agriculture (SOFA)*. 2019, Food and Agriculture Organization of the United Nations: Rome, Italy. p. 182.
15. Gustavsson, J., et al., *Global food losses and food waste: Extent, causes and prevention*. 2011, Food and Agriculture Organisation of the United Nations: Rome. p. 37.
16. Boden, M.A., *Artificial Life*, in *The MIT Encyclopedia of the Cognitive Sciences (MITECS)*, R.A. Wilson and F.C. Keil, Editors. 2001, MIT Press: MA, USA / London, England. p. 37-39.
17. Bedau, M.A., *Artificial Life*, in *The Cambridge Handbook of Artificial Intelligence*, K. Frankish and W.M. Ramsey, Editors. 2014, Cambridge University Press: Cambridge, United Kingdom. p. 296-315.
18. Pyykkö, H., M. Suoheimo, and S. Walter, *Approaching Sustainability Transition in Supply Chains as a Wicked Problem: Systematic Literature Review in Light of the Evolved Double Diamond Design Process Model.* Processes, 2021. 9(12): p. 2135.
19. Barreteau, O., *Our Companion Modelling Approach.* Journal of Artificial Societies and Social Simulation, 2003. 6(1).
20. Bromwich, B., et al., *Systems Analysis for Water Resources. Report to Defra, The Department for Environment, Food and Rural Affairs, UK Government 2020.* 2020. Available from: http://randd.defra.gov.uk/Document.aspx?Document=14947_WT15121.FinalReport.pdf.
21. Kamalongo, D.M. and N.D. Cannon, *Advantages of bi-cropping field beans (Vicia faba) and wheat (Triticum aestivum) on cereal forage yield and quality.* Biological Agriculture & Horticulture, 2020. 36(4): p. 213-229.
22. Baum, C., W. El-Tohamy, and N. Gruda, *Increasing the productivity and product quality of vegetable crops using arbuscular mycorrhizal fungi: a review.* Scientia horticulturae, 2015. 187: p. 131-141.
23. Tortia, E.C., V.L. Valentinov, and C. Iliopoulos, *Agricultural cooperatives.* Journal of Entrepreneurial and Organizational Diversity, 2013. 2(1): p. 23-36.
24. Khandker, S.R. and G.B. Koolwal, *How has microcredit supported agriculture? Evidence using panel data from Bangladesh.* Agricultural Economics, 2016. 47(2): p. 157-168.
25. Andersen, R., et al., *Community seed banks: sharing experiences from North and South.* 2018: Paris. p. 44. Available from: https://cgspace.cgiar.org/handle/10568/92510.
26. Carson, R., *Silent Spring*. 1962, Great Britain: Penguin Books.
27. Gleadow, R., J. Hanan, and A. Dorin, *Averting robo-bees: why free-flying robotic bees are a bad idea.* Emerging Topics in Life Sciences, 2019. 3(6): p. 723-729.
28. Dorin, A., et al., *Simulation-governed design and tuning of greenhouses for successful bee pollination*, in *Artificial Life*, T. Ikegami, et al., Editors. 2018, MIT Press: Tokyo, Japan. p. 171-178.
29. Gomes, E., et al., *Modelling future land use scenarios based on farmers' intentions and a cellular automata approach.* Land Use Policy, 2019. 85: p. 142-154.

30. Hanan, J., et al., *Simulation of insect movement with respect to plant architecture and morphogenesis.* Computers and Electronics in Agriculture, 2002. 35(2-3): p. 255-269.
31. Stricklin, W., et al., *Artificial pigs in space: using artificial intelligence and artificial life techniques to design animal housing.* Journal of Animal Science, 1998. 76(10): p. 2609-2613.
32. Dobbie, S., et al., *Agent-based modelling to assess community food security and sustainable livelihoods.* Journal of Artificial Societies and Social Simulation, 2018. 21(1): p. 1-23.
33. Lansing, J.S. and J.N. Kremer. *Emergent properties of balinese water temple networks: co-adaption on a rugged fitness landscape*. in *Artificial Life III. Studies in the Sciences of Complexity*. 1994. Addison Wesley p. 201-223.
34. Schlüter, M., B. Müller, and K. Frank, *The potential of models and modeling for social-ecological systems research: the reference frame ModSES.* Ecology and Society, 2019. 24(1): p. 1-31.
35. Rebaudo, F. and O. Dangles, *Adaptive management in crop pest control in the face of climate variability: An agent-based modeling approach.* Ecology and Society, 2015. 20(2): p. 1-18.
36. Powles, S.B., *Evolved glyphosate-resistant weeds around the world: lessons to be learnt.* Pest Management Science, 2008. 64(4): p. 360-365.
37. Bronson, K., *Looking through a responsible innovation lens at uneven engagements with digital farming.* NJAS - Wageningen Journal of Life Sciences, 2019. 90-91: p. 100294.
38. Berger, T., *Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis.* Agricultural Economics, 2001. 25(2-3): p. 245-260.
39. Choudhary, V., *Comparison of Software Quality Under Perpetual Licensing and Software as a Service.* Journal of Management Information Systems, 2014. 24(2): p. 141-165.
40. Kujala, S., et al., *UX Curve: A method for evaluating long-term user experience.* Interacting with Computers, 2011. 23(5): p. 473-483.
41. Lowder, S.K., J. Skoet, and T. Raney, *The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide.* World Development, 2016. 87: p. 16-29.
42. Shults, F.L., et al. *Artificial Societies in the Anthropocene: Challenges and Opportunities for Modeling Climate, Conflict, and Cooperation*. in *Winter Simulation Conference (WSC)*. 2021. IEEE p. 1-12.DOI: doi: 10.1109/WSC52266.2021.9715391.
43. Berger, T. and C. Troost, *Agent-based Modelling of Climate Adaptation and Mitigation Options in Agriculture.* Journal of Agricultural Economics, 2014. 65(2): p. 323-348.
44. Marin, A., P.V. Zwanenberg, and A. Cremaschi, *Bioleft: A collaborative, open source seed breeding initiative for sustainable agriculture*, in *Transformative Pathways to Sustainability: Learning Across Disciplines, Cultures and Contexts*, A. Ely, Editor. 2021, Routledge, Taylor and Francis: London. p. 90-108.
45. Van Zwanenberg, P., et al., *Seeking unconventional alliances and bridging innovations in spaces for transformative change: the seed sector and agricultural sustainability in Argentina.* Ecology and Society, 2018. 23(3): p. 1-11.
46. Roling, N.G. and M.A.E. Wagemakers, eds. *Facilitating sustainable agriculture: participatory learning and adaptive management in times of environmental uncertainty*. 2000, Cambridge University Press: Cambridge, United Kingdom. 348.