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Deep mutual learning: incentives and trust through collaborative integration of artificial intelligence into sustainability science

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Sustainability science increasingly requires computationally intensive predictive and decision-making tasks across varied temporal and spatial scales. We argue that these needs in sustainability science offer opportunities to develop trusted and transparent artificial intelligence (AI) based on principles that we define here as relevance, abundance, complexity, transferability, and specificity. Collaborations between AI and sustainability scientists should adopt the proposed "deep mutual learning" that integrates engagement with practitioners to build a shared incentive structure, and innovate question creation and an environment of co-creation with co-location. We emphasize a shared incentive structure that rests on fully integrating practitioners in the collaboration, including industry, municipalities, and the public. This approach will guide us towards sustainable policies with far-reaching societal benefits.

Sustainability spotlight

Artificial intelligence (AI) has greatly advanced scientific capabilities, but has also garnered considerable criticism. Sustainability science is predestined to benefit from computational capabilities offered by AI, as the needs for addressing the diverse UN sustainable development goals require considerations of trade-offs and multiple different and often divergent needs by practitioners. As sustainability science is becoming more complex, AI approaches are becoming more computationally intensive, and require specialized knowledge. It is therefore timely to develop clear guidelines on how to foster productive co-creation processes across science and practitioner domains. Here, we chart several foundational approaches in scientific collaboration, industry relations, and education that we feel are pivotal to move sustainability science forward using trusted and transparent AI collaborations. We focus on a shared incentive structure that puts practitioners at the center of the collaborative network.

Justification

Artificial intelligence (AI) has made large conceptual advances and will continue to open possibilities in science and society that we could not have anticipated even a few years ago. The proliferation of AI has also met with considerable trepidation, as it can obscure cause and effect in science as much as lead to myth building in public discourse.[1] Similar to large language models,[2] the question remains whether AI may combat or exacerbate misinformation in the sustainability sciences. The opportunities for advancing sustainability science using AI have been demonstrated in earth science[3] to develop sustainable solutions.[4] These include diverse objectives as listed in the sustainable development goals[5] and have ushered in transformative change in sustainability in the last few years,[6] many based on accelerating the speed of scientific discovery.[7] Educational approaches have been discussed[8] and a new workforce will have experienced more cross-training, while research collaborations in this rapidly evolving field remain fundamentally challenged[9] by entrenched organizational and disciplinary incentive structures.[10] Sustainability and environmental sciences promise larger potential benefits from using AI compared to other disciplines, but unfortunately the share of collaborative papers between AI and environmental scientists is the lowest among disciplines,[11] highlighting the need for developing mechanisms to foster cross-disciplinary collaboration. Therefore, we develop a conceptual framework specifically emphasizing an urgently needed joint incentive structure through developing trust by integrating practitioners (*e.g.*, farmers, policy makers, industry, consumers) and their needs.

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Our proposal

Here we propose 'deep mutual learning' as a bridge between sustainability scientists and AI scientists to develop trusted and transparent policy and societal impact through (1) a shared incentive structure; (2) a focus on creation of appropriate questions that focus on the needs of practitioners; and (3) re-design of the work ecosystem.

A key challenge is an eye-level and transparent collaboration where everyone benefits in their own area of scholarship and develop trusted policy and societal impact together with farmers, policy makers, industry, and the public (Fig. 1). All too often, the AI computer scientists may be asked to 'help' the sustainability scientists to achieve their goals, similar to a statistical consultancy services commonly available at research institutions, rather than advancing AI science itself. However, the AI scientists must still advance their own scientific discipline, and the use case of sustainability may in our view provide an attractive training ground to achieve that. At the same time, sustainability scientists must create trust when communicating scientific results to practitioners through transparent AI methodology. Unfortunately, sustainability and AI scientists speak different scientific languages and have, in our experience with large national and international programs on AI, remained largely separated from each other. In the following sections, we first outline the opportunities that should in our opinion be leveraged to then develop the methodology of deep mutual learning through a shared incentive structure, create questions and an enabling work ecosystem based on co-creation with co-location.

Creating opportunities

What are the opportunities and associated risks that sustainability science provides to accelerate AI science and *vice versa*? What makes sustainability science an attractive training ground for AI science? We have identified relevance, abundance, complexity, transferability, and specificity as the most important attributes that sustainability scientists can leverage and that we call 'deep mutual learning' (Fig. 2).

Relevance

Young AI professionals have many high-paying industry options to apply their talents. However, many students may also prioritize working on topics that strike an emotional chord—such as saving humanity from catastrophic climate change, rescuing endangered plant and animal species from extinction, or securing drinking water—as these areas offer a sense of meaningful impact.[12] Here, we suggest that interactions with farmers, industry or policymakers which are essential to achieving sustainability add to perceived relevance to society and can be leveraged for students in the computer sciences to choose a career in sustainability. This requires collaboration between sustainability scientists and AI scientists to attract the best young researchers. Alarmingly, only 33% of papers using AI are currently co-authored by both computer scientists and domain scientists.[11] In comparison, the share of collaborative publications in engineering has increased from 21% to 44% over the past two decades.[11] We propose that broader collaborations including those that justify and result in co-authorship can be achieved by including the needs of practitioners into projects. The experience of some of us leading a US national AI Institute showed that practitioner input provides highly motivating guidance to ask questions in the basic sciences that would otherwise not be apparent. We propose to employ the already established collaborative intelligence (CI) approach[13–15] in sustainability sciences precisely to integrate such views and needs of practitioners which appears to not have been explored in sustainability science.[16] Key is that AI remains explainable to avoid risks which builds on a long history in information systems research.[17]

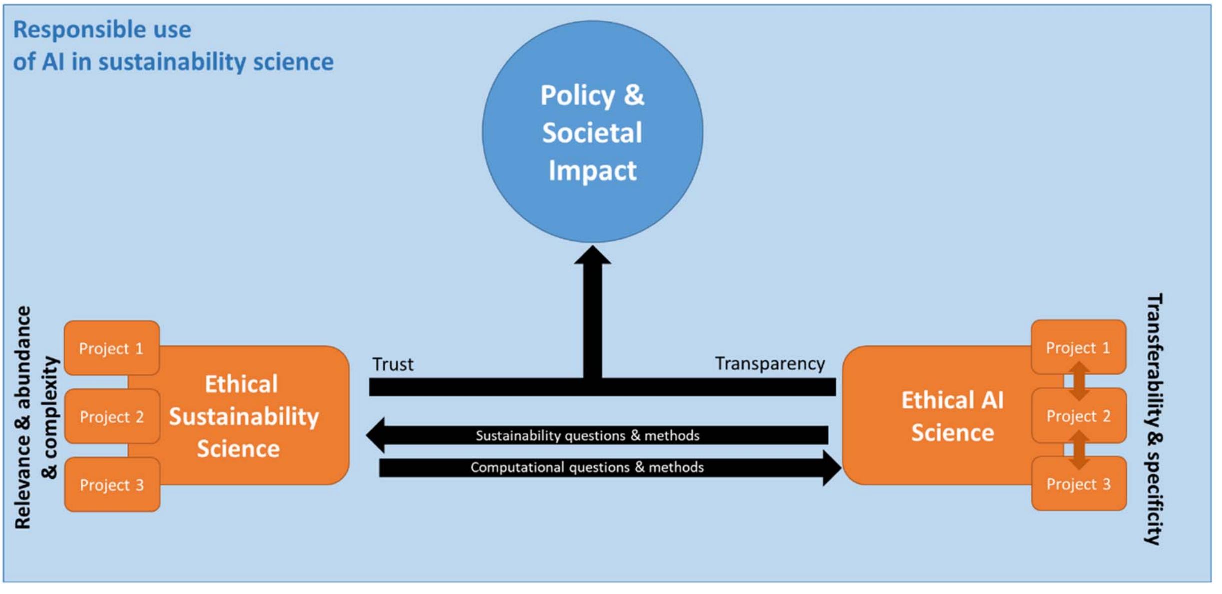

Fig. 1 Outline of collaboration between sustainability and AI scientists as a two-way street, in order to generate transparent and trusted policy and societal impact.

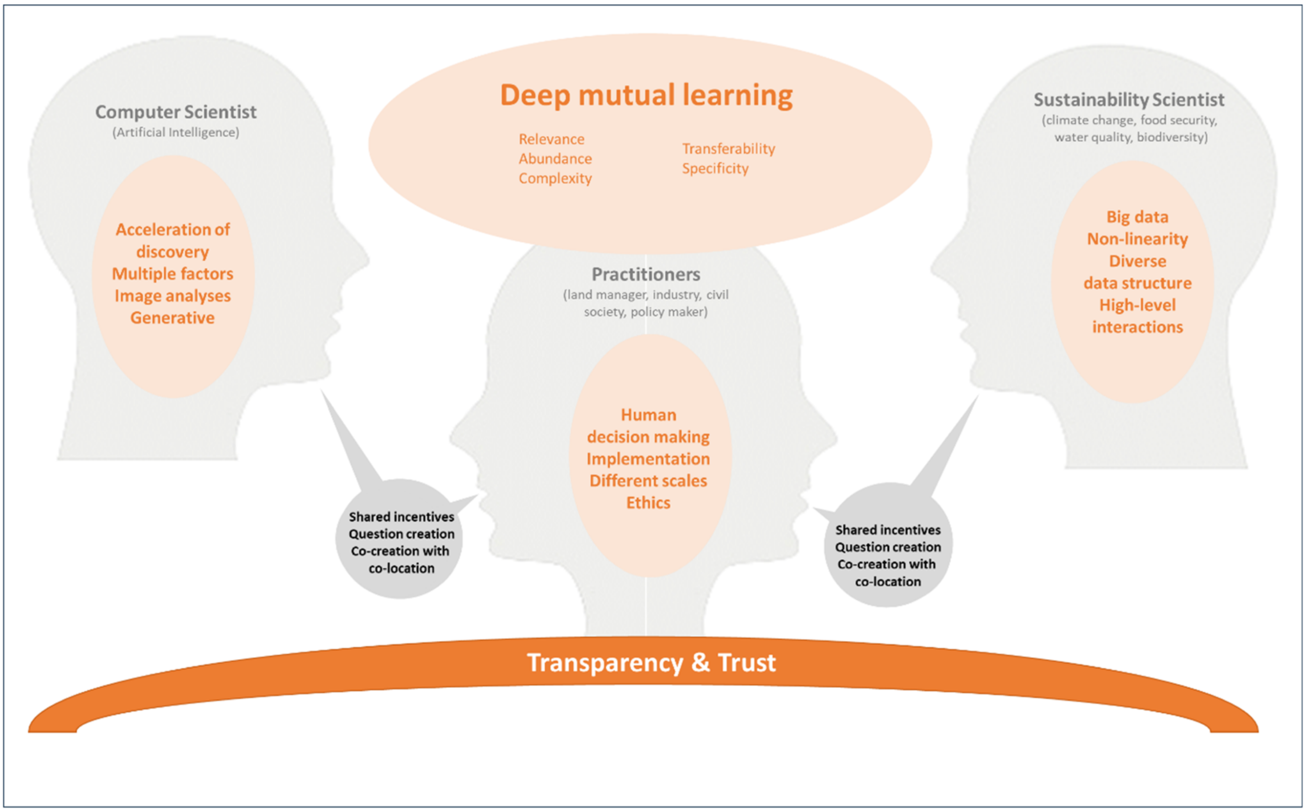

Fig. 2 Conceptual proposal of how to utilize divergent incentives, resources, and ways of working to leverage AI through deep mutual learning, which comprises relevance, abundance, complexity, transferability and specificity (outlined in more detail in the text) in order to build a trusted and transparent bridge between computer and sustainability scientists in collaboration with practitioners.

Abundance

We suggest that complex sustainability science offers an abundance of questions relevant to real-life settings that require development of newer and more sophisticated computational approaches.[5] Nature-based climate solutions in agriculture for example rely on spatially explicit assessment of carbon cycles[18] with computational needs exceeding traditional modeling approaches. This is an important example where new AI approaches at the intersection with mechanistic modeling can prove transformational.[19] The ever-changing challenges in sustainability are also attractive as training grounds, because they include newly emerging drivers of global environmental change (*e.g.*, microplastic, PFAS). For example, AI can help in water quality management with respect to PFAS through appropriate operation and management of groundwater resources.[20] Here, again, the application and link to the needs of practitioners is providing attractive study cases.

Complexity

Sustainability science provides a very complex training ground for AI scientists.[21] Sustainability science thrives on highly non-linear and high-level interactions between many factors (*e.g.*, plants, animals, microbes), processing large numbers of compounds (*e.g.*, gases, nutrients) under rapidly changing conditions at multiple time and space scales. These attributes of sustainability pose a risk of generating unintended consequences as such complex interactions are challenging to verify independently. Ecological systems closely interact with socio-economic factors (policy, governance, acceptance) that make human decision making central to finding sustainability solutions, adding further complexity to the interactions. Therefore, sustainability science is in many cases handling a broad array of different data types, including images, text or numbers, that require new solutions that AI computer science must address in a transparent way. Traditional machine learning methods lack interpretability, emphasize prediction and correlation, rather than causation, and often violate physical constraints. For example, traditional AI machine learning methods assume that testing and training data come from identical data distribution. However, it is violated by the geographic heterogeneity and temporal non-stationarity in sustainability science datasets and use-cases. Also, AI neural network learning algorithms focus on soft constraints such as so-called regularizers,[22] while sustainability science may require so-called hard constraints such as conservation of mass and energy, as in many other domains.[23] This is especially true when addressing the multiple sustainability challenges highlighted by SDGs, which requires a shift from single-objective to multi-objective optimization in evolving AI decision-support systems. AI's capacity to navigate complex trade-offs highlights its potential to clarify interactions as well as points out its transparency issues. As AI becomes a common tool in sustainability science, the need for ethical systems that align with societal values and goals are paramount. This need is logically in conflict with transparency of complex systems. Again, we propose that integration of practitioners into the projects will generate the necessary trust, if that integration is genuine and is done before the research commences. Our experience with focus groups and early practitioner input to research objectives is consistent with this recommendation.

Transferability

The fact that computational processes that allow AI techniques devised within one sustainability problem to be effectively transferred and applied to others is important to AI science, while transferability is usually absent in sustainability science (Fig. 1). Through minimizing computational time, AI scientists can delve deeper into problem complexity, make use of existing solutions, which enables us to transfer known successful strategies for new challenges in the sustainability sciences for which computational solutions are unknown. For example, consider the challenge of designing computationally faster surrogate models to replace computationally more expensive process-based models in sustainability science. In recent decades, deep neural networks have provided computational solutions for this challenge in for example language modeling[24] and are therefore now being evaluated in sustainability science, as well. As another example, multi-entity classification and regression models have been applied across diverse domains, including species distribution modeling,[25,26] materials property prediction, and image classification and detection.[27] In addition, deep reasoning networks that were developed for phase mapping of crystal-structures also showed that they can solve Sudokus.[28] This transferability of computational approaches inherently encourages the emergence of cross-cutting themes in AI, thereby fostering enhanced collaboration between AI and different sustainability researchers. Consequently, it is crucial to identify a core set of such cross-cutting AI problems without introducing risks, opening up applications across diverse fields. A purposeful dialogue between sustainability and AI scientists is therefore essential to ensure that the transfer of computational models and algorithms not only captures, but also fully leverages, the unique aspects of the target problems and does not create artifacts.[21] It is commonly assumed that the rapidly developing computational approaches based on AI can only be made use of in sustainability sciences[29] in a trusted manner through transparent collaborations between AI computer scientists and sustainability scientists.[30] Here, we expand this concept by anchoring the collaborations around specific needs or practitioners.

Specificity

To manage risks in tackling complex computational problems, it is critical to understand the sustainability structure through incorporating prior scientific knowledge. For example, mapping soil carbon for carbon sequestration assessments[18] requires knowledge about carbon transport and transformation in the landscape that goes beyond applying innovative deep learning techniques. Only by harnessing specific domain information, again centered around the needs of practitioners, can we craft appropriate computational models that are efficient, effective, and robust. This approach also proves important in data-limited scenarios, enabling computational models to better handle noise, outliers, or even alterations in the data distribution,[19] while ensuring transparency of where data come from and how they interact. Therefore, specificity is key to interpretability with known risks and uncertainties, which provides the basis for successful translation into policy advice and societal impact.

Deep mutual learning in cross-disciplinary collaboration

Building on these opportunities and risks, we propose a process of deep mutual learning (Fig. 2) that is here defined as a set of organizational, behavioral and educational principles that all aim at and rely on including practitioners in the AI-sustainability nexus. We suggest that a trusted AI can only be achieved by developing a shared incentive structure, focusing on question creation, and insisting on co-creation with co-location. These principles are discussed in detail below.

Shared incentive structure

Probably the most impactful changes can be made here that are more specific to the AI-sustainability nexus than strategies for collaboration that have already been proposed in many other scientific fields.[31] Sustainability scientists must satisfy the needs of one or more practitioners such as land managers, policy makers, *etc.*, while AI scientists must solve computational problems across different domains or fields of inquiry. For example, a sustainability scientist may develop insights that allow more carbon to be sequestered in soil to mitigate climate change to benefit the general public, improve soil health ensuring clean water for the local population and generate revenue for the farmer through carbon trading. The AI scientist, however, must demonstrate that the new AI solution can be applied, for example, to soil carbon sequestration, to semiconductor technology and to the popular game of chance 'Bingo' to demonstrate general applicability of the new algorithm. The sustainability scientist does typically not share interest in electronics or games, whereas professional rewards rest on benefits for widely divergent fields for the AI scientist. Such divergent incentives create unexpected challenges[9] that are not commonly known in the sustainability sciences and are not yet a target for inquiry. This observation is consistent with the finding that only less than one third of scientific AI publications are co-authored by domain scientists such as soil scientists together with computer scientists.[11] The opportunity for collaboration that motivates the AI scientist arises in the sustainability sciences through the need to capture different spatial and temporal scales and human decision making that creates scientifically intriguing complexity. For example, computer scientists may develop novel computational solutions that can then be combined with mechanistic insights in knowledge-guided machine learning projects to identify the most promising places and approaches for soil carbon sequestration in agroecosystems.[19] Through our interactions with practitioners in the land-use sector in the US using focus group sessions in 2024, it also became clear that a severe lack of trust remains whether or not AI will have positive outcomes, which is wide-spread among practitioners as shown for a survey of more than 30 000 individuals across 28 EU countries.[32] Socio-technical barriers and data privacy issues have therefore to be recognized in deep mutual learning. Here we posit that creating the proposed shared incentive structure is essential to develop trust at the AI-sustainability nexus and is within reach through establishing long-term partnerships[8] as a key aspect of deep mutual learning.

For the sustainability scientist, this means prioritizing the needs of practitioners, including farmers or policy makers where again mutual trust is pivotal (Fig. 2). Deep mutual learning therefore involves accepting that sustainability scientists cannot become AI scientists and *vice versa* to fully capitalize on the synergies between these fields of study. An important task then lies in fostering a deep and true understanding by the sustainability scientist not only what the results of the AI mean but also how they were achieved. This puts a large responsibility on the AI scientist to evaluate AI methods for their transparency also and specifically of its risks. Most importantly, we claim that a shared incentive structure by sustainability and AI scientists will provide the bridge for developing trust for practitioners which in turn builds shared incentives for all three groups (Fig. 2).

Question creation

We propose deep mutual learning that iterates between discovery of new AI possibilities and the ability to ask new questions relevant to sustainability, – rather than answering old questions for which AI is already available. Such method development should ideally coincide with the generation of novel research questions that encompass every dimension of sustainability. These dimensions should address not only human well-being but also emphasize the vital importance of safeguarding plants, animals, land, sea, and our climate. This critical step of question creation, which demands substantial interaction between AI scientists and sustainability scientists, is arguably the most important.[33,34] Unfortunately, it is often the most overlooked phase in the research process.[35] Here, generative AI such as large language models implemented in apps such as ChatGPT are already deployed as an intermediate tool to create new questions[36] that may be compared with or even initiate conventional approaches to question creation.[37] Therefore, we have to develop a path from question creation to problem solving that allows formal verification. This may be done by using AI as a tool to create hypotheses that are seeding a new generation of sustainability experiments. Here, it will again be key to start with the needs of practitioners, consistent with the demand for a future where humans and AI collaborate, "with both parties contributing to the creative endeavor without dominating or stifling the other".[38]

Co-creation with co-location

In order to develop trust and transparency, deep mutual learning of AI and sustainability principles is known to have to begin early at the undergraduate level using integrated classroom models that allow discussion time and a low level of entry requirements,[39] as the level of AI education is at present about a tenth lower *e.g.* in geography (an important area of sustainability) than in computer science.[11] Building on such an undergraduate education, universities should create cohorts of young scholars at the graduate education level with sustainability and AI scientists that practice deep mutual learning through for example dedicated place-making[40] graduate programs or temporary institutes or centers (such as AI-LEAF at https://aiinstitutes.org/institute-ai-leaf/). Such cohorts will also allow synergies across different computational sustainability projects through transferability of methods, while taking into consideration and leveraging the specificity of each project. Care must be taken to not misrepresent approaches that work in one area but not in another, which will require deep mutual learning across more than two fields. At all research levels, co-creation with co-location is needed,[40] because sporadic meetings or cross-cutting seminars are not sufficient for breakthrough science.[41] Progressively greater specialization means that full cross-training of sustainability and computer scientists may become even more challenging in the future due to ever more widely divergent skill sets; stacking too many demands on skills and knowledge may fail. Senior scientists and company managers should be tasked with initiating to build bridges for 'undisciplinary' interaction of scientists with diverse backgrounds[42] while students will need to populate these platforms to form teams that are conducting the projects; particular attention must be paid to inclusion of underrepresented minorities, as *e.g.* women and Black scientists are currently associated with lower potential benefits from AI methods in their research output.[11] Key is again that such teams are broadened to co-create viable sustainability solutions jointly with farmers, land managers, and policy makers (Fig. 2).

Such broad teams should also explore making use of generative AI for trusted and transparent scenarios of sustainability outcomes.[43] Examples of the use of AI in probing sustainability solutions through co-creation with co-location[40] in coordination with practitioners may include scenario development such as by world-building to communicate possible futures of the effect of sea level rise in Lagos[44] in the year 2199 or through online games to interrogate whether plants can play.[45] Such "what-if" scenarios are able to generate new questions and anticipate problems that do not emerge through conventional linear thinking. These approaches also give practitioners the opportunity to weigh in on the problems, and explore their own role in it.

Conclusion

These three sets of recommendations are intended to develop deep mutual learning that grow a new generation of sustainability and AI scientists addressing sustainability challenges by including practitioners at the center of the scientific process. Including practitioners provides a bridge and we propose serves as a joint incentive structure between computer and sustainability science that has remained elusive. Institutional policy and funding must be directed to positioning practitioners within such incentive structures to advance a responsible use of AI in sustainability science.

Data availability

No primary research results, software or code have been included and no new data were generated or analysed as part of this review.

Conflicts of interest

There are no conflicts of interest. Artificial intelligence and generative AI was not used at any step of the preparation of any part of this manuscript.

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References

1 G. Spitale, N. Biller-Andorno and F. Germani, *Sci. Adv.*, 2023, **9**, eadh1850.
2 C. Chen and K. Shu, *AI Mag.*, 2024, **45**, 354–368.
3 M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler and N. Carvalhais, *Nature*, 2019, **566**, 195–204.
4 J. Shuford, *J. Artif. Intell. Gen. Sci.*, 2024, **1**, 106–123.
5 N. Tomašev, J. Cornebise, F. Hutter, S. Mohamed, A. Picciariello, B. Connelly, D. C. M. Belgrave, D. Ezer, F. C. van der Haert, F. Mugisha, G. Abila, H. Arai, H. Almiraat, J. Proskurnia, K. Snyder, M. Otake-Matsuura, M. Othman, T. Glasmachers, W. de Wever, Y. W. The, M. E. Khan, R. De Winne, T. Schaul and C. Clopath, *Nat. Commun.*, 2020, **11**, 2468.
6 M. Sahle, S. A. Lahoti, S. Y. Lee, C. Kamiyama, X. Tan, R. Kozar, O. Saito and K. Takeuchi, Mapping the evolving research landscape of sustainability science from 2006 to 2023: unveiling its transformation, *Sustain. Sci.*, 2024, **19**, 1735–1750.
7 V. Khurana, *Emerg. Trends Machine Intel. Big Data*, 2024, **16**, 38–53.
8 D. Pennington, I. Ebert-Uphoff, N. Freed, J. Martin and S. A. Pierce, *Sustain. Sci.*, 2020, **15**, 647–661.
9 K. Rana, S. J. Aitken and R. Chimoriya, *Science*, 2025, **15**, 72.
10 M. J. Burtscher and J. Hüffmeier, *Team Perform. Manage. Int. J.*, 2025, **31**, 226–246.
11 J. Gao and D. Wang, *Nat. Hum. Behav.*, 2024, **8**, 2281–2292.
12 M. A. Goralski and T. K. Tan, *Int. J. Manage. Educ.*, 2020, **18**, 100330.
13 S. L. Epstein, *Artif. Intel.*, 2015, **221**, 36–45.
14 H. J. Wilson and P. R. Daugherty, *Harv. Busin. Rev.*, 2018, **96**, 114–123.
15 K. Goldberg, *Nat. Mach. Intell.*, 2019, **1**, 2–4.
16 E. Schleiger, C. Mason, C. Naughtin, A. Reeson and C. Paris, *Appl. Artif. Intell.*, 2024, **38**, 2327890.
17 C. Meske, E. Bunde, J. Schneider and M. Gersch, *Inf. Syst. Manage.*, 2022, **39**, 53–63.
18 T. Tan, G. Genova, G. Heuvelink, J. Lehmann, L. Poggio, D. Woolf and F. You, *Environ. Sci. Technol.*, 2024, **58**, 11492–11503.
19 L. Liu, W. Zhou, K. Guan, B. Peng, S. Xu, J. Tang, Q. Zhu, J. Till, X. Jia, C. Jiang, S. Wang, Z. Qin, H. Kong, R. Grant, S. Mezbahuddin, V. Kumar and Z. Jin, *Nat. Commun.*, 2024, **15**, 357.
20 A. Hosseinzadeh, A. Altaee, X. Li and J. L. Zhou, *Curr. Op. Chem. Engin.*, 2023, **42**, 100983.
21 C. P. Gomes, D. Fink, R. B. Van Dover and J. M. Gregoire, *Nat. Rev. Materials*, 2021, **6**, 645–647.
22 T. Kotsilieris, I. Anagnostopoulos and I. E. Livieris, *Electronics*, 2022, **11**, 521.
23 J. Pan, *Nat. Computat. Sci.*, 2021, **1**, 244.
24 R. Miikkulainen, J. Liang, E. Meyerson, A. Rawal, D. Fink, O. Francon, B. Raju, H. Shahrzad, A. Navruzyan, N. Duffy and B. Hodjat, in *Artificial Intelligence in the Age of Neural Networks and Brain Computing*, ed. R. Kozma, C. Alippi, Y. Choe, F. C. Morabito, Academic Press, New York City, 2024, pp. 269–287.
25 C. L. Davis, Y. Bai, D. Chen, O. Robinson, V. Ruiz-Gutierrez, C. P. Gomes and D. Fink, *Ecology*, 2023, **104**, e4175.
26 G. Zhang, H. Ren, W. Zhen, X. Ma, L. Wang and H. Dong, in *IEEE 5th International Conference on Advanced Electrical and Energy Systems (AEESIEEE)*, 2024, pp. 344–348.
27 O. Mac Aodha, E. Cole and P. Perona, in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2019, pp. 9596–9606.
28 D. Chen, Y. Bai, S. Ament, W. Zhao, D. Guevarra, L. Zhou, B. Selman, R. B. van Dover, J. M. Gregoire and C. P. Gomes, *Nat. Mach. Intell.*, 2021, **3**, 812–822.
29 L. H. Kaack, P. L. Donti, E. Strubell, G. Kamiya, F. Creutzig and D. Rolnick, *Nat. Climate Change*, 2022, **12**, 518–527.
30 C. G. García, K. J. Bagstad, J. Brun, R. Chaplin-Kramer, T. Dhu, N. J. Murray, C. J Nolan, T. H. Ricketts, H. M. Sosik, D. Sousa and G. Willard, *Environ. Res. Letters*, 2023, **18**, 011003.
31 E. V. Eikey, M. C. Reddy and C. E. Kuziemsky, *J. Biomed. Informat.*, 2015, **57**, 263–277.
32 N. Omrani, G. Rivieccio, U. Fiore, F. Schiavone and S. Garcia, *Agreda Technol. Forecast. Soc. Change*, 2022, **181**, 121763.
33 U. Alon, *Mol. Cell*, 2009, **35**, 726–728.
34 I. Yanai and M. Lercher, *Gen. Biol.*, 2019, **20**, 1–5.
35 J. Lehmann, R. G. Cole and N. E. Stern, *Leonardo*, 2023, **56**, 488–495.
36 E. Agathokleous, M. C. Rillig, J. Peñuelas and Z. Yu, *Trends Plant Sci.*, 2023, **29**, 210–218.

37 E. M. Armstrong, E. R. Larson, H. Harper, C. R. Webb, F. Dohleman, J. Araya, C. Meade, X. Feng, B. Mukoye, M. J. Levin, B. Lacombe, A. Bakirbas, A. A. Cardoso, D. Fleury, A. Gessler, D. Jaiswal, N. Onkokesung, V. S. Pathare, S. S. Phartyal, S. A. Sevanto, I. Wilson and C. S. Grierson, *New Phytol.*, 2023, **238**, 470–481.
38 F. Vinchon, T. Lubart, S. Bartolotta, V. Gironnay, M. Botella, S. Bourgeois-Bougrine, J. M. Burkhardt, N. Bonnardel, G. E. Corazza, V. Glăveanu and M. Hanchett Hanson, *J. Creative Behav.*, 2023, **57**, 472–484.
39 A. S. George, *Partners Univ. Innov. Res. Publ.*, 2023, **1**, 112–136.
40 M. B. Hesjedal, *Sci., Techn., Human Val.*, 2023, **48**, 1110–1137.
41 Y. Lin, C. B. Frey and L. Wu, *Nature*, 2023, **623**, 987–991.
42 A. Freiband, K. L. Dickin, M. Glass, M. A. Gore, J. Hinestroza, R. Nelson, V. Platt, N. Rooks, A. Sachs, N. Stern and J. Lehmann, *Human. Soc. Sci. Commun.*, 2022, **9**, 172.
43 M. C. Rillig, M. Ågerstrand, M. Bi, K. A. Gould and U. Sauerland, *Environ. Sci. Technol.*, 2023, **57**, 3464–3466.
44 P. W. Keys and M. P. Keys, *Ecol. Soc.*, 2022, **27**, 40.
45 S. Ruzanka, in *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 2023, pp. 228–230, DOI: **10.1145/3573382.3616049**.