Software and data for circular economy assessment
Donati, F.

6 THE FUTURE OF ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF INDUSTRIAL ECOLOGY

Published in: Journal of Industrial Ecology (2022), 26 (4), pp. 1175-1181.

AUTHORS

Franco Donati, Sébastien M.R. Dente, Chen Li, Xaysackda Vilaysouk, Andreas Froemelt, Rohit Nishant, Gang Liu, Arnold Tukker, Seiji Hashimoto

ABSTRACT

Artificial Intelligence (AI) applications and digital technologies (DTs) are increasingly present in the daily lives of citizens, in cities and in industries. These developments generate large amounts of data and enhance analytical capabilities that could benefit the industrial ecology community and sustainability research in general. With this communication we would like to address some of the opportunities, challenges and next steps that could be undertaken by the Industrial Ecology community in this realm. This article is an adapted summary of the discussion held by experts in Industrial Ecology, AI and sustainability during the 2021 Industrial Ecology Day conference session titled *"The future of artificial intelligence in the context of industrial ecology"*. In brief, building on previous studies and communications, we advise the Industrial Ecology community to: 1) create internal committees and working groups to monitor and coordinate AI applications within and outside the community; 2) promote and ensure transdisciplinary efforts; 3) determine optimal infrastructure and governance of AI for IE to minimize undesired effects; 4) act on effective representation and on reduction of digital divides.

KEYWORDS

Industrial Ecology, Artificial Intelligence, Sustainability, Digital technologies, Interdisciplinary research, Data

6.1 INTRODUCTION

The increasing diffusion of artificial intelligence (AI) applications such as machine learning, expert systems, computer vision, along with the rapid expansion of digital technologies (DTs) for data collection, storage and consumption, are providing society with an unprecedented capacity to generate insights on how to improve the quality of life and environment (UNSGHL, 2019). These developments, often referred to as the fourth industrial revolution (Combes et al., 2018), provide opportunities to improve the sustainability of society's production and consumption system and its governance (Nishant et al., 2020).

While a commonly shared definition of AI remains in many cases evasive (Frolov et al., 2021), in this paper we define it as software employing methods and models aimed at emulating or exceeding humans' intelligence and ability to accomplish given tasks of different level of complexity (Ertel, 2017; Frolov et al., 2021; Negnevitsky, 2011b). Applications of AI span across the following fields (Russell & Norvig, 2010b): Natural Language Processing; Knowledge Representation; Automated Reasoning; Machine Learning; Computer Vision; and Robotics.

However effective AI methods may be, they rely on good quality data to provide good quality insights. As such, it is paramount to discuss the potential of AI in industrial ecology (IE) in combination with data processed to generate insights. Data can come from a variety of sources using traditional quantitative and qualitative data collection methods such as surveys, interviews, etc.; but also, from sensors spread across society and a variety of applications. In this article, we also refer to global digital infrastructure as the global network of interconnected DTs such as Information and Communication Technologies (ICT) for the purpose of collecting, storing and consuming data from a multitude of sources (e.g., statistical offices and organizations, remote sensing technologies such as satellite data, smart devices, and sensors for the Internet-Of-Things, Smart Cities and Industries, and many others).

Since its foundation, IE has provided tools and knowledge to support a sustainable management of resources and environmental impacts and investigate the unintended consequences of human activities (Ayres &

Ayres, 2002a). The increasing use of AI and the expansion of DTs present great opportunities but also challenges for the IE community. The scientific and societal role of IE could be strengthened by increasing the timeliness, details and insightfulness of policy recommendations designed to tackle the great environmental challenges of our time. For example, Luque et al. (2020) argued that industrial sensing technologies could be combined with Life Cycle Assessment (LCA) and machine learning to provide real time environmental monitoring and improvement of industrial operations. Rolnick et al. (2019) presented ways in which machine learning could be employed to tackle climate change for thirteen domains from the electricity system to education and finance.

There are however challenges in the development of a global digital infrastructure and the use of AI for sustainability. For example, Xu, Cai, and Liang (2015) indicated that while big data obtained from DTs could offer new data and opportunities for analytical techniques enabling IE to develop more realistic complex system models based on the capture of the "*temporal, spatial and demographic heterogeneity of industrial systems"*, we should be aware that *"bigger data is not always better data"*. Similarly, bigger and more complex models resulting from the use of AI may not always be preferable or better than simpler ones. In fact, they may prove difficult to understand and explain or require substantial resources (i.e., energy and materials) (Lottick et al., 2019). Additionally, they could perpetrate societal biases and unfair allocation of resources, or have economic barriers causing unequal access to information and enjoyment of its benefits through society. They could cause systemic cascading shocks due to failures of nested and decentralized AI systems, or the promotion of unstainable practices that prioritize few objectives over the overall spectrum of sustainability (Galaz et al., 2021).

The recent (2022) special issue of Data Innovation in the Journal of Industrial Ecology addresses multiple of these questions with special attention to opportunities (Majeau-Bettez et al., 2022), and similar efforts are addressed also in other disciplines under the environmental science umbrella (Hsieh, 2022; McGovern et al., 2022; Rolnick et al., 2019). The present article builds on these efforts and summarizes the seminar discussion on "The future of artificial intelligence (AI) in the context of industrial ecology (IE)" which took place on the 21st of June 2021 during the Industrial Ecology Day (ISIE, 2021). Based on this knowledge, we propose a vision for the role of the AI and DTs in the future of IE. This article contextualizes the opportunities and challenges, and it indicates next steps to be taken by the IE community.

6.2 Envisioning the role of AI in IE

The diffusion of AI can greatly benefit the IE field by strengthening its capacity of mapping flows and stocks of materials and energy across society and identifying solutions to reach society's sustainability goals. We divide the IE community work in descriptive and prescriptive, where the former concerns the analysis of current and past factors and trends of societies' economic and environmental flows and stocks; while the latter is the analysis of possible and alternative future scenarios based on this accounting and other factors.

In recent years, descriptive efforts have taken advantage of remote sensing, and geographic information systems (GIS) to reach a higher level of spatio-temporal details of material flows and stock . Froemelt, Buffat, and Hellweg (2020) used machine learning to combine remote sensing and GIS-data with household budget surveys and agent-based models to develop a spatially resolved large-scale bottom-up model that is able to derive highly-detailed environmental profiles for individual households. Techniques of text mining, mode and image recognition (e.g. google street view), and analysis of night-time lights from satellite images can allow a high-resolution capture of material types and volumes in the built-environment (Arbabi et al., 2022; Corea, 2019; Mesta et al., 2019). Additionally, the expansion of *Open & Agile Smart Cities* is providing additional information through sensing technologies (Degbelo et al., 2016; *Open & Agile Smart Cities*, n.d.). Some of these data are also available in data marketplaces such as *Fiware* (Cirillo et al., 2019) and European Union Data Portal (*Datasets - Data.Europa.Eu*, n.d.) and others may also arise. These data sources could be used with AI methods such as computer vision techniques to infer additional information about the built environmental, transport modality, emissions and biodiversity in cities (Ibrahim et al., 2020).

Direct data collection could be strengthened by the expansion of DTs in industrial operations. Better data could then be used directly to assess and monitor the environmental performance of supply chains by connecting it to LCA (Luque et al., 2020). However, this is only possible if relationships between IE practitioners and industrial actors have been established. Where such privileged relationship is missing, industrial ecologists could rely on simulation tools and support the development of digital twins. Digital twins are *"digital replications of living as well as nonliving entities"* (El Saddik, 2018) such as in digital twins of the earth system (Bauer et al., 2021), of the built environment (Ketzler et al., 2020), and industrial activities.

While data collection through DTs is of great importance, the community cannot have the expectation of being able to collect all possible data. In fact, this may not even be desirable, practical or even feasible given the material requirements of DTs and concerns of data protection. For this purpose, estimation through machine learning and data mining techniques could be useful. For example, there are opportunities to be investigated in conversion of domain specific data into data useful for Life Cycle Inventories, as shown by Mittal et al (2018) in the use of data mining to convert industrial process databases in data useful for LCI. Zhao et al (2021) show how unit process data can also be estimated using machine learning. Such developments could not only benefit LCA but also Input-Output databases in mapping activities and products as well as their environmental extensions. Some authors have also started using these approaches to estimate missing data in impact categories for Life Cycle Impact Assessment starting from diverse national databases (Cashman et al., 2016). The use of these approaches should be encouraged and supported, as they reduce dependency on data requests from industrial actors.

Such approaches in data collection and estimation, as well as model creation, could then be instrumental for prescriptive efforts in the implementation of sustainability solutions. The prescriptive efforts of IE concern the prognostication of the impacts of future policies and technologies for sustainability. For example, AI can facilitate a better comprehension of households' consumption and environmental impacts by linking diverse data sources and sub-models (physically-based, agent-based and data-driven approaches) (Froemelt et al., 2018, 2020b, 2021), which can then be combined with top-down input-output models to investigate system-wide effects of demand-side sustainability solutions (Froemelt et al., 2021). It could also provide more effective energy load levelization by combining AI with energy models, and shedding light on additional factors affecting new energy systems (Zahraee et al., 2016). It could also check the validity of recommendations and optimize them against multiple values (e.g., social and environmental performance). Furthermore, intelligent systems embedded in consumer products and services could help avoid undesired effects of novel technologies, rebound effects or problem shifting, by supporting consumers toward the adoption of sustainable lifestyles or embedding sustainable management systems within a given technology.

More generally, AI can help society in designing targeted and more timely policies that take multiple values into consideration and optimize them to reduce unintended consequences. Such a holistic viewpoint has been at the core of methodologies developed by the IE community, for example in LCA. To this end, multivariate assessment and optimization of current systems and future solutions could be instrumental to avoid political and technological interventions where mitigation of ecological issues in one part of the supply chain simply shifts problems toward other parts, negatively affecting other desired outcomes. While IE methods such as LCA, Material Flow Analysis, and Environmental Input-Output Analysis have played core roles in detecting problem shifting, the combination of IE methods with AI and DTs could achieve unparalleled spatio-temporal granularity and make results more meaningful for scientists and policy makers at different level.

The severity of many social and environmental impacts depends on time and place of emissions or resource extraction. For example, companies are rapidly expanding data collection along their supply chains thanks to embedded tracking technologies. As they assess their operations, environmental impacts and the wellbeing of workers could also be quantified. This data could then be used to support their decision support systems to reduce socio-economic and environmental risks (Alavi et al., 2021) and improve their operations. In this context, AI in combination with IE methodologies can help the business community create new sustainable business models answering the social-economic and environmental challenges of our times.

6.3 CHALLENGES

In this study we identified three main challenges:

- Resource requirements
- Data accessibility and governance
- Explainability, interpretability and causality

6.3.1 Resource requirements

Industrial ecologists have an active lead in assessing the energy and material flows and stocks embodied in products and infrastructures, and their environmental impacts. The tremendous insight generation of DTs and the use of AI require energy and materials that could exacerbate environmental pressures. For example, AI models have known issues of high energy consumption which are also projected to growth beyond 2% of the world energy consumption (Lacoste et al., 2019; Lottick et al., 2019; Strubell et al., 2019). For this reason, tools have been developed to assess the carbon intensity of models (Schmidt et al., 2022)[5, 6] which should accompany other efficiency and typical metrics (e.g., accuracy and robustness) as a push toward yielding "*novel results without increasing computational cost, and ideally reducing it"* (i.e., Green AI) (Schwartz et al., 2019). Additionally, the resource consumption of DTs has also environmental impacts of its own, so it is important to mitigate burden shifting across environmental areas of concern (e.g., from resource depletion to climate change). In this regard, attention should be given to: 1) containing the need for large Graphical Process Unit (GPU) clusters; 2) mitigating excessive dispersion of sensing technologies for monitoring; 3) avoiding repetitive data harvesting practices. Given the long history of industrial ecologists assessing unintended consequences of policies and technology implementation (Font Vivanco & van der Voet, 2014), the community has a responsibility to hold Green AI

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[5] ML CO_2 Impacts tool: https://mlco2.github.io/impact/

[6] Python based CodeCarbon: https://codecarbon.io/; https://pypi.org/project/codecarbon/

standards together with the study of minimal expansion of digital technologies.

6.3.2 Data accessibility and governance

The issue of data governance is inherently political and concerns many aspects such as data ownership, data storage, data dissemination and the question of unequal access to the digital economy. These problems often have clear reasons. For instance, detailed information from which we can derive material and energy efficiency of processes, production volumes or product compositions, are often at the core of the competitive advantage of firms. Additionally, managing and exploiting big data has become a highly profitable business model for a very limited number of internet companies. They hold and monetize vast amounts of data while they may provide limited access by the public and scientific community.

Gathering data and maintaining big databases are labor-intensive and costly activities. This creates an inherent problem in making data open access as database curators need to be concerned with financial sustainability of their operations and data confidentiality. As a result, many of the most used datasets in the IE field, such as the Life cycle inventory database *Ecoinvent* (Frischknecht & Rebitzer, 2005) or the IEA (e.g. the IEA Energy balances), are licensed and for the most part only accessible for a fee. With the expansion in data volumes there is a risk that these business models become more common and that reliance on private services to handle and manipulate such data in the AI infrastructure increases.

This represents a barrier for an equal enjoyment of data (e.g., economic, industrial and environmental data) and AI solutions regardless of the income level of data users, and it exacerbates global inequalities in data accessibility and deployment of DTs (i.e., digital divide). Data access, quality and internet infrastructure notoriously differ across regions which risk endangering sustainability (Mehrabi et al., 2020). The digital divide will continue growing unless there are policy interventions. The use of AI for sustainability should heighten awareness of these inequalities and address them whenever possible. In various cases data accessibility and openness should be expanded, such as for geographic information and the built environment.

Industrial ecologists should investigate how public and private data may be governed to serve its objective of aiding decision making for a sustainable society. They can investigate different policy frameworks and mechanisms to ensure compliance to these frameworks (Mahanti, 2021) such that quality data is available for effective use of AI. One such mechanism could be the creation of openly accessible benchmark models and datasets for common IE analytical tasks (e.g., data estimation for LCI and EEIO, or environmental impact assessment under different climate scenarios). In a variety of other AI fields, such benchmarks (e.g., MNIST and CIFAR) have been instrumental in providing quality input data to train models, promoting transparency, comparability of models and focused progress (benchmarks.ai, 2022). The existence of such benchmarks would also be in line with the current efforts for open and shared data in the IE community (Hertwich et al., 2018).

Furthermore, in order to support data availability, the system of incentives for scientists may also need to be modified to promote timeliness, wide access and interoperability of data and software of fundamental importance to sustainability objectives. Currently, scientists may not always want to publicly disseminate their work, for example, until they are able to submit a given number of publications or to ensure co-authorship in publications using their work. However understandable these practices may be, they remain undesirable behaviors which may slow down the community's ability to provide timely and replicable analysis for sustainability.

At last, AI, DTs and annexed services can be intrusive in the private life of citizens and have profound influence on their physical, mental, and financial well-being. At the same time, AI could also induce new behaviors and help reach sustainability objectives (Froemelt et al., 2018). However, currently there is a significant risk that AI could be used to support and exacerbate unsustainable levels of consumption and production. If there is no purposeful choice of direction toward sustainability from the governance perspective, the choice will be of those with the higher resources in the market to leverage AI and DTs developments. In this regard, AI and DTs should be closely scrutinized.

6.3.3 Explainability, interpretability and causality

The way AI models are able to explain the world (i.e., explainability) and their ability to be understood by humans (i.e., interpretability) are of great importance to ensure trust in sustainability insights and effectiveness of sustainability solutions. Real-world data carries over biases to intelligent systems thereby perpetuating misconceptions, discrimination and enhancing the risks of other injustices. Improving explainability could prevent these issues by better representing the heterogeneity of complex socio-economic and ecological systems, highlighting where and how humans should intervene to correct AI models and reduce biases. Additionally, in the scope of industrial ecology, especially concerning scenarios analysis and dynamic systems, it is of fundamental importance to ensure clarity between cause and outcome. For example, in the use of multi-objective optimization of production and consumption system under different climate scenarios, we need to ensure that we can identify influential factors in such scenarios and explain the dynamics governing them. This is especially important in cases where AI is employed to enhance decision making. Recent studies such as Sgaier, Huang, and Charles (2020), present strong argument in favor of causal AI as acting on outputs from AI models that do not explain the root causes leading to ineffective, biased, poor decisions.

6.4 RECOMMENDATIONS

We have several recommendations for the IE community in moving forward in the use of Artificial Intelligence (AI) and Digital Technologies (DTs):

- Creation of internal committees and working groups for AI and DTs research. Such committees and working groups could:
    - Provide research directions, and promote standards and protocols for governance of data, models and software within and outside of IE;
    - Support knowledge transfer from and to fields that successfully embarked on interoperable data sharing and best practices in AI applications;
    - Establish and/or promote data and model benchmarks as well as good modeling practices;

    - Provide a platform for networking among researchers and establish relationships with other interest groups and institutions to promote governance of AI toward sustainability.
- Support transdisciplinary and cross-societal efforts to ensure a successful implementation and use of sustainability knowledge and solutions. In particular:
    - Computer science, data science and mathematics are at the core of the expansion of the digital technologies and developments in AI and collaborations should be actively sought out to improve our methodological and technological approaches;
    - Anthropologists, social scientists, and law experts are also indispensable in understanding the consequences of AI on the social and economic organization of society. These experts carry with them different perspectives and approaches on the complex issues of sustainability;
    - Strengthen links between citizens, research, policy, industry, and communication.
- Privilege simplicity and fair trade-off between complexity, and explainability, interpretability and causality. The community objective should not be to create models as complex as the world itself, but to provide systems that not only aid sustainability but embody it while improving insights, and quality and coherency in data and models; The community should also strive to avoid always prioritizing predictive models and also direct effort to building better causal models that help us develop a better understanding of our dynamic and complex world.
- Maintain awareness of inadvertent impacts of AI and DTs due to material and energy requirements. Determining the optimal amount of data and connectivity that are required to support decision making and sustainable solutions. While IE should embrace AI developments enthusiastically, it is paramount that we are critical of the way AI is implemented and that we try to understand what such developments entail.
- Maintain awareness of the digital divide, biases, and issues of demographic diversity and representation in data and in AI enabled decision making. The IE community should employ methods of data

collection to increase representativeness and create models that take these issues into account.

In conclusion, AI can be an important instrument to solve the greatest sustainability challenges that are currently faced by humanity. However, it should not be seen as a silver bullet but, rather, as a helpful instrument to be handled with scrutiny. The IE community has a promising and yet rapidly changing path ahead. AI and digital technologies are changing the way data is handled, services and products manufactured and consumed, and society and industries governed. IE can provide tools and insights to direct such changes toward sustainability. At the same time, these advancements also have a potential to greatly support the work performed by IE. These mutually beneficial opportunities should be nurtured and actively directed to ensure we reach our sustainability objectives.

References

Alavi, Behrouz, Madjid Tavana, and Hassan Mina. 2021. "A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy." *Sustainable Production and Consumption* 27 (July): 905–20. https://doi.org/10.1016/J.SPC.2021.02.015.

Arbabi, Hadi, Maud Lanau, Xinyi Li, Gregory Meyers, Menglin Dai, Martin Mayfield, and Danielle Densley Tingley. 2022. "A Scalable Data Collection, Characterization, and Accounting Framework for Urban Material Stocks." *Journal of Industrial Ecology 26* (1): 58–71. https://doi.org/10.1111/jiec.13198.

Ayres, Robert U, and Leslie Ayres. 2002. *A Handbook of Industrial Ecology*. Edward Elgar Publishing.

Bauer, Peter, Bjorn Stevens, and Wilco Hazeleger. 2021. "A Digital Twin of Earth for the Green Transition." *Nature Climate Change 2021, 1*(2): 80–83. https://doi.org/10.1038/s41558-021-00986-y.

benchmarks.ai. 2022. *"Benchmarks.AI - Directory of AI Benchmarks."* 2022. https://benchmarks.ai/.

Cashman, Sarah A., David E. Meyer, Ashley N. Edelen, Wesley W. Ingwersen, John P. Abraham, William M. Barrett, Michael A. Gonzalez, Paul M. Randall, Gerardo Ruiz-Mercado, and Raymond L. Smith. 2016. "Mining Available Data from the United States Environmental Protection Agency to Support Rapid Life Cycle Inventory Modeling of Chemical Manufacturing." *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.6b02160.

Cirillo, Flavio, Gürkan Solmaz, Everton Luís Berz, Martin Bauer, Bin Cheng, and Ernö Kovacs. 2019. "A Standard-Based Open Source IoT Platform: FIWARE." *IEEE Internet of Things Magazine, 2* (3): 12–18. https://doi.org/10.1109/IOTM.0001.1800022.

Combes, Benjamin, Celine Herweijer, Pia Ramchandani, and Jasnam Sidhu. 2018. "Harnessing Artificial Intelligence for the Earth." *World Economic Forum: Fourth Industrial Revolution for the Earth Series.*

Corea, Francesco. 2019. "AI Knowledge Map: How to Classify AI Technologies.". https://doi.org/10.1007/978-3-030-04468-8_4.

"Datasets - Data.Europa.Eu." n.d. Accessed April 19, 2022. https://data.europa.eu/data/datasets?categories=envi&page=1&locale=en.

Degbelo, Auriol, Carlos Granell, Sergio Trilles, Devanjan Bhattacharya, Sven Casteleyn, and Christian Kray. 2016. "Opening up Smart Cities: Citizen-Centric Challenges and Opportunities from GIScience." *ISPRS International Journal of Geo-Information, 5*(2): 16. https://doi.org/10.3390/ijgi5020016.

Ertel, Wolfgang. 2017. *Introduction to Artificial Intelligence* (Undergraduate Topics in Computer Science). Book.

Font Vivanco, David, and Ester van der Voet. 2014. “The Rebound Effect through Industrial Ecology’s Eyes: A Review of LCA-Based Studies.” *International Journal of Life Cycle Assessment.* https://doi.org/10.1007/s11367-014-0802-6.

Frischknecht, Rolf, and Gerald Rebitzer. 2005. “The Ecoinvent Database System: A Comprehensive Web-Based LCA Database.” *Journal of Cleaner Production, 13*(13–14): 1337–43. https://doi.org/10.1016/j.jclepro.2005.05.002.

Froemelt, Andreas, René Buffat, and Stefanie Hellweg. 2020. “Machine Learning Based Modeling of Households: A Regionalized Bottom-up Approach to Investigate Consumption-Induced Environmental Impacts.” *Journal of Industrial Ecology*. https://doi.org/10.1111/jiec.12969.

Froemelt, Andreas, David J. Dürrenmatt, and Stefanie Hellweg. 2018. “Using Data Mining to Assess Environmental Impacts of Household Consumption Behaviors.” *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.8b01452.

Froemelt, Andreas, Arne Geschke, and Thomas Wiedmann. 2021. “Quantifying Carbon Flows in Switzerland: Top-down Meets Bottom-up Modelling.” *Environmental Research Letters, 16*(1): 014018. https://doi.org/10.1088/1748-9326/abcdd5.

Frolov, Denys, Wojciech Radziewicz, Volodymyr Saienko, Nina Kuchuk, Mykhailo Mozhaiev, Yurii Gnusov, and Yurii Onishchenko. 2021. “Theoretical And Technological Aspects Of Intelligent Systems: Problems Of Artificial Intelligence.” *International Journal of Computer Science and Network Security, 21*(5): 35–38. https://doi.org/10.22937/IJCSNS.2021.21.5.6.

Galaz, Victor, Miguel A. Centeno, Peter W. Callahan, Amar Causevic, Thayer Patterson, Irina Brass, Seth Baum, et al. 2021. “Artificial Intelligence, Systemic Risks, and Sustainability.” *Technology in Society*, *67*(November): 101741. https://doi.org/10.1016/J.TECHSOC.2021.101741.

Haberl, Helmut, Dominik Wiedenhofer, Franz Schug, David Frantz, Doris Virag, Christoph Plutzar, Karin Gruhler, et al. 2021. “High-Resolution Maps of Material Stocks in Buildings and Infrastructures in Austria and Germany.” *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.0c05642.

Hertwich, Edgar, Niko Heeren, Brandon Kuczenski, Guillaume Majeau-Bettez, Rupert J. Myers, Stefan Pauliuk, Konstantin Stadler, and Reid Lifset. 2018. “Nullius in Verba1: Advancing Data Transparency in Industrial Ecology.” *Journal of Industrial Ecology.* https://doi.org/10.1111/jiec.12738.

Hsieh, William W. 2022. “Evolution of Machine Learning in Environmental Science—A Perspective.” *Environmental Data Science, 1.* https://doi.org/10.1017/eds.2022.2.

Ibrahim, Mohamed R., James Haworth, and Tao Cheng. 2020. “Understanding Cities with Machine Eyes: A Review of Deep Computer Vision in Urban Analytics.” *Cities 96*(January): 102481. https://doi.org/10.1016/j.cities.2019.102481.

ISIE. 2021. *International Industrial Ecology Day 2021* - International Society for Industrial Ecology https://is4ie.org/events/event/international-industrial-ecology-day-2021.

Ketzler, Bernd, Vasilis Naserentin, Fabio Latino, Christopher Zangelidis, Liane Thuvander, and Anders Logg. 2020. “Digital Twins for Cities: A State of the Art Review.” *Built Environment, 46*(4): 547–73. https://doi.org/10.2148/BENV.46.4.547.

Lacoste, Alexandre, Alexandra Luccioni, Victor Schmidt, and Thomas Dandres. 2019. “Quantifying the Carbon Emissions of Machine Learning.” *ArXiv:1910.09700 [Cs]*, November. http://arxiv.org/abs/1910.09700.

Lottick, Kadan, Silvia Susai, Sorelle A. Friedler, and Jonathan P. Wilson. 2019. “Energy Usage Reports: Environmental Awareness as Part of Algorithmic Accountability.” *ArXiv:1911.08354 [Cs, Stat],* December. http://arxiv.org/abs/1911.08354.

Luque, Amalia, Ana De Las Heras, María Jesús Ávila-Gutiérrez, and Francisco Zamora-Polo. 2020. “ADAPTS: An Intelligent Sustainable Conceptual Framework for Engineering Projects.” *Sensors (Switzerland)*. https://doi.org/10.3390/s20061553.

Mahanti, Rupa. 2021. Data Governance and Compliance. Data Governance and Compliance. https://doi.org/10.1007/978-981-33-6877-4.

Majeau-Bettez, Guillaume, Jean-Marc Frayret, Anu Ramaswami, Yang Li, and Niko Heeren. 2022. “Data Innovation in Industrial Ecology.” *Journal of Industrial Ecology 26*(1): 6–11. https://doi.org/10.1111/jiec.13256.

McGovern, Amy, Imme Ebert-Uphoff, David John Gagne, and Ann Bostrom. 2022. “Why We Need to Focus on Developing Ethical, Responsible, and Trustworthy Artificial Intelligence Approaches for Environmental Science.” *Environmental Data Science, 1*. https://doi.org/10.1017/eds.2022.5.

Mehrabi, Zia, Mollie J. McDowell, Vincent Ricciardi, Christian Levers, Juan Diego Martinez, Natascha Mehrabi, Hannah Wittman, Navin Ramankutty, and Andy Jarvis. 2020. “The Global Divide in Data-Driven Farming.” *Nature Sustainability 2020 4(*2): 154–60. https://doi.org/10.1038/s41893-020-00631-0.

Mesta, Carlos, Ramzy Kahhat, and Sandra Santa-Cruz. 2019. “Geospatial Characterization of Material Stock in the Residential Sector of a Latin-American

City." *Journal of Industrial Ecology, 23*(1): 280–91. https://doi.org/10.1111/jiec.12723.

Mittal, Vinit K., Sidney C. Bailin, Michael A. Gonzalez, David E. Meyer, William M. Barrett, and Raymond L. Smith. 2018. "Toward Automated Inventory Modeling in Life Cycle Assessment: The Utility of Semantic Data Modeling to Predict Real-World Chemical Production." *ACS Sustainable Chemistry and Engineering*. https://doi.org/10.1021/acssuschemeng.7b03379.

Negnevitsky, Michael. 2011. *Artificial Intelligence: A Guide to Intelligent Systems (3rd E-Book)*. Addison Wesley.

Nishant, Rohit, Mike Kennedy, and Jacqueline Corbett. 2020. "Artificial Intelligence for Sustainability: Challenges, Opportunities, and a Research Agenda." *International Journal of Information Management.* https://doi.org/10.1016/j.ijinfomgt.2020.102104.

"Open & Agile Smart Cities." n.d. Open & Agile Smart Cities. Accessed April 19, 2022. https://oascities.org/.

Peled, Yoav, and Tomer Fishman. 2021. "Estimation and Mapping of the Material Stocks of Buildings of Europe: A Novel Nighttime Lights-Based Approach." *Resources, Conservation and Recycling.* https://doi.org/10.1016/j.resconrec.2021.105509.

David Rolnick, Priya L. Donti, Lynn H. Kaack, Kelly Kochanski, Alexandre Lacoste, Kris Sankaran, Andrew Slavin Ross, Nikola Milojevic-Dupont, Natasha Jaques, Anna Waldman-Brown, Alexandra Sasha Luccioni, Tegan Maharaj, Evan D. Sherwin, S. Karthik Mukkavilli, Konrad P. Kording, Carla P. Gomes, Andrew Y. Ng, Demis Hassabis, John C. Platt, Felix Creutzig, Jennifer Chayes, and Yoshua Bengio. 2022. Tackling Climate Change with Machine Learning. *ACM Comput. Surv. 55*, 2, Article 42 (February 2023), 96 pages. https://doi.org/10.1145/3485128

Saddik, Abdulmotaleb El. 2018. "Digital Twins: The Convergence of Multimedia Technologies." *IEEE Multimedia, 25*(2): 87–92. https://doi.org/10.1109/MMUL.2018.023121167.

Schmidt, Victor, Goyal-Kamal, Benoit Courty, Boris Feld, SabAmine, Franklin Zhao, Aditya Joshi, et al. 2022. *Mlco2/Codecarbon: V2.0.0*. Zenodo. https://doi.org/10.5281/zenodo.6421732.

Schwartz, Roy, Jesse Dodge, Noah A. Smith, and Oren Etzioni. 2019. "Green AI." *ArXiv:1907.10597 [Cs, Stat]*, August. http://arxiv.org/abs/1907.10597.

Sgaier, Sema K., Vincent Huang, and Grace Charles. 2020. "The Case for Causal AI." Stanford Social Innovation Review 18 (3): 50–55. https://doi.org/10.48558/KT81-SN73.

Strubell, Emma, Ananya Ganesh, and Andrew McCallum. 2019. "Energy and Policy Considerations for Deep Learning in NLP." *ArXiv:1906.02243 [Cs]*, June. http://arxiv.org/abs/1906.02243.

UNSGHL. 2019. *"The Age of Digital Interdependence, Report of the UN Secretary General's High-Level Panel on Digital Cooperation."* Geneva: Un Secretary General.

Xu, Ming, Hua Cai, and Sai Liang. 2015. "Big Data and Industrial Ecology*." Journal of Industrial Ecology, 19*(2): 205–10. https://doi.org/10.1111/jiec.12241.

Zahraee, S. M., M. Khalaji Assadi, and R. Saidur. 2016. "Application of Artificial Intelligence Methods for Hybrid Energy System Optimization." *Renewable and Sustainable Energy Reviews.* https://doi.org/10.1016/j.rser.2016.08.028.

Zhao, Bu, Chenyang Shuai, Ping Hou, Shen Qu, and Ming Xu. 2021. "Estimation of Unit Process Data for Life Cycle Assessment Using a Decision Tree-Based Approach." *Environmental Science & Technology, 55*(12): 8439–46. https://doi.org/10.1021/acs.est.0c07484.