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DISCUSSION PAPER

Machine intelligence, systemic risks, and sustainability

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Artificial intelligence, systemic risks and sustainability

Abstract

Automated decision making and predictive analytics through artificial intelligence, in combination with rapid progress in technologies such as sensor technology and robotics are likely to change the way individuals, communities, governments and private actors perceive and respond to climate and ecological change. Methods based on various forms of artificial intelligence are already today being applied in a number of research fields related to climate change and environmental monitoring. Investments into applications of these technologies in agriculture, forestry and the extraction of marine resources also seem to be increasing rapidly. Despite a growing interest in, and deployment of AI-technologies in domains critical for sustainability, few have explored possible systemic risks in depth. This article offers a global overview of the progress of such technologies in sectors with high impact potential for sustainability like farming, forestry and the extraction of marine resources. We also identify possible systemic risks in these domains including a) algorithmic bias and allocative harms; b) unequal access and benefits; c) cascading failures and external disruptions, and d) trade-offs between efficiency and resilience. We explore these emerging risks, identify critical questions, and discuss the limitations of current governance mechanisms in addressing AI sustainability risks in these sectors.

1. Introduction

Technological change is a fundamental component of scientific and economic breakthroughs (Arthur, 2009), and has the potential to dramatically influence global efforts toward sustainability (Galaz, 2014; Westley et al., 2011). As the pressure of human activities increasingly shapes the biosphere and the climate system, so does the hope that artificial intelligence (AI)[1] (here including both machine learning and deep learning) and associated technologies such as robotics and the Internet of Things (IoT), will be able to increase societies' capacities to detect, adapt and respond to climate and environmental change (Campbell et al., 2019; Herweijer and Waughray, 2018; Joppa, 2017). Numerous reports highlight how applications of AI and automation may help address climate change and biodiversity loss, contribute to more effective monitoring and uses of natural resources, and further progress towards the achievement of the Sustainable Development Goals (SDGs) (e.g. Campbell et al., 2019; Future Earth, 2020; Vinuesa et al., 2020).

While increased applications of AI and associated technologies could lead to more effective uses of land- and seascapes, augmented environmental monitoring capacities, and improved transparency in supply chains, it could also create new systemic sustainability risks as AI technologies diffuse into new social, economic, and ecological contexts. Some recent syntheses have discussed these risks briefly (e.g. van Wynsberghe, 2021; Future Earth, 2020; Wearn et al., 2019), yet their potential allocative harms (Barocas et al., 2017) and unexpected social and ecological effects (Galaz and Mouazen, 2017) are poorly elaborated, and more often than not, overlooked. Prominent agenda-setting reports about the social impacts of AI, for example, either ignore sustainability dimensions altogether (e.g. House of Lords 2018), or underemphasize their possible social, economic and ecological risks (e.g. ITU, 2019; Joppa, 2017; World Economic Forum, 2018; Microsoft and PricewaterhouseCoopers, 2019).

In this article, we offer an overview and elaborate possible systemic risks[2] for sustainability created by the diffusion of AI and associated technologies. Here, we do

[1] Here we use the term "artificial intelligence/AI" to refer to technologies that employ machine learning (ML) including "deep learning" (DL) methods (see House of Lords 2018). We write "AI and associated technologies" in cases where AI is an integrated part of a technology, such as a "smart tractor" or Unmanned Aerial Vehicles that employ computer vision. Hence our main interest in this paper is in the social and ecological impacts of AI and associated technologies, rather than the underlying ML or DL technique *per se*.

[2] By risk, we refer to the possibility of harm, commonly quantified as the product of the probability and severity of the harm (Kaplan and Garrick, 1981). By 'systemic risks' we mean risks that evolve from complex interactions emerging from human, machine and environmental interactions, and that could lead to disruptions that propagate through these systems through the process of contagion (Centeno et

not focus on known direct impacts such as the energy consumption or the carbon footprint of deep learning and data-mining (García-Martín et al., 2019), nor on opportunities for AI in helping address climate change (Rolnick et al., 2019; The Royal Society 2020). Our focus is instead on complementing this literature by exploring networked risks that result from an increased connectivity between humans, machines and social-ecological systems.

Our empirical analysis and discussion focus exclusively on early applications of AI and associated technologies in domains critical for what some have denoted biosphere-based sustainability (Folke et al., 2016). That is, we focus on critical ecosystems such as agriculture and forestry along with the technical infrastructure underpinning resource management and extraction. These living systems are often overlooked in current analyses of the connection between AI and sustainability, despite their fundamental importance for the climate system and human development (Folke et al., 2021). Here, we combine a literature synthesis with analysis of new data and ask:

a) Where in the world, and into which sectors directly relevant for biosphere-based sustainability, is AI and associated technologies diffusing?
b) Which systemic risks from a sustainability perspective could emerge as the result of this diffusion?
c) To what extent do current notions and principles related to "responsible AI" acknowledge systemic risks related to sustainability?
d) Which possible governance mechanisms could be developed to help mitigate these risks?

Our ambition is to bring together previously disconnected research fields (i.e. studies of the wider social and economic implications of AI, research on systemic risk, and the sustainability sciences) to help guide future research, and inform current policy debates about the regulation of AI and its potential to help accelerate climate action.

2. The growing importance of artificial intelligence for sustainability

AI-based technologies are gaining increased interest applied in a number of research fields related to the environmental, sustainability and climate sciences. Examples include AI applications in climate and Earth system modeling (Rasp et al., 2018; Reichstein et al., 2019); AI-augmented environmental monitoring (Hino et al., 2018);

al., 2015; Helbing, 2013). By 'sustainability' we refer specifically to the importance of the biosphere and a stable Earth system for ongoing human development and prosperity (Folke et al., 2016; Steffen et al., 2015).

autonomous underwater marine conservation interventions and data collection (Girard and Du Payrat, 2017, Nunes et al., 2020); AI-supported tracking of illegal wildlife trade (Di Minin et al., 2019); and "smart" urban planning for sustainable development (Ilieva and McPhearson, 2018; Goddard et al., 2021).

The potential for AI and associated technologies seems to be driving a growing interest from the private sector. According to estimates, nearly 12 million IoT sensors will be installed and in use on farms around the world by the year 2023 (Meola, 2021). Agricultural technology (agtech) investment reached a new record of $1.5 billion in 2017, and venture capital investment in the space has grown 80 percent annually since 2012 (Rotz et al., 2019). The precision forestry market could grow from USD 3.9 billion in 2019, to reach USD 6.1 billion by 2024 (Markets and Markets, 2019). With goals to improve urban livability and sustainability, planners could increasingly rely on AI for traffic management, smart policing, lighting control, facial recognition, and smart waste disposal systems (Goddard et al., 2021). The smart city market is expected to reach USD 460 billion by 2027 (Grand View Research, 2019), smart city AI software alone is projected to total USD 5 billion annually by 2025 (Tractica, 2020), and the market for robotics and autonomous systems in cities is expected to grow from 6.2 billion USD in 2018, to 17.7 billion USD in 2026 (Goddard et al., 2021).

Applications of AI and other associated technologies for sustainability could be viewed as examples of technological "niche-innovations" capable of rapid upscaling and diffusion if followed by increased investments, enabling legal conditions, and growing public and consumer interest (Geels et al., 2017). The COVID-19 pandemic seems to have triggered a growing interest from the private sector and governments to accelerate digitization and automation in supply chains and other parts of the economy (World Economic Forum 2020; European Union, 2020). The diffusion of AI-technologies unfolds not only through increased direct investments however, but also by the much less visible infusion of e.g. deep learning systems into existing technologies (Engström and Strimling, 2020).

These converging trends suggest that the development and deployment of AI and associated technologies are likely to not only have social consequences, but will very likely impact climate, biodiversity, and ecosystems around the world (Dauvergne, 2020; Wynsberghe, 2021). Their diffusion hence merits increased attention from a sustainability perspective.

Figure 1 shows the geographical distribution of AI and associated technologies (here including applications of IoT, robotics and analysis supported by artificial intelligence) with a focus on companies and investments in sectors linked to the

management of land- and seascapes. The data has been extracted from the international technology company and investor database *Crunchbase,* with a specific focus on companies operating in the selected sectors (see Supplementary Information for methodological details).

As the data shows, the agricultural sector seems to be the most prominent sector for the development and deployment of AI and associated technologies through digital farming/precision agriculture. This is not surprising considering the very strong push internationally towards increased production and reduced uses of scarce resources such as water through the application of new technologies and "digitalization" (World Bank Group 2019; Clapp and Ruder, 2020; Lajoie-O'Malley et al., 2020).

The differences in access to funding between different regions in the world is notable, and follows the same pattern as other studies of the "digital divide" (Basso and Antle, 2020; Salemink et al., 2017; United Nations Development Programme, 2019). The prominent position of China in terms of investments (Figure 1B) also seems to follow AI-investment patterns in general (Castro and McLaughlin, 2021; see also Birner et al., 2021 for digital agriculture)

[Figure 1. Global distribution of AI technologies and investments in farming, forestry and the marine/aquaculture sectors]

3. Artificial intelligence, Systemic risks and Sustainability

As we discussed in the previous section, there seems to be a growing interest, and increased investment in the development and deployment of AI and associated technologies in sectors critical for sustainability. The technologies' effectiveness and broader social, economic, and ecological impacts however, unfold within a wider social, technological and environmental context (Markolf et al., 2018) making their distributional consequences and sustainability risks difficult to predict with specificity (Olsson et al., 2014).

In the following sections, we identify and explore four areas where the use of AI and associated technologies in the pursuit of sustainability goals could give rise to systemic risks. These risks could, if not managed proactively, unravel the progress and even decrease elements of sustainability. These are related to a) algorithmic bias and allocative harms; b) unequal access and benefits; c) cascading failures and external disruptions; and d) trade-offs between efficiency and resilience. We also identify a number of important research questions to help advance our understanding of

sustainability risks created by AI and associated technologies. While not an exhaustive list of the potential systemic risks from AI technologies in this space, we view these as important starting points that should be addressed by academia and policy-makers alike.

3.1. Algorithmic bias and allocative harms

The risks and impacts of possible *algorithmic biases and their allocative harms* (as defined by Barocas et al., 2017) has gained considerable attention in the last years. As has been shown in other domains such as policing and the health sector (e.g. Barocas and Selbst, 2016; Obermeyer et al., 2019), inconsistencies and biases in training data, security breaches leading to corrupted data capture and decision-making systems, and flawed AI-models can have detrimental impacts as AI-systems are applied.

Growing volumes of environmental, social and ecological data are a fundamental prerequisite for the application of artificial intelligence in, for example, conservation and digital farming (Basso and Antle, 2020). Environmental and ecological data have well known limitations however, both in their temporal coverage, and geographical spread (Joppa et al., 2016; Siddig, 2019; Poisot et al., 2020). While the rapid growth of data from mobiles and satellites offer vast opportunities to map and respond to social vulnerabilities such as poverty and malnutrition, it has become increasingly clear that solutions supported by "big data" and AI-analysis can be strongly skewed since the "most disadvantaged people tend to be the least represented in new sources of digital data" (Blumenstock, 2018).

Algorithmic biases of this sort can have a number of sources (Danks and London, 2017), and may very well emerge in the sustainability domain in the following ways:

Training data bias could emerge if AI-systems are designed with poor, limited, or biased data sets. For example, AI systems developed for precision agriculture in data poor contexts could - if not validated properly with local knowledge and expert opinion - result in incorrect management recommendations to small-scale farmers who would struggle to maintain high, stable yields (Jiménez et al., 2019).

Transfer context bias could emerge when AI-systems are designed for one ecological, climate, or social-ecological context, and then incorrectly transferred to another. While the training data and the resulting model may be developed and suitable for the initial social-ecological situation (say, a large industrial farm in a data rich context), using it in a different setting (e.g. a small farm) could lead to flawed and damaging results. Such bias may emerge, for example, as individuals and companies use off-the-shelf

AI-software for their purposes (Chouldechova and Roth, 2018). The use of simpler forest monitoring and carbon sequestration models has already led to controversies partly due to their tentative transfer context bias (Ochieng, 2017).

The fact that ecosystems both on land and in the ocean are changing rapidly as the result of climate and ecological change (Hobbs et al., 2009) also pose serious challenges as AI-models, and lead to a type of concept drift (Tsymbal, 2004). AI-systems built on historical ecological conditions hence are likely to fail as the ecosystems on land- and seascapes shift surprisingly and at times irreversibly. This latter phenomenon is well-known in ecology as "regimes shifts" which may emerge without prior warning with large repercussions on ecosystems and those who depend on them (Hastings and Wysham 2010; Rocha et al., 2015).

Even if both the training data, and the context in which the algorithm is used is appropriate, their application can still lead to ***interpretation bias***. In this type of bias, an AI-system might be working as intended by its designer, but the user does not fully understand its utility, or tries to infer different meaning that the system might not support. Developers of AI-support systems for digital agriculture, as an example, are still unable to convert complex geospatial information into appropriate crop management actions, resulting in misinterpretation and misuse of data. For example, many farmers utilize precision technology incorrectly to apply more (instead of less) nitrogen (N) fertilizer in the hope of increasing yields (Lajoie-O'Malley et al., 2020).

A contributing element to these bias types is a lack of appropriate data. Data gaps can partly be tackled using satellites, drones, mobile devices, sensors and social media, and can be combined with various AI-techniques to help overcome challenging scarce or incomplete data (Blumenstock, 2016; Ilieva and McPhearson, 2018). Increased data collection about systems and individuals result in their own challenges however. Urban sustainability scholars have already raised a number of issues related to AI and tentative threats to privacy, research ethical challenges, and the risk of building decisions on spurious correlations (Creutzig et al., 2019). For example, location-tracking systems via smartphones and vehicles make it possible to not only extract data that is helpful for urban planning purposes, but can also allow for the triangulation of a person's identity and other personal information, even with sparse data. This highlights the need to match data collection for sustainability goals with robust and transparent data management policies (Ilieva and McPhearson 2018).

Whether from inappropriate training data, unsuitable contexts, or user interpretation errors, algorithmic biases are common, and need to be thoughtfully considered in the sustainability domain. In the fields of agriculture, environment, and sustainability,

such biases can result in for example, risks to critical elements of food security and ecosystem resilience.

Key future questions:

- *To what extent are insights and risk management solutions about algorithmic biases from other domains applicable to sectors such as digital farming, digital forestry, urban planning and marine extraction and management?*
- *How is the predictive potential and efficacy of AI-models affected by the fact that ecosystems such as land- and seascapes are changing rapidly due to e.g. climate change?*
- *Which social, economic and ecological impacts may result from these biases, and how should these be prevented?*

3.2. Unequal access, benefits, and impacts

Resource constraints, and unequal access to information and communication technologies (Salemink et al., 2017; United Nations Development Programme, 2019) create additional risks as AI-technologies start to diffuse into new sectors. The growing interest in digital, data-driven or precision farming is a good example of this.

At present, smallholder farmers account for a considerable proportion of global food production (Graeub et al., 2016), and especially in less wealthy countries, many people depend on small-scale family-farms to meet their nutritional needs (Lowder et al., 2016). While applications of AI in combination with increased automation for farming have been suggested to contribute to increased yields and resource efficiency (World Bank Group, 2019), the equitable distribution of such benefits cannot be taken for granted. Even non-AI technologies for intensifying agriculture are often deemed unaffordable by members of poor local communities (Jiren et al., 2020). In addition, there is a clear "digital divide" in data-driven farming with small-scale farmers facing serious obstacles to access big data and mobile technologies, which is likely to distribute the benefits of these technologies in unequal ways (Mehrabi et al., 2020).

The economic benefits of AI applications in farming also appear to be greatest for larger farms that can spread their fixed costs over many acres, and that can reduce labor costs through automation (Lajoie-O'Malley et al., 2020). As a result, critics have argued that the growing interest in "digital agriculture" by influential international actors such as the World Bank and the UN Food and Agriculture Organization (FAO) overemphasize the need to increase aggregate food production for a growing population, while ignoring underlying well-known socio-political issues driving food insecurity such as poverty and social inequalities (Sen, 1982; Lajoie-O'Malley et al., 2020).

Equal access to AI-technologies does not guarantee equal or fair outcomes however. Even if farmers are able to optimize their specific operations cost-effectively, widespread use of AI in farming may still result in concentration of capital and deepened inequality. As many traditional input and equipment providers are increasingly positioning themselves as data companies, this accumulated information might be put to use to extract rents, lock farmers into unfavorable contracts, or price discriminate across services (Clapp and Ruder, 2020; Mateescu and Elish, 2018). There are also concerns about the impacts of automation replacing jobs in these sectors, especially as it could prove detrimental for vulnerable social groups such as migrant workers (Rotz et al., 2019). Small-scale fisheries and coastal communities (estimated to employ some 37 million people FAO, 2019), and small-scale enterprises in the forestry sector (providing employment for an additional estimated 41 million people, FAO and United Nations Environment Programme, 2020) may face similar challenges related to allocative harms, and unequal distribution of benefits as applications of AI-technologies make their progress into their domains (Bayne and Parker, 2012; Girard and Du Payrat, 2017).

Key future questions:

- *What are the possible distributional impacts that result from the increased adoption of AI-technologies and automation in farming, forestry and other sectors related to the extraction of natural capital?*
- *Which legal, economic and/or governance mechanisms can help prevent such distributional risks, and support the deployment of AI that is of benefit to vulnerable groups in these sectors?*

4. Shocks, cascading failures and attacks

AI and associated technologies create numerous new complex interactions not only between humans and machines, and machines and machines (Rahwan et al., 2019), but also increasingly with machines and ecosystems and the Earth system as a whole (Galaz, 2014; Markolf et al., 2018). The addition of AI and associated technologies into the worlds of agriculture and resource management could be seen as adding more nodes and connections to these already complex social-ecological and socio-technical systems.

The growing interactions between humans, machines, and ecology could be viewed through the lens of complex adaptive systems (McPhearson et al., 2016). Such systems are susceptible to unexpected shocks, and cascades that develop endogenously, also known as “normal accidents” (Perrow, 2011). This implies that especially if the components of the system are optimized and managed properly (say, a regional network of IoT-connected farms), internal failures can emerge unexpectedly and ripple and

amplify across network links (e.g. a regional food supply chain) and create failures in the system as a whole (this issue is explored in more detail in the next section).

Malicious external attacks can expose such endogenous vulnerabilities as well, and even the most advanced AI-systems based on deep neural networks are vulnerable to sabotage (Heaven, 2019). Connectivity and flows of information are prerequisites for the operation of AI-technologies in digital farming, forestry, and aquaculture, but also represent potentially serious weak points in the system's security. For example, digital farming systems and applications of AI for "smart cities" rely on data transfer, sensor access to wireless and other communication networks, remote transmission and system actuation, typically in real time (West, 2018). Each of these can be disrupted intentionally and thus affect the operation of e.g. semi-automated farming systems with both detrimental social and ecological impacts (Cooper, 2015; Gupta et al., 2020), some of which may involve serious data-breaches (Cheng et al., 2017). Box 1 elaborates this issue in more detail.

These endogenous and exogenous risks created by novel human-machine-ecological interactions have gain limited attention so far, despite a growing interest and investments in these technologies.

Key future questions:

- *What cybersecurity risks could emerge in digital farming, forestry and other extractive sectors as AI-enhanced technologies gain prominence in these sectors?*
- *What are the most important features of resilient infrastructures that would minimize the risks of cyberattacks and "normal accidents", while also securing the integrity of production ecosystems such as agroecosystems?*

Box 1. Cyberattacks in agriculture and ecosystem management

Using sensors and other technologies to create increasingly accurate models of farms and ecosystems can produce valuable information for management and monitoring. "Virtual farms," based on data from sensors, can be analyzed with AI algorithms for meaningful insights from management strategies to yield predictions (Bronson and Knezevic, 2016). These analyses require considerable amounts of computational power, which is rarely housed on the farm itself. Instead, valuable information is often transmitted, stored, and interpreted offsite using cloud storage and data analytics, and can be susceptible to data breaches at multiple stages (Cooper, C., 2015; Chi et al., 2017;).

The data and algorithms used in digital agriculture are also vulnerable to more traditional security risks. As recently as November of 2019, for example, an ex-employee of Monsanto with plans to sell information to a foreign government was indicted for economic espionage after being caught at the airport with copies of a software technology known as the "Nutrient Optimizer" (USDOJ 2019). This predictive algorithm is a critical component of an online platform, which collects, stores, and visualizes farming data from the field to increase productivity. While these productivity increases are important to seek out, it is critical to remember that using complex, remote, and potentially insecure technological networks can make valuable agricultural information available to nefarious actors around the globe. In the wrong hands, this information could have significant economic consequences, and the systemic risks of cybersecurity need to be managed effectively.

5. AI, efficiency and resilience

Technological advances play a key role as societies strive for increased control and productivity of ecosystems in both land- and seascapes as a means to secure human development (Rist et al., 2014). The use of AI and associated technologies in farming and other forms of extraction of natural resources such as sea food and biomass may very well lead to increased efficiency and productivity, as often noted by prominent international organizations and think-tanks such as the World Bank (2019), Microsoft and PriceWaterHouseCooper (2019), and the World Economic Forum (2018). Such efficiency gains could happen through data-driven temporal and site-specific farm management, reduced waste, and the use of autonomous seeding or weed control, just to mention a few (Finger et al., 2019).

While increased efficiency in resource use is not dangerous in and of itself, and may well be desirable for engineered systems like energy and traffic systems, there are several potential downsides for living systems such as agricultural landscapes, forests, and marine ecosystems. The key issue is that optimizing system performance to maximize efficient generation of a small set of goods (say, a particular crop), often undermines overall system functioning and resilience over the long term (Holling and Meffe, 1996). As these systems become increasingly optimized and efficient, they also become more brittle and vulnerable to undesirable so-called "regime shifts", which are characterized by abrupt, unwanted, and sometimes irreversible changes in a given ecosystem (Rocha et al., 2015).

Thus, for example, industrial agricultural landscapes around the world now generate high yields of a few crop species, but have led to declines in many other ecosystem

services also valued by societies, including biodiversity, scenic beauty, and climate or flood regulation (Foley et al., 2005). Biodiversity in particular provides many functions directly relevant for the sustainable production of food, fuel and fiber, such as the decomposition of organic matter, pest control or pollination. Even when key species are maintained, declines in the diversity of crop and wild species reduce the resilience of ecosystems making them increasingly vulnerable to shocks such as a drought, or a newly introduced pest (Nyström et al., 2019).

Applications of AI and increased automation – including AI-systems that prioritize efficiency over redundancy and diversity - could accelerate such loss of resilience. Since the economic benefits of automation and associated applications of AI and automation seem to be the greatest for larger farms (Basso and Antle, 2020), investments in these technologies could create strong incentives for both larger and more simplified agricultural landscapes (Lajoie-O'Malley et al., 2020), despite evidence that smaller farms tend to be most productive and biodiverse over longer time periods (Ricciardi et al., 2021). In addition, local farming strategies and knowledge are often developed over generations, and are not easily captured by data-driven approaches (Jiménez et al., 2016). Such simplification has been suggested to affect social relationships among people with the possible loss of local knowledge, which could lead to accelerated loss of ecosystems (Riechers et al., 2020; Šūmane et al., 2018). This could undermine the foreseen benefits created by the use of AI-technologies. The economic and technological logic of AI and their associated technologies could hence be in conflict with the logic of resilient ecosystems. Assessing whether AI-applications lead to additional simplification empirically however, will be challenging as changes in land-use and forest cover are driven by a number of factors, many of which are not directly related to technology (Meyfroidt et al., 2018).

Key future questions:

- *Does the increased adoption of AI and associated technologies lead to additional simplification, which may lead to a loss of resilience, of living systems such as agricultural landscapes and forest ecosystems?*
- *How are local strategies and ecological knowledge likely to be affected by an increased deployment of AI-technologies such as predictive analytics and automation?*
- *How can AI and associated technologies be developed and deployed in ways that prioritize resilience over efficiency and simplification?*

6. "Responsible AI", Sustainability and Governance

As we have discussed in previous sections, the development and deployment of AI and increased automation entail both opportunities for sustainability, but also numerous poorly explored systemic risks as humans, machines and ecosystems interact in new ways. Some of these risks could potentially be ameliorated through the application of principles defining "ethical AI", "responsible AI" or "AI for Good" that have emerged in the last years (Fjeld et al., 2020; Jobin et al., 2019), especially those that address (social) bias, privacy, accountability, security and transparency. The development of such ethical guidelines is a major approach proposed for the governance of AI systems. Critics of the current focus of governance of AI through such ethical guidelines have emphasized a number of limits to operationalizing fairness through principles, including the practical limits of providing algorithmic explainability and/or transparency, and the lack of professional accountability mechanisms needed to ensure the consistent implementation of these principles (Haas et al., 2020; Mittelstadt et al., 2018).

It should be noted that such principles consistently overlook climate, sustainability and environmental dimensions. Figure 2 summarizes our analysis of 186 publicly available documents exploring principles for the benevolent use of AI (see Supplementary Information for details about methodology). The data builds on strategic searches of keywords in the documents to assess the frequency of mentions of key dimensions of "responsible AI", and sustainability respectively. We realize that this is a rough and imperfect metric, but can still be used as an indication of the strong emphasis on social rather than sustainability dimensions of current discussions on "responsible" or "ethical AI" worthy of further discussions.

[Figure 2. Summary of analysis of ethical principles of AI, or responsible AI from the public and private sector, including international organizations]

Many of the principles related to algorithmic bias and transparency are indeed applicable for some of the sustainability risks identified in previous sections (e.g. algorithmic bias in digital farming AI-technologies). Nonetheless, issues of environmental sustainability pose distinctive challenges (elaborated in previous sections) that we believe warrant dedicated attention and further refinement in existing ethical AI-principles, as well as stronger guidelines and governance mechanisms.

These mechanisms could, at least in principle, evolve through *sectors-specific guidelines*, *product and process standards,* or through *new or amended legal-regulatory frameworks.*
Sector-specific guidelines for example, are emerging in areas such as medical technology and digital manufacturing, but there have been relatively few guidelines for areas related to sustainability. International organizations and the EU have expressed a

commitment to responsible and trustworthy AI in the context of sustainable development through, for example, the proposed *Artificial Intelligence Act* (European Commission, 2021). These commitments however, are related to principles of non-discrimination, diversity, and inclusivity, rather than on responding to the specific dynamics between AI -technologies and sustainability. For example, climate change and sustainability are only mentioned in passing in the Act, with "environmental sustainability" being suggested as one possible and voluntary "additional requirement" by those developing AI systems (see p. 36, paragraph 81 in the *Artificial Intelligence Act)*.

Standards-making organizations have also looked at ways to translate ethical principles into *product and process standards* that ensure the responsible development, deployment, and monitoring of AI systems. Recent examples include: ISO/IEC TR 24028:2020 'Trustworthiness in Artificial Intelligence'; the IEEE 'Ethics Certification Program for Autonomous and Intelligent Systems'; ISO/IEC 24028 'Bias in AI systems and AI aided decision-making'; or BS 8611:2016 'Robots and robotic devices: Guide to the ethical design and application of robots and robotic systems.' Again, these initiatives focus mostly on organizational governance mechanisms and procedural guidance for managing known social AI risks – such as transparency and accountability – rather than broader systemic considerations linked to the impact of these technologies on sustainability.

In addition, these organizational procedures and considerations need to be further incorporated in emerging sectoral standards for smart farming, agricultural electronics or greenhouse gas management standards, such as ISO/TC207 - Environmental Standards or ISO/TC23 - Tractors and machinery for agriculture and forestry. Thus, systemic risk considerations pertaining to the complex dynamics between AI technologies, ecological and environmental safety, supply chain resilience and their wider distributional consequences for sustainability are rarely featured in current standards packages.

As AI and associated technologies continue to develop, proposals for their regulation have increased in recent years as well. These include either amendments to existing legal-regulatory frameworks in data protection, safety and/or cybersecurity, new regulations to protect consumers against algorithmic bias and provide transparency and accountability, or increased oversight powers for existing or new regulatory agencies (Erdélyi and Goldsmith, 2020). Until now however, these regulatory proposals focus largely on individual risks (e.g. product safety regulations protecting the consumer), as opposed to systemic risks (Black and Murray, 2019) that characterize the complex

human-machine-ecological systems described here. This creates a potentially problematic governance gap that should be addressed.

The lack of adoption, enforcement, and commitment to govern systemic sustainability risks created by AI becomes particularly problematic in the climate and environmental domain where strong regulatory and enforcement capacities cannot be taken for granted. Even though a few industrialized countries see some reductions in e.g. climate emissions (Le Quéré et al., 2019), neither the capacities of international organizations nor of national governments have been able to address the continued erosion of ecosystems, biodiversity and other critical natural capital. Existing legal frameworks and governance mechanisms hence cannot be assumed to compensate for the lack of robust and responsible governance of AI systems and technologies.

Key future questions:

1. *How can existing principles of "responsible AI" and similar, be leveraged to also advance sustainability ambitions?*
2. *What governance mechanisms could support synergies between environmental and technological regulation in ways that minimizes systemic sustainability risks?*
3. *How can such mechanisms be developed in ways that are adaptive to technological and environmental change at the same time?*

7. Conclusion

Artificial intelligence, digitization and automation seem to be gaining traction in sectors of fundamental importance for sustainability. The driving forces behind the diffusion of these technologies are the result of both technological advancements, and societal and environmental pressures. On the technological side, leaps forward in predictive analysis through various forms of AI, IoT, satellite technologies, increasing computational capacity, and new developments in robotics industries, have paved the way for new approaches to efficiency, productivity, and decision making under uncertainty. Secondly, demands from society to better manage scarce natural resources and understand the scope and impacts of rapid climate and environmental change have also spurred research and development in this promising field. As we have discussed here, however, this progress could (and should) be matched with a growing recognition of not only opportunities, but also possible systemic risks for sustainability.

Our analysis shows that the most rapid development of AI and associated technologies in the sustainability domain, seem to be unfolding in farming, with substantial investments in these technologies in China and the United States in particular. As we

discuss, such diffusion could lead to new types of systemic risks resulting from various forms of algorithmic biases, distributional effects, and tentative networked vulnerabilities. These risks can partly be addressed through a growing number of principles and standards that govern the deployment of AI, but need to be complemented with governance mechanisms that are able to integrate sustainability dimensions explicitly.

Many of the risks discussed here are tentative, and difficult to quantify with precision. System risks that evolve out of complexity and poorly understood system interactions between humans, machine, and ecology are particularly challenging. Governing AI risks for sustainability are likely to require hybrid and highly adaptive approaches (Brass and Sowell, 2020) with the capacity to respond to changes in ecological systems, and advances in AI-technologies at the same time. Such governance approaches should in similar ways, as for other challenges characterized by complexity, bring together governmental and private actors, as well as self-regulatory and mandatory regulatory interventions to secure polycentric and flexible responses. Investors, governments and the private sector should take these issues seriously as AI-augmented technologies are increasingly being promoted as a key solution to a turbulent climate future.

Future discussions about how to best govern these technologies from a sustainability perspective need to acknowledge the complex features of ecosystems, their fundamental importance for human development, and the pressures they face under accelerating climate change. One key issue is the possible negative distributional implications of increased applications of AI-technologies on social groups that depend directly on the resources and services provided by these ecosystems on land- and seascapes. Hopefully this article can contribute to future discussions about how to better understand and govern AI risks for sustainability.

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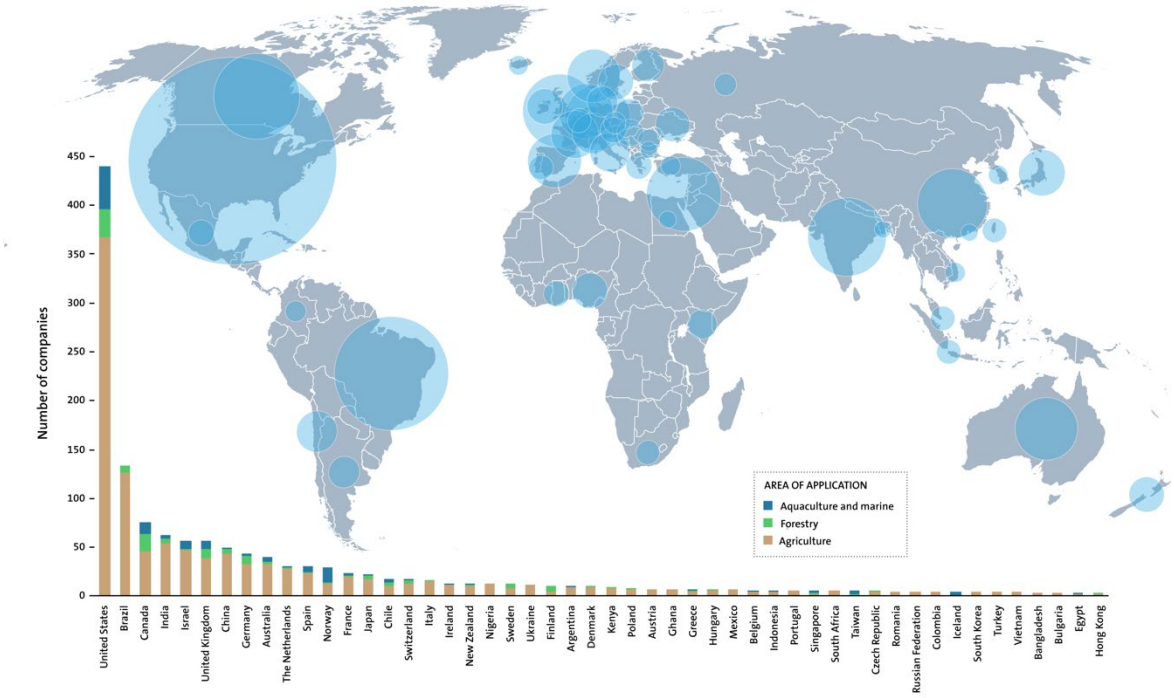
Figure 1. Global distribution of AI technologies and investments in farming, forestry and the marine/aquaculture sectors



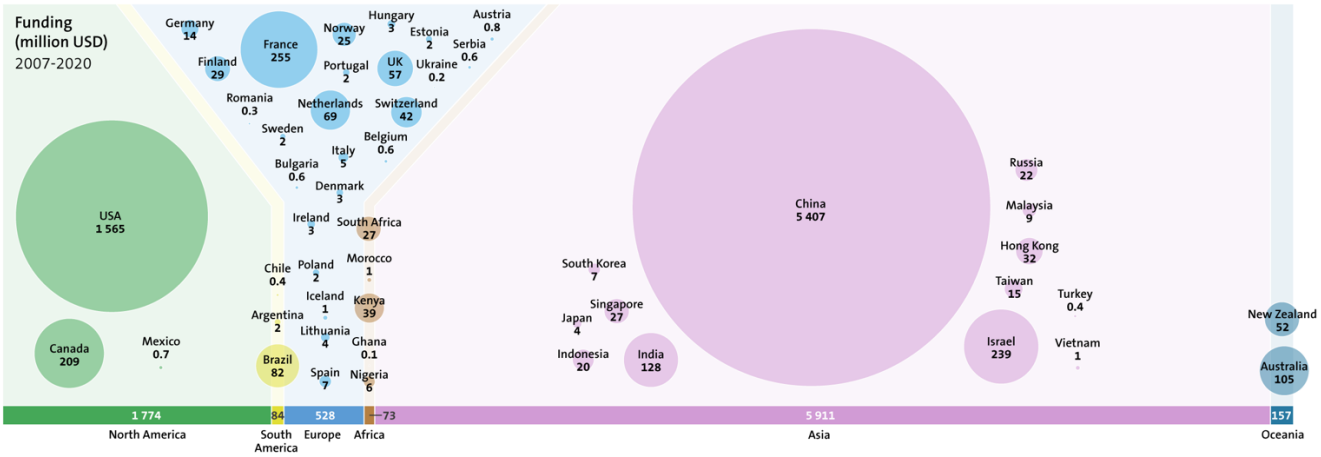


Figure 1A. Geographical and sectoral distribution of companies that develop applications of IoT, sensors, robotics and AI-supported analytics for aquaculture, forestry and agriculture. Total number of companies N=1,114. ***Figure 1B.*** Geographical distribution of investments in companies listed in 1A. See Supplementary Information for details.

Figure 2. Summary of analysis of ethical principles of AI, or responsible AI from the public and private sector, including international organizations

Comment: Visualized numbers show frequency of mentions of key words found in published "responsible AI" principles. Selected keywords are related to core ethical principles (gray columns), compared to key words related to sustainability (green columns). Number of documents analyzed N=186, see Supplementary Information for details about methods.

Supporting Information for "Artificial intelligence, systemic risks and sustainability"

Supporting information 1.
Methods and data for visualization in Figure 1A and Figure 1B.

Figure 1A is based on data extracted from database Crunchbase. Crunchbase includes data about companies and start-ups in the technology sector all over the world, and combines self-reporting with information from large investor network and community contributors, automated searches of the web and news publications for information, and quality control through machine learning methods (Dalle et al., 2017). The database contains known biases such as an overrepresentation of young start-ups (Marra et al., 2020), and geographical gaps (Dalle et al., 2017; Kemeny et al., 2017). However, alternative databases (such as United States Patents, the Kauffman Indicators of Entrepreneurship) are either highly skewed towards the US, or contain similar information as Crunchbase (e.g. the OECD Entrepreneurship Financing Database, see Dalle et al., 2017). The database is thus still widely used as a useful source of information about developments in the technology sector (e.g. Marra et al. 2015; Marra, Antonelli, and Pozzi 2017; Dalle et al., 2017; Kemeny et al., 2017).

Figure 1A and 1B is based on data extraction using broad search terms as suggested by (Kézai et al., 2020) to capture the geographical and sectoral distribution of AI-technologies in agriculture, forestry and aquaculture. We combine searches in these sectors with keywords such as: 'IoT', 'Geospatial Analysis', 'Robotics', 'Software', 'AI', 'Drones', 'Satellites', 'Marine robotics', 'Marine Sensors', and others (the search string can be found below).

The full list of extracted companies identified was double-checked manually by a research assistant and the corresponding author in cases when Crunchbase categories were unclear or ambiguous. The assessment was based on information provided by Crunchbase itself (such as classification keywords and company summaries), and when possible combined with information from company webpages. Misclassified companies, or when in cases when company information was too limited to make an assessment, were removed from the final dataset. As an example, a company that includes "forest" in its company name, but that operate in another sector (e.g. a cryptocurrency), or companies that seem to provide simple software and/or consulting services that only superficially relate to the sector/s and technologies of interest, were removed from the dataset. Companies that develop technologies that are explicitly applied in two sectors at the same time (e.g. drones and automated image analysis for both digital farming and forestry) were classified as companies operating in both sectors.

The assessment is based on information provided by Crunchbase such as classification keywords and company summaries, and when possible combined with information from respective company webpages. Our manual analysis led to the exclusion of 44 companies in the agricultural sector, 27 companies in the forestry sector, and 59 companies in the marine/aquaculture industry. The marine/aquaculture sector had the highest proportion of misclassified companies, and were all checked manually before inclusion. The total selection includes 1,114 companies in the agricultural sector, 98 companies in the forestry sector, and 84 companies in the marine/aquaculture industry. The final selected list of companies can be received by request from the corresponding author.

Figure 1B builds on funding data (2007-2019) for the final selection of companies extracted from the *Crunchbase* database. Funding information includes angel investment, debt

financing, grants, and other sources. Additional information about the types of funding included in the database, can be found here.

Search pipeline

	Forestry	**Aquaculture**	**Agriculture**
keywords sector	Forestry	Aquaculture	Digital Agriculture/Farming, Precision Agriculture/Farming, AI Agriculture/Farming, Artificial Intelligence Agriculture/Farming, Autonomous Agriculture/Farming, Drones Agriculture/Farming, Software Agriculture/Farming, IoT Agriculture/Farming, Internet of Things Agriculture/Farming, Fintech Agriculture/Farming, Robotics Agriculture/Farming, Sensors Agriculture/Farming
keywords total AI	IoT, Internet of Things, Geospatial Analysis, Robotics, Software, AI, Artificial Intelligence, Drones, Satellites, Sensors	IoT, Internet of Things, Drones, Marine equipment, Marine Geospatial Analysis, Robotics, Sensors, Aquaculture Systems, AI, Artificial Intelligence, Satellites	Digital Agriculture/Farming, Precision Agriculture/Farming, AI Agriculture/Farming, Artificial Intelligence Agriculture/Farming, Autonomous Agriculture/Farming, Drones Agriculture/Farming, Software Agriculture/Farming, IoT Agriculture/Farming, Internet of Things Agriculture/Farming, Fintech Agriculture/Farming, Robotics Agriculture/Farming, Sensors Agriculture/Farming
keywords included in table	IoT, Geospatial Analysis, Robotics, Software, AI, Drones, Satellites, Sensors	IoT, Drones, Marine equipment, Marine Geospatial Analysis, Robotics, Sensors, Aquaculture Systems, AI, Satellites	IoT, Biotech, Drones, Autonomous equipment / Autonomous machinery, Fintech, Geospatial Analysis, Robotics, Sensors, Software, Indoor agriculture tech, AI, Precision Agriculture/Farming, Digital Agriculture/Farming

Breakdown of companies and technologies in each specified sector

Forestry

	World	**North America**	**South America**	**Europe**	**Africa**	**Asia**	**Oceania**	**Unknown**
IoT	10	2	4	2	0	2	0	0
Geospatial Analysis	2	1	0	0	0	1	0	0
Robotics	10	7	0	1	0	1	1	0
Software	85	28	7	32	1	9	3	5
AI	13	4	1	4	0	3	0	1
Drones	13	5	1	2	0	3	1	1

Satellites	9	3	0	5	0	1	0	0
Sensors	8	1	2	1	0	3	0	1
Total	98	31	9	36	1	12	3	5

Agriculture

	World	**North America**	**South America**	**Europe**	**Africa**	**Asia**	**Oceania**
IoT	170	44	19	43	13	44	7
Biotech	2	1	0	0	0	0	1
Drones	110	37	12	23	7	27	4
Autonomous equipment / Autonomous machinery	7	6	0	0	0	1	0
Fintech	33	12	8	3	7	3	0
Geospatial Analysis	2	1	0	0	1	0	0
Robotics	187	84	8	47	1	40	7
Sensors	127	52	11	41	1	20	2
Software	882	334	127	220	32	131	38
Indoor agriculture tech	2	1	1	0	0	0	0
AI	179	56	17	43	8	50	5
Precision Agriculture/Farming	211	86	23	55	6	36	5
Digital Agriculture/Farming	93	30	16	23	10	11	3
Total	**1114**	**408**	**149**	**279**	**51**	**183**	**44**

Aquaculture and marine resources

	World	North America	South America	Europe	Africa	Asia	Oceania	Unknown
IoT	15	5	0	1	0	7	0	2
Software	35	13	1	12	0	6	1	2
Drones	5	3	0	1	0	1	0	0
Marine equipment	1	0	0	1	0	0	0	0
Marine geospatial analysis	0	0	0	0	0	0	0	0
Robotics	5	3	0	2	0	0	0	0
Sensors	15	2	1	7	0	4	0	1
Aquaculture systems	40	19	1	11	1	6	1	1
Precision Aquaculture	0	0	0	0	0	0	0	0
AI	20	6	1	4	0	6	1	2
Satellites	2	0	0	2	0	0	0	0
Total	84	30	3	27	1	18	2	3

Supporting information 2.
Analysis of principles for "AI for Good" and "responsible AI"

The analysis builds on the UK foundation Nesta's "AI Governance Database" available online. The database includes metainformation about 255 governance initiatives related to artificial intelligence, including national plans, strategy documents and ethical principles. Each document was downloaded, and scanned for a strategic selection of keywords related to core standard ethical principles, and keywords normally associated with sustainability issues. 73 documents were not available, or assessed to be irrelevant for this study. We chose to also include a number of key missing documents: the 'Ethics Guidelines for Trustworthy Artificial Intelligence (AI)' prepared by the European Commission's High-Level Expert Group on Artificial Intelligence (AI HLEG); Google's Ethical AI principles; Intel's ethical AI principles; and the The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems. Hence the data displayed in Figure 3 builds on the analysis of a total of 186 documents.

The search terms include:

1. **Core ethical principles:** transparency; accountability; bias (algorithms, allocative harms); sustainability (note: non-environmental sustainability, e.g. cybersecurity or other).
2. **Key sustainability issues:** climate change, global warming, carbon budget, decarbonization, Paris Agreement; biodiversity, ecosystems, biosphere; agriculture, farming, farmers, forest, forestry; ocean, oceans, marine, fish, fisheries; sustainability, (note: environmental, ecological, sustainability, including Agenda 2030, Sustainable Development Goals, SDGs.

The coded datafile can be received by request from the corresponding author.

References for Supporting Information

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