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Artificial intelligence, systemic risks, and sustainability

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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.

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1. Introduction

Technological change is a fundamental component of scientific and economic breakthroughs [1], and has the potential to dramatically influence global efforts toward sustainability [2,3]. As the pressure of human activities increasingly shapes the biosphere and the climate system, so does the hope that artificial intelligence (AI)[1] 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 [4–6]. 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. Refs. [4,7,8].

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. Refs. [7,9,10], yet their potential allocative harms [11] and unexpected social and ecological effects [12] 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. Ref. [13], or underemphasize their possible social, economic and ecological risks (e.g. Refs. [6,14–16].

In this article, we offer an overview and elaborate possible systemic risksfor sustainability[2] created by the diffusion of AI and associated technologies. Systemic risks – i.e. risks that evolve from networked interactions in complex systems [17,18] – are of particular interest since the application of AI-technologies in combination with globalization processes, are likely to create novel connections between humans, machines and the living planet including ecosystems and the climate system. Such poorly understood human-nature-machine interactions increase the possibilities for disruptions that propagate through contagion in key sectors of society, such as food, energy and commodity production systems dependent on resilient ecosystems and associated ecosystem services [19].

Here, we do not focus on known direct impacts such as the energy consumption or the carbon footprint of deep learning and data-mining [20], nor on opportunities for AI in helping address climate change [21,22]. 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 [23]. 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 [24]. Here, we combine literature from seldom connected strands of research, 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 not to conduct a systematic literature review, but 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 governance of AI and its potential to help accelerate climate action. We conclude by posing broadly formulated research questions as a way lay the foundation for multi- and transdisciplinary work across these diverse, and until now poorly connected strands of research.

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 [25,26]; AI-augmented environmental monitoring [27]; autonomous underwater marine conservation interventions and data collection [28,29]; AI-supported tracking of illegal wildlife trade [30]; and "smart" urban planning for sustainable development [31–33].

The Royal Society in addition, has identified "digital twins" augmented through AI-analysis as key components of potentially planetary digital "control loops" for effective climate mitigation action, and more robust farming practices [22]. The ability of "digital twins" – that is, advanced digital replications of complex and evolving systems using "big" real-time data - has gained increased attention in the sustainability domain. Such tools allow its users to simulate, explore, optimize and help identify risks in various sectors related to sustainability ambitions, including in infrastructure development, and resource consuming systems of various forms (e.g. energy and water) in e.g. cities [34–36].

The potential for AI and associated technologies also 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 [37]. Agricultural technology (agtech) investment reached a new record of $1.5 billion in 2017, and venture capital investment in the space has grown 80% annually since 2012 [38]. The precision forestry market could grow from USD 3.9 billion in 2019, to reach USD 6.1 billion by 2024 [39]. 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 [32,33]. The smart city market is expected to reach USD 460 billion by 2027 [40], smart city AI software alone is projected to total USD 5 billion annually by 2025 [41], 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 [33].

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 [42]. 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

[1] Here we use the term "artificial intelligence/AI" to refer to technologies that employ machine learning (ML) including "deep learning" (DL) methods (see Ref. [13]. 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 [130]. By 'sustainability' we refer specifically to the importance of the biosphere and a stable Earth system for ongoing human development and prosperity [23,131].

of the economy [43,44]. 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 [45].

These converging trends suggest that the development and deployment of AI and associated technologies are likely to not only have social and economic consequences, but will very likely impact climate, biodiversity, and ecosystems around the world [46]; Wynsberghe, 2021). Their diffusion hence merits increased attention from a sustainability perspective.

Fig. 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 the living planet, i.e. 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" [47–49].

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" [50–52]. The prominent position of China in terms of investments (Fig. 1B) also seems to follow AI-investment patterns in general [53]; see also [54] for digital agriculture).

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

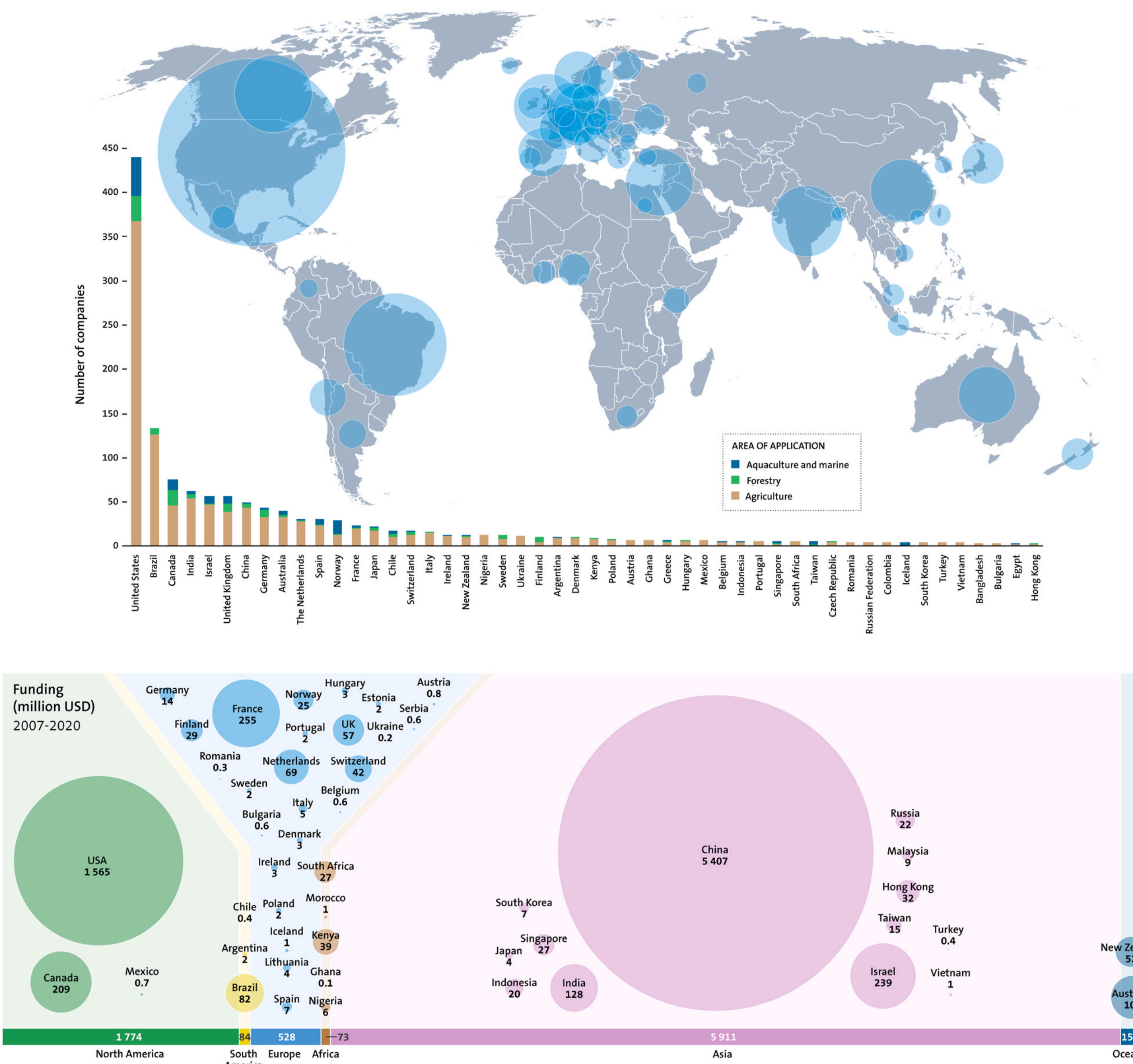

Fig. 1. *Global distribution of AI technologies and investments in farming, forestry and the marine/aquaculture sectors.* Fig. 1A. Geographical and sectoral distribution of companies that develop applications of IoT, sensors, robotics and AI-supported analytics for aquaculture, forestry and agriculture. Total number of companies N = 1114. Fig. 1B. Geographical distribution of investments in companies listed in 1A. See Supplementary Information for details about methods and data.

and environmental context [55] making their distributional consequences and sustainability risks difficult to predict with specificity [56].

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 Ref. [11] has gained considerable attention in the last years. As has been shown in other domains such as policing and the health sector (e.g. Refs. [57,58], 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 (e.g. Refs. [10,50]. Environmental and ecological data have well known limitations however, both in their temporal coverage, and geographical spread [59–61]. 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" [62].

Algorithmic biases of this sort can have a number of sources [63], 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 [64].

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 [65]. The use of simpler forest monitoring and carbon sequestration models has already led to controversies partly due to their tentative transfer context bias [66].

The fact that ecosystems both on land and in the ocean are changing rapidly as the result of climate and ecological change [67] also pose serious challenges as AI-models, and lead to a type of concept drift [68]. 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 [69,70].

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 [49].

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 [31, 71]. 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 [72]. 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 [31], and responsible innovation approaches [32].

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 [51,52] 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 [73], and especially in less wealthy countries, many people depend on small-scale family-farms to meet their nutritional needs [74]. While applications of AI in combination with increased automation for farming have been suggested to contribute to increased yields and resource efficiency [47], 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 [75]. 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 [76].

Similar concerns and uncertainties about the tentative loss of employment opportunities resulting from increased automation [77] are present in these sectors as well of course [78]. While it might seem premature to raise this as a possible risk, early studies indicate that the economic benefits of AI applications in farming appear to be greatest for larger farms that can spread their fixed costs over many acres, and that can reduce labor costs through automation [49]. 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 [49,79], and the detrimental impacts on technological development resulting from corporate concentration in the food sector [80].

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 [48,81]. 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 [38]. Small-scale fisheries and coastal communities (estimated to employ some 37 million people [82], and small-scale enterprises in the forestry sector (providing employment for an additional estimated 41 million people [82], may face similar challenges related to allocative harms, and unequal distribution of benefits as applications of AI-technologies make their progress into their domains [28,83].

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 [84], but also increasingly with machines and ecosystems, and with the Earth system as a whole [2,55]. 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 [85]. Such systems may through the use of AI and associated technologies, contribute to the emergence of "distributed AI" (DAI) - decentralized systems with the ability to bring together information and agents across levels and domains, at the same time as they (partly) autonomously react, adapt and learn pro-actively to changing circumstances [86]. Applications of DAI for industrial purposes are well-known (e.g. Ref. [87], including in technical infrastructure such as energy systems [88,89]. These processes of decentralized adaptive problem-solving have also been observed for astonishingly complex yet resilient indigenous farming systems in Bali [90], and could as proposed by some, be augmented and automatized through the extensive use of AI and associated technologies to support artificially intelligent curation of wild places and nature (e.g. Ref. [91]. DAI could also, at best, help interpret and respond to the complex systems properties and the continuous changes that characterize farming, forestry and marine systems under rapid change due to human activities and climate change.

However, increasingly nested and complex systems are also susceptible to unexpected shocks, and cascades that develop endogenously, also known as "normal accidents" [92]. This implies that 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), especially if the components of the system are optimized and managed properly (say, a regional network of IoT-connected farms).

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 [93]. 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 [94]. 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 [95,96], some of which may involve serious data-breaches [97]. Box 1 elaborates this issue in more detail.

These endogenous and exogenous risks created by novel human-machine-ecological interactions have gained 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?*

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 [103]. 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 [47]; Microsoft and Price Water House Cooper [16]; and the World Economic Forum [15]. 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 [104].

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 [105]. 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 [70].

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 [106]. 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 [19].

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

Box 1
Cyberattacks in farming, food systems 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 [98]. 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 [95,99]. These risks have been raised the last years (e.g. Ref. [100], and became highly visible in June 2021 when ransomware cyberattacks forced the shutdown of numerous meat plants in the U.S. [101].

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" [102]. 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.

and associated applications of AI and automation seem to be the greatest for larger farms [50], investments in these technologies could create strong incentives for both larger and more simplified agricultural landscapes [49], despite evidence that smaller farms tend to be most productive and biodiverse over longer time periods [107]. The latter have proven to be key for the food security of communities in the most fragile regions of the world [108].

In addition, local farming strategies, as well as social and ecological knowledge are often developed over generations. These contain numerous social, cultural and even spiritual practices, some of which have proven key to support the resilience of communities and the ecosystems they manage in the face of changing social and environmental circumstances [109,110]. Such tacit sources of knowledge and are not easily captured by data-driven approaches [111].

Simplification of ecosystems such as agricultural and forest landscapes has been suggested to affect social relationships among people, with the possible loss of local knowledge, which could lead to accelerated loss of ecosystems [112,113]. These processes 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 related directly to technology [114].

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 [115,116], especially those that address fairness, non-discrimination, accountability, transparency, privacy and security. Principles-based guidelines have thus become the dominant approach to governing AI systems.

However, such principles have at least historically consistently overlooked climate, sustainability and environmental dimensions. Owe and Baum [117] for example, argue that AI ethics in general, have failed to give serious moral consideration to "nonhumans", i.e. nonhuman animals and the environment. Fig. 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 environmental sustainability dimensions of current discussions on "responsible" or "ethical AI".

Many of the principles related to algorithmic bias and transparency are nevertheless applicable for some of the sustainability risks identified in previous sections. If effectively implemented, these principles could help mitigate the risks of algorithmic biases such as transfer context bias, by incentivizing companies and governments to make sure AI-systems in e.g. forestry are explainable and adaptive to changing climate conditions. Some of these principles have come to even include environmental and sustainability dimensions, such as the High-Level Expert Group on AI (HLEG) and their recommendation that "AI systems should be sustainable and benefit all human beings, including future generations" [44].

The fact that climate and environmental risks and costs tend to systematically be externalized and challenging to quantify [118], may very well undermine the economic and legal incentives of AI-developers and users to implement such principles in practice if they are associated with costs. Critics of the current principles-based approach to AI governance have emphasized a number of limits to operationalizing fairness, the practical limits of providing algorithmic explainability or transparency, and the lack of professional accountability mechanisms needed to ensure their consistent implementation [119–121]. We suggest that issues of environmental sustainability pose distinctive challenges in what Weernart denotes "high-stake settings" (Weernart, 2021) for both people and nature, thus warranting dedicated attention and further refinement of existing AI principles-based governance frameworks, as well as more precise guidelines for how to implement and continuously monitor their performance.

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

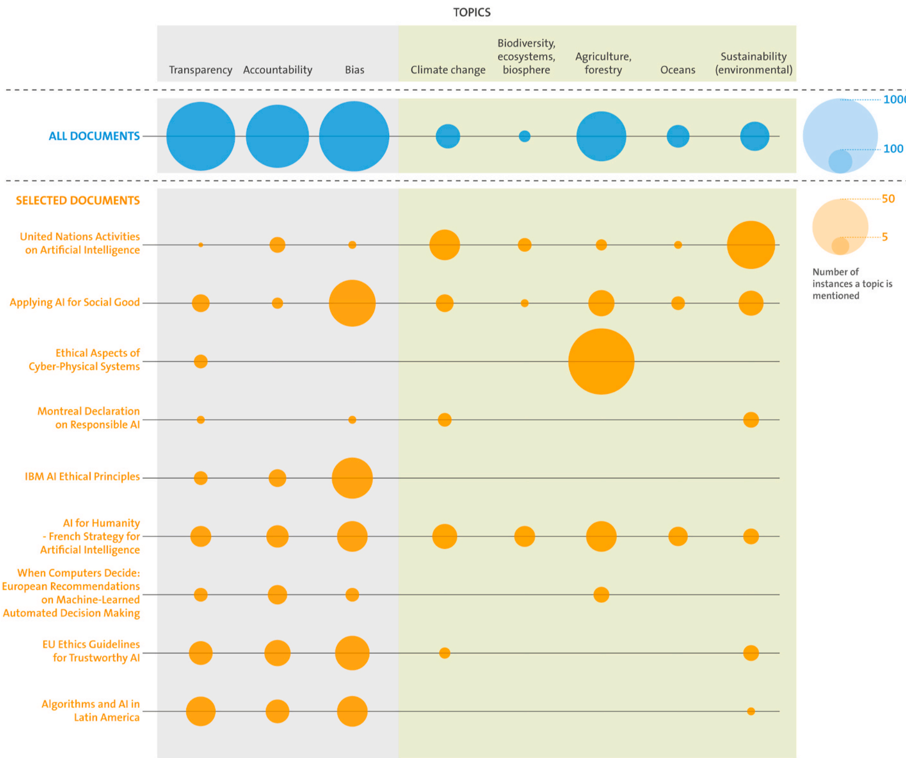

Fig. 2. *Summary of analysis of ethical principles of AI, or responsible AI from the public and private sector, including international organizations.* **Comment**: Visualized numbers show frequency of mentions of key words found in published "responsible AI" principles. Selected keywords are related 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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* [122]. These commitments however, are related to principles of non-discrimination, diversity, and inclusivity, rather than on responding to the specific dynamics between AI-based technologies and environmental 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 lack of 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 [123], including independent audits of AI-systems [119]. Until now however, these regulatory proposals focus largely on individual risks (e.g. product safety regulations protecting the consumer), as opposed to systemic risks [124] that characterize the complex human-machine-ecological systems described here. In addition, 'safety' is consistently viewed from the perspective of individuals rather than from a wider environmental sustainability perspective (e.g. Ref. [119]. This creates a 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 [125], neither the capacities of international institutions nor of national governments have been able to address the continued erosion of ecosystems, biodiversity and other critical natural capital [126]. Existing legal frameworks and governance mechanisms in the environmental and sustainability domain 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 both technological and environmental change, including climate disruptions and surprises, 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-methods, IoT-systems, 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. In addition, the fact that both the development and use of these technologies are nascent makes it difficult to assess to what extent the risks identified are intrinsic to AI and associated technologies themselves, or the result of “pacing problems” [127] created by novel uses of AI-technologies in new social and environmental contexts.

Our limited predictive abilities as these AI-risks diffuse into the sustainability domain requires what Shannon Valor calls “technomoral humility” [128], but also to strike a balance between stringent and adaptive modes of governance. We suggest that governing AI risks for sustainability due to the limited predictability created by systemic risks that emerge through human-nature-machine interactions are likely to require hybrid and highly adaptive approaches [129]. These need to be developed with the capacity to respond to changes in the climate system, 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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Appendix A. Supplementary data

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Author statement

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