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# Machine intelligence, systemic risks, and sustainability

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# Machine intelligence, systemic risks, and sustainability

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## Abstract

Automated decision making and predictive analytics in combination with rapid progress in sensor technology and robotics are likely to change the way individuals, communities, governments and private actors perceive and respond to climate and ecological change. Machine intelligent methods are already today being applied within 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. Here we elaborate the various ways by which machine intelligence is making progress in domains of critical importance for sustainability, with a special emphasis on possible systemic risks. These risks include a) algorithmic bias and allocative harms; b) unequal access and benefits; c) cascading failures and external disruptions; d) mis- and disinformation, and e) trade-offs between efficiency and resilience. We explore these emerging risks and discuss the limitations of current governance mechanisms in addressing the impact of MI risks on sustainability.

## 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 shape the biosphere and the climate system, so does the hope that machine intelligence (MI)[1] (including artificial intelligence through 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, and adapt and respond to climate and environmental change (Campbell et al., 2019; Herweijer and Waughray, 2018; Joppa, 2017). Numerous reports highlight how applications of MI and robotics may help address climate change and biodiversity loss and contribute to more effective monitoring and uses of natural resources as well as achievement of the Sustainable Development Goals (SDGs) (Future Earth, 2020; Vinuesa et al., 2020).

While this growing machine intelligent "digital ecosystem for the planet"(Campbell et al., 2019) 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 MI technologies diffuse into new social, economic and ecological contexts. While some early syntheses have attempted to tackle these risks (Future Earth, 2020; Wearn et al., 2019), potential allocative harms (Barocas et al., 2017) and unexpected social and ecological effects (Galaz and Mouazen, 2017) remain either overlooked or poorly elaborated. Prominent agenda-setting reports about the social impacts of AI either ignore sustainability dimensions altogether (Veale et al., 2018), or underemphasize possible social, economic and ecological risks (Joppa, 2017; Lajoie-O'Malley et al., 2020).

In this article, we explore systemic risks for sustainability created by the diffusion of MI.[2] Hence, we do not focus on already explored direct climate impacts such as the energy consumption or the carbon footprint of deep learning and data-mining (García-

[1] Here we use the terms "artificial intelligence", "machine intelligence" and "machine intelligent" to refer to technologies that employ either machine learning (ML) and/or "deep learning" (DL) methods (see House of Lords 2018). ML and DL are different from a technical point of view, but our main interest in this paper is in the social and ecological impacts of machine intelligence, rather than the underlying technique *per se*.

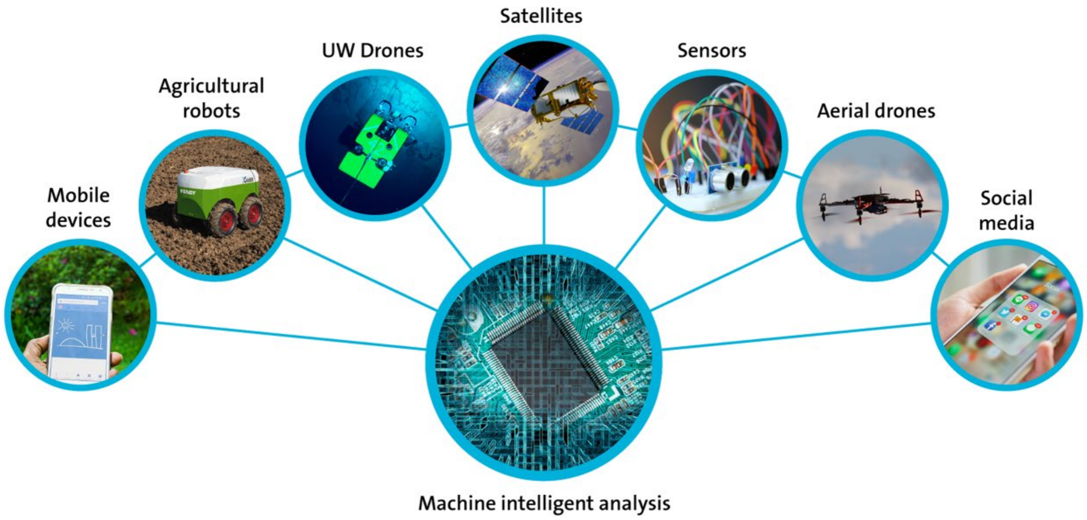
[2] By risk, we refer to a measure of the probability and severity of adverse effects (Lowrance, 1976). By 'systemic risks' we mean risks that evolve from complex interactions emerging from human, machine and environmental interactions, and that could lead to disruptions that propagate through these systems through the process of contagion (Centeno et al., 2015; Helbing, 2013). By 'sustainability' we refer specifically to the importance of the biosphere and a stable Earth system for human development and prosperity (Folke et al., 2016; Steffen et al., 2015).

Martín et al., 2019), nor on opportunities for MI in helping address climate change (Rolnick et al., 2019), but on 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 MI in domains critical for biosphere-based sustainability - that is, the management and resilience of so-called 'production ecosystems' such as agriculture and forestry; the technical infrastructure underpinning their production; and information technologies that humans use to make sense of, and act collectively on, a changing planet and climate. More specifically we ask:

a) What is the relationship between increased applications of machine intelligence, notions of "responsible AI", and biosphere-based sustainability?
b) Where in the world, and into which sectors directly relevant for biosphere-based sustainability, are machine intelligent technologies diffusing?
c) Which are the most prominent systemic risks from a sustainability perspective?
d) What could be learnt from other domains about the possible governance of these systemic sustainability risks?

Our analysis combines a literature synthesis with new data to gain a deeper empirical understanding of these issues. Figure 1 describes the MI technologies, key sustainability opportunities and systemic risks discussed in this article.

***Figure 1. Illustration of machine intelligent technologies and their general sustainability opportunities and risks discussed in this article***




***Sustainability Opportunities***

- Increased efficient use of natural resources and energy
- Addressing social, climate, ecological data gaps
- Augmented real-time monitoring of environmental change
- Refined predictive ecological and climate modeling
- MI-supported management strategies

***Sustainability Systemic Risks***

- Algorithmic bias and allocative harms
- Unequal access, benefits, and impacts
- 'Normal accidents' and targeted attacks
- Information pollution and misinformation
- Inaccurate estimates of resilience versus efficiency trade-offs

## 2. The growing importance of machine intelligence for sustainability

MI-based methods are already now being applied in a number of research fields related to the environmental, sustainability and climate sciences. Examples include machine intelligent applications in climate and Earth system modeling (Rasp et al., 2018; Reichstein et al., 2019); precision or digital farming and forestry (Joppa et al., 2016); environmental monitoring (Hino et al., 2018); autonomous underwater marine interventions (Girard and Du Payrat, 2017) and marine data collection (Nunes et al., 2020); tracking of illegal wildlife trade (Di Minin et al., 2019); and “smart” urban development (Ilieva and McPhearson, 2018). Supervised and semi-supervised convolutional neural networks for example, can help find and make short term predictions about extreme weather patterns and anomalies in changes in land use (Helbing, 2013), thus offering important information for policy-makers, companies and insurance agencies trying to act proactively on the impacts of climate change. Data driven methods supported by MI can also help farmers align planting, sowing, and management practices to specific local conditions, and adapt to market fluctuations (Jiménez et al., 2016).

The potential for MI seems to be driving a growing interest from the private sector. The smart city market is expected to reach USD 460 billion by 2027 (Grand View Research, 2019) and smart cities AI software alone is projected to total USD 5 billion annually by 2025 (Tractica, 2020) relying on MI for traffic management, smart policing, lighting control, facial recognition, and smart waste and disposal systems all with goals to improve urban livability and sustainability. According to estimates, nearly 12 million IoT sensors will be installed and in use on farms around the world by the year 2023 (Meola, 2020), and agricultural technology (agtech) investment reached a new record of $1.5 billion in 2017, and since 2012, venture capital investment in agtech has grown by 80 percent annually (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).

Figure 2 shows our analysis of the geographical distribution of MI-technologies (including applications of IoT, robotics and analysis supported by machine intelligence) in sectors linked to the management of land- and seascapes.

*Figure 2. Global distribution of MI technologies and investments in farming, forestry and the marine/aquaculture sectors*

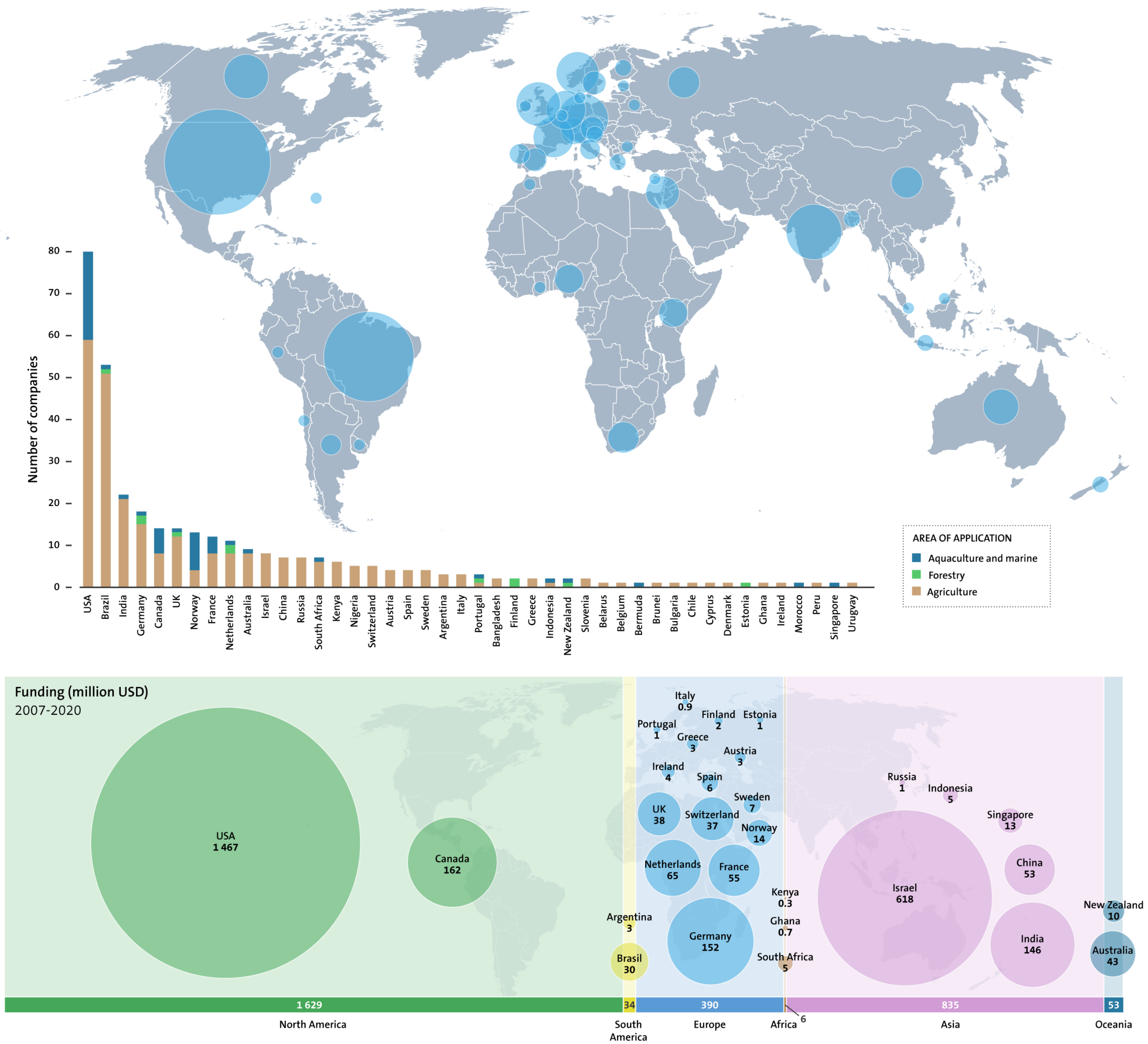



***Figure 2A.*** Geographical and sectoral distribution of companies that develop applications of IoT, sensors, robotics and MI-augmented analytics for aquaculture, forestry and agriculture. Total number of companies N=339. ***Figure 2B.*** Geographical distribution of investments in companies listed in 1A. Note that funding information (including angel investment, debt financing, grants, and other) is only available for N=177 companies. See Supplementary Information for details.

Hence while still nascent in terms of both scale and impact, applications of MI and other associated technologies such as intelligent underwater monitoring drones, and digital forestry, could be viewed as examples of technological “niche-innovations” (Geels et al., 2017) capable of rapid upscaling and diffusion with impacts on the climate system, as well as biodiversity and ecosystem impacts across multiple regions. It also should be noted that the diffusion of MI-technologies unfolds not only through increased investments, but also by the much less visible infusion of e.g. deep learning systems into existing technologies (Engström and Strimling, 2020).

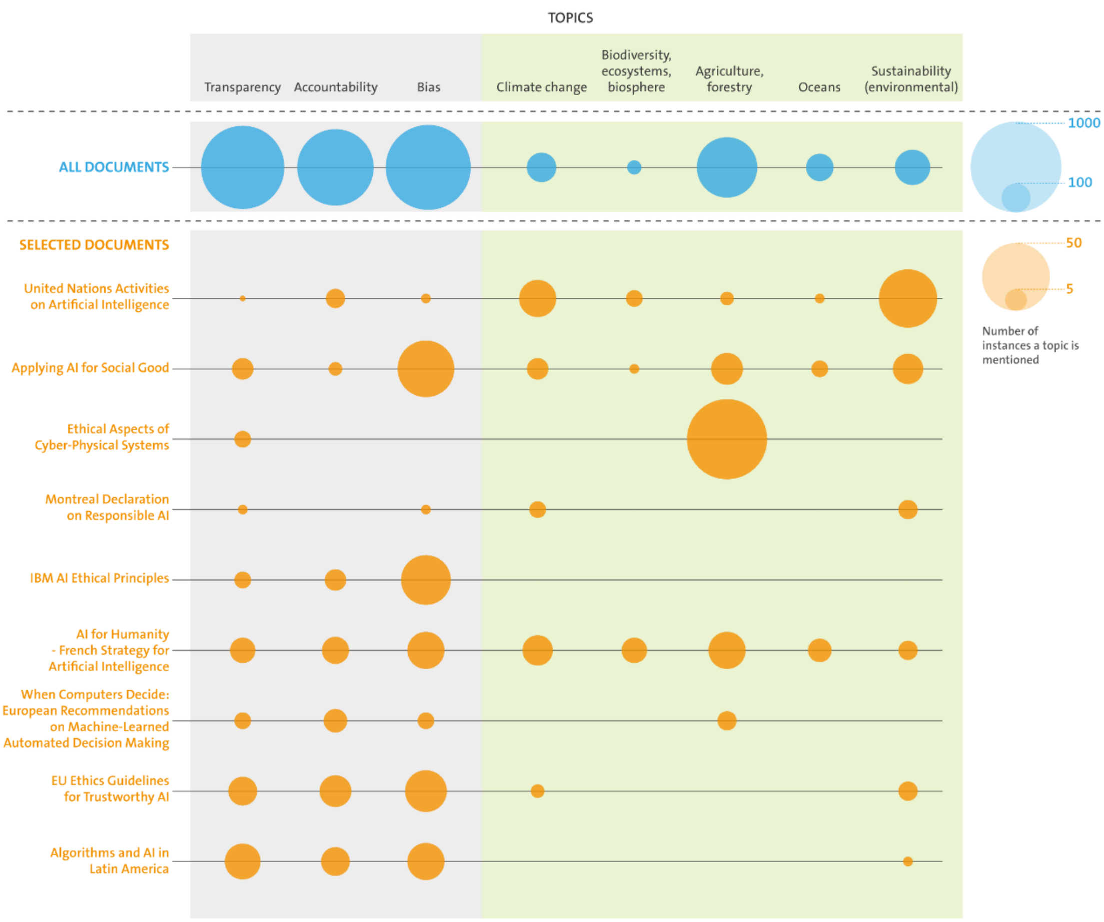
## 2.1 “Responsible AI” and Sustainability

There is a growing recognition that the increased diffusion of MI in society not only entail opportunities but also risks by amplifying gender discrimination, and increase social inequalities. Numerous attempts to define “ethical AI”, “responsible AI” or “AI for Good” that have emerged in the last years repeatedly elaborate upon issues such as social bias, privacy, accountability, security and transparency (Fjeld et al., 2020; Jobin et al., 2019). However, this growing body of principles and initiatives typically do not seem to address sustainability risk dimensions.

Figure 3 summarizes our analysis of 186 documents exploring principles for the benevolent use of AI. As the data indicates, climate, sustainability and environmental dimensions are consistently overlooked, or addressed to a far lesser extent than issues like transparency, bias and accountability. Many of the principles related to algorithmic bias and transparency are indeed applicable for some of the issues discussed below. Nonetheless, issues of environmental sustainability pose distinctive challenges that warrant dedicated attention in AI ethical principles.

We argue that five areas related to a) algorithmic bias and allocative harms; b) unequal access and benefits; c) cascading failures and external disruptions; d) mis- and disinformation, and e) trade-offs between efficiency and resilience, will prove critical for future discussions about MI for sustainability.

*Figure 3. Summary of analysis of publicly available 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.

## 3. Machine intelligence, algorithmic bias and allocative harms

Machine intelligent technologies could transform the ways in which the climate system, farmlands, oceans, urban ecology and other ecosystems are monitored, managed and protected. However, their 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). However, drawing from insights from other domains such as policing and health care, a number of foreseeable risks could be acted upon proactively.

The first risk relates to possible *algorithmic biases and their allocative harms* (Barocas et al., 2017). Growing volumes of environmental and ecological data are a fundamental prerequisite for the application of machine intelligence for e.g. conservation and digital farming (Basso and Antle, 2020). Environmental and ecological data however, have well known limitations, both in their temporal coverage, and geographical spread (Joppa et al., 2016). Satellites, drones, mobile devices, sensors and social media have created an abundance of data with multiple applications for both science and practice, can be combined with additional data gathering technologies, and analyzed using various machine intelligent methods to resolve challenging data gaps (Blumenstock, 2016; Campbell et al., 2019; Creutzig et al., 2019; Herweijer and Waughray, 2018; Vinuesa et al., 2020).

Urban sustainability scholars have already raised a number of issues related to MI and tentative threats to privacy, research ethical challenges, and the risks resulting from spurious correlations (Girard and Du Payrat, 2017). For example, location-tracking systems via smartphones and vehicles make it possible to not only know location, but to triangulate a person's identity, even with relatively little data. Such risks highlight the need for robust and transparent data management policies. Our own simple overview of the data management policies of the selected companies presented in Figure 2, show that only 14% have publicly available data principles, policies, and practices (see details in Supplementary Information).

Several AI design problems could potentially have negative ecological and social repercussions in the sustainability domain. These include inconsistencies and biases in training data; security breaches leading to corrupted data capture and decision-making systems; flawed machine intelligent models; or incorrect applications (as has been shown in other domains such as policing and the health sector (Barocas and Selbst, 2016; Obermeyer et al., 2019) could potentially also have negative ecological and social repercussions in the sustainability domain. Algorithmic biases can have a number of sources (Danks and London, 2017), illustrated for our purposes in Box 1.

***Box 1. Algorithmic bias in the sustainability domain***

***Training data bias*** – Machine intelligent algorithms that are designed with poor, limited, or biased data sets fall victim to this type of bias. Algorithms will learn and recognize patterns from training inputs, regardless of whether or not they are representative of the real-world. For example, machine learning algorithms developed in data poor contexts could, if not validated properly with local knowledge and expert opinion, lead to incorrect management recommendations to small-scale farmers who would struggle to maintain high, stable yields (Jiménez et al., 2019).

***Transfer context bias*** – Machine intelligent algorithms that are designed for one ecological, climate, or social-ecological context, and then transferred to another exhibit the "transfer context bias." Such bias may emerge as individuals and companies use off-the-shelf machine intelligent software for their purposes (Chouldechova and Roth, 2018). While the training data and the resulting model may be developed and suitable for the initial social-ecological situation (say, a big farm in a data rich context), using it in a different setting (e.g. a small farm) could lead to flawed and damaging results. For example, forest monitoring and carbon sequestration models developed in Australia and transferred to Indonesia 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 models built on historical ecological conditions, could fail as the climatic and ecological context shifts.

***Interpretation bias*** – 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, a mismatch between what the algorithm produces and what the user needs can lead to unsuitable application of the results. A machine intelligent system (e.g. decision support tool) might be working as intended by its designer, but if the user does not fully understand its utility, or tries to infer different meaning that the algorithm might not support, biases can begin to present themselves on the application side. Algorithm developers 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 to apply more (instead of less) nitrogen (N) fertilizer to low-yielding portions of rain-fed fields in the hope of increasing yields (Lajoie-O'Malley et al., 2020).

## 4. Unequal access, benefits, and impacts

The unequal distribution of risks and benefits can also emerge as the result of existing resource constraints, and unequal access to information and communication technologies (Salemink et al., 2017; United Nations Development Programme, 2019). 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 MI for farming could contribute to increased yields and resource efficiency (World Bank Group, 2019), the distribution of such benefits cannot be taken for granted. On a general level, it is well-known that even very simple non-MI technologies for intensifying agriculture are often deemed unaffordable by poor members of 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 to big data and mobile technologies (Mehrabi et al., 2020).

The economic benefits of MI 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 on "digital agriculture" by influential international actors such as the World Bank, 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 security such as poverty and social inequalities (Lajoie-O'Malley et al., 2020; Sen, 1982).

Equal access to MI-technologies does not guarantee equal or fair outcomes however. Even if farmers are able to optimize their specific operations cost-effectively, widespread use of MI 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, it has been argued that 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 (Ileva and McPhearson, 2018). 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 MI-technologies make their progress into their domains (Bayne and Parker, 2012; Reichstein et al., 2019).

## 5. Shocks, cascading failures and attacks

Machine intelligent technologies create numerous new complex interactions not only between humans and machines, as well as between machine intelligent systems (Rahwan et al., 2019), but also increasingly with ecosystems and the Earth system (Galaz, 2014; Markolf et al., 2018). These growing interactions between humans, machines and ecology could be viewed as 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 even if the components of the system are managed properly (say, a regional network of IoT-connected farms), risks can ripple and amplify across network links (e.g. a regional food supply chain).

Malicious external attacks can expose these endogenous vulnerabilities. Connectivity and flows of information are prerequisites for the operation of machine intelligent technologies in digital farming, forestry and aquaculture. For example, digital farming systems and applications of MI 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 semi-automated farming systems (Cooper, 2015; Gupta et al., 2020). As MI-enhanced technologies continue to play a larger role in agriculture, urban system management, and resource management, designing resilient infrastructures for them has been argued to have become increasingly difficult. Box 2 elaborates this issue in more detail.

***Box 2. Cyberattacks and how they propagate***

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 MI 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 (Chi et al., 2017; FAO and United Nations Environment Programme, 2020).

The data and algorithms used in digital agriculture are also vulnerable to more traditional security risks. As recently as November of 2019, for example, a Chinese national who worked at Monsanto 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.

## 6. Machine intelligent information pollution and misinformation

MI-technologies not only facilitate information sharing and analysis to users in easily delineated sectors like farming and forestry but are increasingly affecting online conversations about climate and environmental issues in a media ecosystem that is become more heavily automated. The participatory aspects of social media give it a central role in shaping individual attitudes, feelings and behaviors (Williams et al., 2015), and for social mobilization and protests (Steinert-Threlkeld et al., 2015). This new digital information landscape is however also affected by the abundant spread of misinformation, including hoaxes, conspiracy theories, click-bait headlines, and 'junk science' (Shao et al., 2018).

Climate and environmental misinformation and disinformation campaigns have a long history, and they are particularly challenging in digital media for several reasons. First, climate and environmental issues are prone to polarization due to their connection to all aspects of society (say, ranging from dietary choices to tax policies), and to deeper differences in perception, values and ideologies (Ballew et al., 2019).

The role of online media in general in diffusing and amplifying climate and environmental mis- and disinformation is getting increased attention (Treen et al., 2020). To what extent such information has been (or could be) augmented through MI, is nonetheless poorly understood. MI-fueled information operations through the voluminous automated diffusion of climate misinformation through "social bots"

(Woolley, 2016); micro-targeting and search engine optimization (Bradshaw, 2019), and targeted uses of emotional content (Bakir and McStay, 2018); could in principle act as an effective amplifier of existing confusion and discontent (Jang and Hart, 2015; Shao et al., 2018; Woolley, 2016). The resulting polarization, mistrust in science and incorrect climate information could undermine climate action and crisis responses in detrimental ways, as illustrated by the voluminous spread of misinformation and conspiracy theories during the US wildfires in September 2020.

Some early evidence suggests that semi-automated misinformation campaigns augmented through “social bots” have started to emerge during international environmental crises and high-profile international climate events. This includes reports about attacks in social media by “trollbots” targeting climate activist Greta Thunberg, and the diffusion of conspiracy theories during the Australian bushfires in 2019. However, none of these studies (Marlow et al., 2020; Weber et al., 2020) have been subject to peer-review, and should therefore be interpreted with care. As many other adversarial MI cases, content pollution and social bot detection are in an arms race that complicates the identification of automated accounts on social media (Ferrara et al., 2016).

## 7. Machine intelligence, efficiency and resilience

Technological advances have historically played, and will continue to play, a key role as societies strive for increased control and productivity of ecosystems in both land- and seascapes (Rist et al., 2014). The use of new technologies in farming and other forms of extraction of natural resources such as sea food and biomass through e.g. robotics, predictive optimization algorithms, and the analysis of big data may very well lead to increased efficiency and productivity through e.g. temporal and site-specific farm management, reduced waste, and allowing autonomous activities such as seeding or weed control (Finger et al., 2019). While increased efficiency in resource use is not dangerous in and of itself, there are several potential downsides to deploying increasingly automated and autonomous technology in the context of natural resource management. The key issue is that optimizing system performance to maximize efficient generation of a small set of goods (say, a particular crop), is known to undermine system functioning and resilience over the long term (Holling and Meffe, 1996), which could lead to undesirable regime shifts that significantly and sometimes irreversibly change a given ecosystem (Rocha et al., 2015).

Thus, for example, industrial agricultural landscapes around the world now generate high yields of few crop species, but has led to unintended 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 MI and increased automation could accelerate these trends. Since the economic benefits of automation and associated applications of MI 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). 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), which could undermine the foreseen benefits created by the use of machine intelligent technologies.

## 8. Implications for environmental governance, ethics and law

The increased application of MI systems and associated technologies across critical sectors of the economy and public service provision has raised heightened interest in how best to manage the risks associated with these technological developments. It has been argued that technological solutions alone, including human-centered design solutions, cannot mitigate emerging risks from the growing application of MI (Gangadharan and Niklas, 2019).

The development of ethical guidelines has represented the dominant approach proposed for the governance of MI systems. Over 200 such guidelines have been developed in recent years, focusing on key ethical principles such as transparency, explainability, robustness, security, safety, and accountability. Sector-specific guidelines are also 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 (European Commission, 2020), but these are largely related to principles of non-discrimination, diversity, and inclusivity, rather than on responding to the specific dynamics between MI systems and sustainability.

In addition, critics of the MI ethics approach have emphasized the limits of operationalizing fairness when setting up decision models, the reduced enforceability of these guidelines, the practical limits of providing algorithmic explainability 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).

Standards-making organizations have looked at ways to translate ethical principles into product and process standards that ensure the responsible development, deployment and monitoring of MI 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'. However, these initiatives focus mostly on organizational governance mechanisms and procedural guidance for managing known MI 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 MI technologies, ecological and environmental safety, supply chain resilience and their wider distributional consequences for sustainability rarely feature in current standards packages.

Proposals for regulating MI have also increased in recent years. 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). However, it has been shown that these regulatory proposals focus largely on individual risks (e.g. product safety regulations protecting the consumer), as opposed to systemic risks that characterize the complex human-machine-ecological systems described here (Black and Murray, 2019).

The lack of adoption, enforcement and commitment to govern systemic sustainability risks created by MI becomes particularly problematic in the climate and environmental domain where strong regulatory and enforcement capacities cannot be taken for granted, and hence cannot be assumed to compensate for the lack robust and responsible governance of MI systems and technologies.

## 9. Conclusion

Machine intelligence and automation could be gaining traction in sectors of fundamental importance for sustainability in the next decade. The driving forces behind the diffusion of these technologies are the result of both technological advances in IoT satellite technologies and increasing computational capacity, and increasing demands from society to better manage scarce natural resources, and understand the scope and impacts of rapid climate and environmental change.

As we have discussed here, this progress could (and should) be matched with a growing recognition of not only opportunities, but also possible risks for sustainability. 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 MI 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 machine intelligent technologies. 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.

Such new governance approaches need to acknowledge the complex features of ecosystems and their fundamental importance for human development, as well as possible negative distributional implications of increased applications of MI-technologies. Investors, governments and the private sector should take these issues seriously as MI-augmented technologies are increasingly being promoted as a key solution to a turbulent climate future.

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# Supporting Information for
# "Machine intelligence, systemic risks and sustainability"

- Supporting information 1. Methods and data for visualization in Figure 2A and Figure 2B.
- Supporting information 2. Additional details about data for visualization in Figure 2A and Figure 12.
- Supporting information 3. Analysis of principles for "AI for Good" and "responsible AI"
- Supporting information 4. Availability of data principles, policies, practices for selection of companies in Figure 2A, 2B.

*Supporting information 1. Methods and data for visualization in Figure 2A and Figure 2B.*

**Figure 1A** is based on data extracted from online sources. Step one included internet-based keywords search in English on Google, Google Scholar, and Microsoft Bing web search engines. The search encompassed five keywords categories (i.e., precision agriculture, forestry, marine, geography, and finance) that were used in various combinations; from a simple search including using only three keywords (e.g., one key word from each category) to using combination of keywords from three types of terms (Box 1).

The searches in step one identified several detailed precision agriculture reports published by organizations such as *Ag Funder, Finistere Ventures, Goldman Sachs, Tractica, United Nations* and the *European Commission* (see list below). The research in step two was focused on detailed analysis of the information from these reports identified in step one, with a focus on identifying new companies and initiatives that were not identified through the searches from step one since these potentially contain sample bias due to searches being done in English.

Furthermore, step one and two led to step three in which the study listed 339 companies. After composing the list, we used information available through company information available on Twitter and LinkedIn, and on a few occasions Facebook and Instagram accounts of examined companies, whenever available, and read their tweets and LinkedIn news feeds, if available, since January 1st 2015. Lastly, the authors inspected all 339 companies to differentiate which companies are working with machine learning and algorithms systems, which companies are developing software and precision data analytics, which companies are developing IoT systems that combine software and different machines at the same times, etc. In total 2,000 searches between July 2018 and February 2020 were done on Google, Google Scholar, and Microsoft Bing using combinations of the 56 keywords from three main categories (Box 1).

**Box 1. Search terms**

**Precision agriculture-, forestry- and aquaculture-related keywords used:** ‘precision agriculture’, ‘digital agriculture’, ‘aquaculture’, ‘maritech’, ‘smart agriculture’, ‘sustainability farming’, ‘animal technologies’, ‘plant science’, ‘crop management’, ‘farm technologies’, ‘indoor agriculture’, ‘site specific agriculture’, ‘decision agriculture’, ‘robot agriculture’, ‘forestry’, ‘digital forestry’, ‘precision forestry’, ‘ag fintech’, ‘sensors’, ‘smart farm’, ‘imagery’, ‘satellite’, ‘agtech’, ‘algorithms’, ‘coding’, ‘robotics’, ‘machine learning’, ‘ai’, ‘complexity’, ‘startup’, and ‘resilience’.

**Geography-related keywords used:** ‘European Union’, ‘United States of America’, ‘China’, ‘India’, ‘Brazil’, ‘Russia’, ‘Africa’, ‘Europe’, ‘Latin America’, ‘North America’, ‘Asia’, ’Middle East’, ‘Oceania’ and ‘Australia’.

**Finance-related keywords used:** ‘finance’, ‘investments’, ‘venture capital’, ‘angel investors’, ‘capital’, ‘funds’, ‘equity’, ‘debt’, ‘impact investment’, ‘sustainability investment’, and ‘business incubator’.

Our research led us to identify 424 companies operating in digital agriculture, forestry, aquaculture and marine extraction sectors between July 2018 and February 2020. Based on a general sample of companies in these sectors, we selected a subset of companies that have an explicit application of big data analytics and MI. That subset was identified by looking through company profiles with a special emphasis on the type of technology being applied.

It is important to mention that after we assembled the list of the companies we did a thorough review of companies in order to determine which companies are eligible for the survey. This inquiry led us to discard 37 companies which did not have any email contact details or could not be reached by phone after several attempts to inquire for their email address or had malfunctioning email addresses. Furthermore, we decided to discard additional 48 organizations that did not fit the description of digital agriculture, forestry, aquaculture and marine extraction companies. The excluded organizations include universities, research institutes and cross-border research projects in the agriculture sector. Our final selection includes 339 companies in total, including in the sectors digital agriculture (N=275), forestry (N=11), aquaculture and marine extraction sectors (N=53).

The breadth of technologies developed by these corporations varies considerably, as listed in Supplementary Table 1. The classification is based on the classification system used by Finistere 2018 Agtech Investment Review, using publicly available information online (such as company websites or LinkedIn profiles).

*Supplementary Table 1. Selected companies and main product types*

| ***Digital agriculture*** | | | ***Digital forestry*** | | |
|---|---|---|---|---|---|
| **Product type** | **Number of companies** | **% of all digital agriculture companies** | **Product type** | **Number of companies** | **% of all digital forestry companies** |
| *IoT* | 50 | 18% | *IoT* | 2 | 18% |
| *Biotech* | 4 | 2% | *Geospatial analysis* | 3 | 27% |
| *Drones* | 26 | 9% | *Robotics* | 1 | 9% |
| *Autonomous equipment and machinery* | 18 | 7% | *Software* | 2 | 18% |
| *Fintech* | 4 | 2% | *Other/undefined* | 3 | 27% |

| | | | | | |
|---|---|---|---|---|---|
| *Geospatial analysis* | 32 | 12% | **Sum** | **11** | **100%** |
| *Robotics* | 22 | 8% | | | |
| *Sensors* | 13 | 4% | | | |
| *Software* | 35 | 13% | | | |
| *Indoor agriculture tech* | 12 | 4% | | | |
| *Other/undefined* | 59 | 20% | | | |
| **Sum** | **275** | **100%** | | | |

***Digital aquaculture or marine resource extraction***

| Product type | Number of companies | % of all digital aquaculture and marine extraction companies |
|---|---|---|
| *IoT Marine* | 1 | 2% |
| *IoT Aquaculture* | 5 | 10% |
| *Aquaculture software* | 2 | 4% |
| *Marine drones* | 7 | 13% |
| *Marine equipment and machinery* | 4 | 8% |
| *Marine geospatial analysis* | 4 | 8% |
| *Marine robotics* | 11 | 21% |
| *Marine sensors* | 2 | 4% |

| | | |
|---|---|---|
| *Precision marine and aquaculture systems* | 15 | 28% |
| *Other* | 2 | 4% |
| **Sum** | **53** | **100%** |

**Figure 2B** builds on funding data extracted from the *Crunchbase* database. The data includes funding information (including angel investment, debt financing, grants, and other) about private and public companies by combining large investor network and community contributors, automated searches of the web and news publications for information, and quality control through machine learning methods (Dalle, Den Besten, and Menon 2017). The data has been used by others for other related research work (Marra et al. 2015; Marra, Antonelli, and Pozzi 2017). Each of 339 companies' names shown in Figure 1 were searched in the database for the total funding amount and funding period data (2007-2019). Figure 1B only includes information for 52% of these companies (N=177), with missing funding information distributed across the selected sectors in the following way: digital farming: N= 130 missing; digital forestry: 2 missing; Marine and Aquaculture: 30 missing. Additional information about the types of funding included in the data, can be found here.

*List of grey reports used for selection of companies*

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De Clercq, Matthieu, Anshu Vats, and Alvaro Biel. 2018. "Agriculture 4.0: The Future of Farming Technology." Oliver Wyman. Accessed November 5, 2019. https://www.worldgovernmentsummit.org/api/publications/document?id=95df8ac4-e97c-6578-b2f8-ff0000a7ddb6

European Parliament. "Precision agriculture – An opportunity for EU farmers." Accessed November 5, 2019. https://www.europarl.europa.eu/RegData/etudes/note/join/2014/529049/IPOL-AGRI_NT%282014%29529049_EN.pdf

Finistere Ventures. 2018. "Finistere Ventures 2018 Agtech Investment Review." Accessed November 12, 2019. https://files.pitchbook.com/website/files/pdf/Finistere_Ventures_2018_Agtech_Investment_Review_xeO.pdf

Goldman Sachs. 2016. "Precision Farming: Cheating Malthus with Digital Agriculture." Accessed November 6, 2019. https://docdrop.org/static/drop-pdf/GSR_agriculture-N1sH6.pdf

International Telecommunications Union. 2019. “United Nations Activities on Artificial Intelligence (AI).” Accessed November 5, 2019. https://www.itu.int/dms_pub/itu-s/opb/gen/S-GEN-UNACT-2019-1-PDF-E.pdf
Organisation for Economic Co-operation and Development. 2016. “Is precision agriculture the start of a new revolution?” Accessed November 6, 2019. https://www.oecd-ilibrary.org/agriculture-and-food/farm-management-practices-to-foster-green-growth/is-precision-agriculture-the-start-of-a-new-revolution_9789264238657-8-en
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Trendov, Nikola M., Samuel Varas, and Meng Zeng. 2019. “Digital Technologies in Agriculture and Rural Areas: Briefing Paper.” FAO. Accessed November 8, 2019. http://www.fao.org/3/ca4887en/ca4887en.pdf
United States Studies Centre at University of Sydney. 2018. “Australian AgTech: Opportunities and challenges as seen from a US venture capital perspective.” Accessed November 12, 2019. http://finistere.com/wp-content/uploads/2018/10/Australian-AgTech-Opportunities-and-challenges-as-seen-from-a-US-venture-capital-perspective.pdf

## *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 Commmission's High-Level Expert Group on Artificial Intelligence (AI HLEG); Google's Ethical AI principles; Intels' 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:

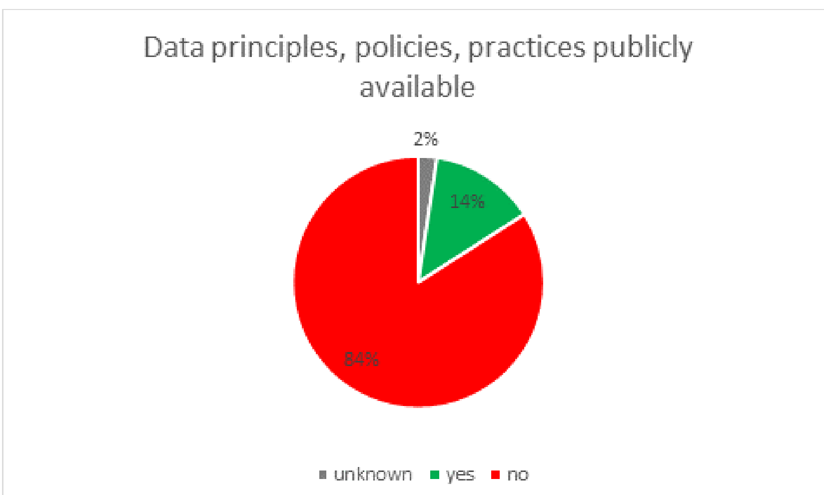
1. **Core ethical principles:** transparency; accountability; bias (algorithms, allocative harms); sustainability (note: non-environmental sustainability, e.g. cybersecurity or other).
2. **Key sustainability issues:** climate change, global warming, carbon budget, decarbonization, Paris Agreement; biodiversity, 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 authors.

*Supporting information 3.*
*Availability of data principles, policies, practices for selection of companies in Figure 2A, 2B.*

The extent to which algorithmic bias and potential allocative harms are issues for machine intelligent systems in digital farming, forestry and marine exploration and exploitation has remained unexplored. In 2020, we created and sent out a survey to all companies (N=339) identified for this study. The survey had 11 questions grouped in multiple choice and open-ended question categories about applications of machine intelligence, issues around data privacy and cybersecurity, and transparency and explanability. The response deadline was set to 10th of March 2020, and postponed to 29th of May 2020 due to the covid-19 pandemic. In total we received 32 responses, 9 rejected and 23 completed the survey out of 339 companies. That is 9.4% response rate. As an alternative method to get an overview of the companies' approach to data management and principles of responsible use, we chose to assess each company's publicly available information on these topics.

In total, 8 out of 339 companies did not have a functioning website, 285 of 339 had a website but no data principles, policies, practices publicly available. Hence only 46 out of 339 (14%) had data principles, policies, practices publicly available. Out of these 46 companies, only 1 company have signed data principles, and 1 provides publicly available data practices. The remaining 44 state in their privacy polices how they deal with personal data when someone uses their service.



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