AI, Society and Environment: a Possible Complex System Framework

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Abstract. *The large-scale deployment of AI models introduces significant uncertainty regarding their systemic behaviour. While these models have the potential to boost productivity and advance fields such as health and climate science, they also pose risks, including the reinforcement of biases, the spread of misinformation, and support for autocratic regimes. This paper examines the interaction between social, environmental, and AI systems from the perspective of a complex system's agent framework, using a resource-impact lens to explore these dynamics.*

Resumo. *O uso em larga escala de modelos baseados em IA aumenta a incerteza sobre o comportamento sistêmico desses modelos. Embora eles possam melhorar a produtividade da economia e promover avanços técnicos em áreas como saúde e mudanças climáticas, também se observam riscos, como o reforço de vieses discriminatórios, o aumento da desinformação e a manutenção de regimes autocráticos. Este artigo examina a interação entre os sistemas sociais, ambientais e de IA através de um framework baseado em sistemas complexos, utilizando uma abordagem de impacto-recurso para explorar essas dinâmicas.*

1. Introduction

Economic transitions, such as the shift towards an AI-driven economy, can introduce systemic vulnerabilities described as "growing pains" rather than severe crises [Keynes 1930]. These vulnerabilities become more complex when they involve interactions between co-evolving multilayer networks [Thurner and Klimek 2018]. Despite AI's high accuracy in domains like climate forecasting [Lam et al. 2023] and drug discovery [Stokes et al. 2020], its deployment carries significant technical and legal risks, including the spread of misinformation, reinforcement of authoritarian regimes, cybersecurity threats, and algorithmic biases against underrepresented groups.

To accurately assess AI's impact, it's essential to consider that systemic interaction between models and society is inherently complex, involving intricate dynamics, non-standard distributions, high-dimensional spaces, and emergent behaviours. This paper proposes a framework considering an *artificial intelligence system* into the resource-impact dynamic between environmental and social systems [Fieguth 2021].

This paper is organized as follows: Section 2 presents some definitions of social, environmental, and AI agents. Section 3 describes the proposed framework. Section 4 presents our main conclusions and path for future research.

2. AI, Social, and Environmental Agents

One way to understand social, environmental, and AI systems is by examining the agents that compose them. Therefore, this section aims to provide a brief overview of what the literature - based on our current knowledge - reveals about these three types of agents.

A social agent refers to an individual, group, or entity that operates within a social system, influencing and being influenced by other agents and the broader social environment. These agents interact with each other according to established protocols that govern their behaviour. [Macal and North 2009] outline several key properties of such protocols, including spatial considerations like collision avoidance, mechanisms for agent recognition, frameworks for communication and information exchange, methods of influence or persuasion, and domain-specific rules tailored to the particular social context.

In natural systems, an environmental agent refers to any biotic or abiotic factor that shapes interactions within ecological frameworks. These agents can encompass living organisms, such as plants and animals, as well as non-living factors like climate, water availability, and soil composition [Levin et al. 2009]. For instance, a predator within a food web acts as an environmental agent by regulating prey populations, thereby influencing the overall health and stability of the ecosystem. Similarly, abiotic factors like temperature fluctuations impact resource availability and drive behavioural adaptations in living organisms.

There are different ways to define an AI agent. A recent perspective [Masterman et al. 2024] describes AI agents as language model-driven entities capable of planning and executing actions across multiple iterations to achieve specific goals.[1] Another definition [Wooldridge and Jennings 1995], defines AI agents as computer systems that that are either conceptualized or implemented using concepts typically associated with human behavior.

3. AI, Social, and Environmental Interactions

The rise of artificial intelligence is not just a technological revolution; it's a societal and environmental one. Understanding its impact requires examining how AI models interact with the very fabric of our world. This section introduces the Environment-Social-AI (ESAI) framework, a novel approach that moves beyond analyzing AI in isolation to understand its complex, systemic effects.

The impact of AI can be analyzed by examining how models, society, and the environment interact systemically, highlighting the emergent behaviours and risks that arise from this perspective. This approach moves beyond isolated aspects, providing a

[1]In this view, AI agent architectures can consist of either a single agent or multiple agents collaborating to solve a problem.

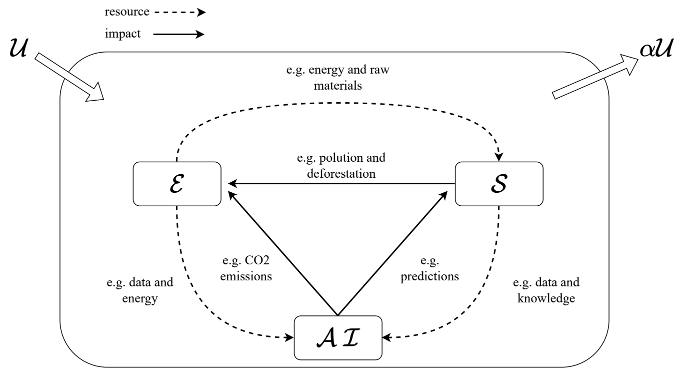

Figure 1. The environment-social-AI framework: social ($\mathcal{S}$), environment ($\mathcal{E}$), and AI ($\mathcal{AI}$). Input uncertainty is $\mathcal{U}$, and output uncertainty is $\alpha\mathcal{U}$. Interactions are governed by resource flows (dashed lines) and impact relationships (solid lines).

broader understanding of the complex resource-impact relationships between systems. In essence, a complex systems framework for evaluating environmental-social-AI (ESAI) interactions is a theoretical approach that attempts to understand and manage the intricate relationships between humans, nature, and artificial intelligence systems. Following, we describe common concepts that motivated the ESAI framework.

Considering *non-linearity*, small changes in one part of a system can lead to disproportionately large effects elsewhere, making predictions and control difficult. *Non-Gaussian* characteristics indicate the presence of extreme events or outliers that deviate from a normal distribution, suggesting that traditional statistical methods may fall. *High dimensionality* highlights the complexity of interactions within the system, where multiple variables influence outcomes in ways that are challenging to untangle. *Emergent behaviours* are patterns or properties that arise from the interactions of simpler elements within the system, which cannot be predicted by analyzing the components in isolation. Together, these concepts emphasize the need to examine ESAI interactions through a framework that accommodates the intricate and often unpredictable nature of complex systems.

An Artificial Intelligence System comprises agents (models) that interact with the environment and society. These systems influence decision-making through predictions and, in some cases, can act autonomously, potentially leading to unforeseen consequences.

The complex interplay between the environment, society, and AI can be visualized as a three-way interaction (Figure 1). The environment provides resources to society, which in turn impacts the environment. AI, as a new entity within this system, has a significant impact on both. AI's energy consumption and water usage contribute to environmental degradation (e.g., carbon emissions from data centers), while its predictions and decision-making influence society (e.g., algorithmic bias in decision-making). A balanced relationship between these systems is crucial to prevent cascading impacts, especially as AI's influence grows.

The flow of resources between the environment and society is essential for human activities. AI-related hardware, however, introduces new demands on these resources, particularly energy for model training and inference. The demand is not necessarily for AI systems, but for the way that we know how to train these systems. While the impact of AI on the environment is still being studied [Wang et al. 2024], it's clear that regulations are needed to mitigate its negative effects [Crowford 2024]. Moreover, the social system is increasingly dependent on AI for decision-making, highlighting the importance of ensuring that AI models are trained on accurate and unbiased data.

4. Conclusion

Integrating AI into society requires a nuanced understanding of its complex interactions with both society and the environment. In this paper, we propose a possible complex system framework based on the interactions between environmental, social, and artificial intelligence systems.

While the complete impact of AI is still uncertain, understanding these complexities is essential for harnessing its benefits while minimizing risks. Future research should further refine the ESAI framework, incorporating quantitative analysis and investigating policy interventions to guide this evolving technology toward a sustainable and fair deployment.

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