Received: 28 December 2022 | Revised: 16 February 2023 | Accepted: 20 February 2023 | Published online: 21 February 2023

REVIEW

Green and Low-Carbon Economy
2023, Vol. 00(00) 1–8
DOI: 10.47852/bonviewGLCE3202608

Toward Sustainable Artificial Intelligence: An Overview of Environmental Protection Uses and Issues

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Abstract: Artificial intelligence (AI) is used to create more sustainable production methods and model climate change, making it a valuable tool in the fight against environmental degradation. This paper describes the paradox of an energy-consuming technology serving the ecological challenges of tomorrow. The study provides an overview of the sectors that use AI-based solutions for environmental protection. It draws on numerous examples from AI for Green players to present use cases and concrete examples. In the second part of the study, the negative impacts of AI on the environment and the emerging technological solutions to support Green AI are examined. It is also shown that the research on less energy-consuming AI is motivated more by cost and energy autonomy constraints than by environmental considerations. This leads to a rebound effect that favors an increase in the complexity of models. Finally, the need to integrate environmental indicators into algorithms is discussed. The environmental dimension is part of the broader ethical problem of AI, and addressing it is crucial for ensuring the sustainability of AI in the long term.

Keywords: artificial intelligence, impact on the environment, sustainability

1. Introduction

Artificial intelligence (AI) is being used to create more sustainable production methods and model climate change, making it a powerful tool in combating environmental degradation. AI has many applications in environmental conservation, including in smart cities, energy, agriculture, natural disaster prediction, and climate change adaptation. In smart cities, AI plays a crucial role in improving citizens' quality of life by effectively managing traffic, waste, energy, and reducing the impact of climate change and natural disasters. In energy, AI supports the transition to renewable energy sources by optimizing performance, reducing energy consumption, and increasing efficiency. In agriculture, AI enhances sustainability and efficiency by collecting and analyzing data for informed decisions on crop production, water usage, pest management, and soil management practices. However, AI also has a significant negative impact on the environment due to the large amount of data and computational power required, which results in high energy consumption and CO2 emissions. Training a single AI model can consume as much energy as the average household uses in a year, and data centers that house AI models are major contributors to global energy consumption and carbon emissions. The production and disposal of AI hardware such as computers and servers also contribute to negative environmental impacts. This study highlights the paradox of a technology that consumes energy in order to address environmental challenges. The first part of the study provides an overview of sectors that are using AI-based solutions for environmental protection and cites examples from AI for Green players. In the second part, the study examines the negative impact of AI on the environment and the emerging technological solutions that support Green AI. Efforts are being made to reduce the environmental impact of AI by improving the efficiency of deep learning models, using renewable energy in data centers, and utilizing hybrid AI. The research on more energy-efficient AI is driven more by cost and energy independence constraints than environmental considerations, which can lead to a rebound effect that favors an increase in the complexity of models. Finally, the study also discusses the need to integrate environmental indicators into AI algorithms, highlighting that the environmental dimension is a crucial part of the broader ethical problem of AI and must be addressed to ensure its sustainability in the long term.

2. AI for Green Applications

AI has many applications in environmental conservation, including in the management of smart cities, energy, agriculture, natural disaster prediction and adaptation to climate change, ecosystem preservation, mobility, and the economy.

2.1. Smart cities

The rise of smart cities is a growing trend in urban development [1, 2]. Smart cities use technology, data, and intelligent systems to improve the quality of life for their citizens. These cities are designed to be more efficient, sustainable, and livable, and they use a range of technologies, such as the Internet of Things, AI, and big data, to achieve these goals. Smart cities are often seen as

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the future of urban development, and many cities around the world are implementing smart city initiatives to improve their infrastructure and services.

AI is being used to manage traffic lights in a more efficient manner, reducing the amount of time vehicles spend stopped and therefore reducing emissions by 20%[1] [3]. In China, AI is used to anticipate air pollution and take preventive measures before dangerous levels are reached [4].

One way to solve the challenges of street cleanliness and waste management in municipalities is to use AI to optimize resources and improve efficiency [5, 6]. Amal et al. [7] used AI and geographic information systems to optimize waste collection routing, resulting in an 8% reduction in operating distance, a 28% decrease in travel time, and a 3% reduction in fuel consumption. AI solutions such as the intelligent waste containers developed by Bin-e [8] and the AI-powered sorting robot are emerging to help manage waste more responsibly [9]. Wilts et al. [10] present empirical data on the use of an AI-based robotic sorting system for mixed municipal waste, with promising results for the purity of sorted waste fractions (97%).

Shreyas Madhav et al. [11] propose an AI system to reduce the need for unskilled labor and the associated hazards involved in collecting and segregating E-waste, as well as decreasing costs by 20% over a period of 5 years.

By using AI, it is possible to anticipate a city's need for energy resources and limit unnecessary expenditure. AI can also be used to reduce the effects of climate change or natural disasters by making urban planning more intelligent. For example, the City of Los Angeles has launched the Tree Canopy Lab program, which uses AI to map the city and recommend where trees should be planted to prevent heat.[2] The development of "urban dashboards" with real-time data on all environmental parameters, such as water and energy consumption, traffic pollution, and weather conditions, could help cities become more environmentally responsible and improve the quality of life of their inhabitants.

2.2. Energy

AI has the potential to play a significant role in the transition to renewable energy sources. By analyzing large amounts of data, AI can help optimize the performance of wind farms and other renewable energy systems, improving their efficiency and reducing their environmental impact. Additionally, AI can be used to anticipate energy demand and identify ways to reduce energy consumption, further contributing to the transition to a more sustainable energy system.

One way to save energy is to promote renewable energy as a substitute for fossil fuels. But it is still necessary for renewable energies to become efficient enough to be used on a massive scale. In this case, AI is proving to be very useful. Thanks to the intervention of AI, it is possible to significantly improve the performance of wind farms by considering meteorological data. AI is used to correlate the speed of each propeller with the direction and power of the wind, which allows for optimization of electricity production from all the wind turbines. AI enhances the efficiency of wind power generation and forecast energy output, resulting in a 20% increase in the value of their wind energy [12]. The European Centre for Medium-Range Weather Forecasts (ECMWF) led the Energy-efficient Scalable Algorithms for Weather Prediction at Exascale (ESCAPE) project, which aimed to develop a sustainable strategy for evolving weather and climate prediction models for next-generation computing technologies. The project involved leading European regional forecasting consortia, university research, experienced high-performance computing centers, and hardware vendors [13].

Some companies, like Google and Huawei, have already implemented AI solutions to control energy consumption in their data centers. Google has reduced its energy consumption by 40% using AI to analyze the times of day when people do energy-consuming searches and optimize the cooling of its data centers [14]. Huawei has improved the energy efficiency of its data centers by using AI to identify and address factors that contribute to increased energy consumption, as well as to predict the future energy efficiency of its data centers [15]. In addition, Microsoft has partnered with Vattenfall to develop a smart grid management solution that optimizes the production of renewable energy based on demand [16].

The application of AI technologies in smart buildings through building management systems and demand response programs has the potential to improve urban energy efficiency [17, 18]. According to Ahn & Cho [19], AI is effective in improving thermal comfort levels by approximately 2.5% in office buildings and 10.2% in residential buildings, and in reducing annual energy consumption by about 17.4% in office buildings and 25.7% in residential buildings. Governments are using AI to prioritize the energy renovation of its public buildings [20].

Energy efficiency can also be applied to digital technologies, particularly in the visualization and display of photos and videos online. Google has also been using AI to compress its images and reduce bandwidth consumption.[3] JPEG has also launched a program to find ways to reduce the size of its photo formats without losing quality using AI [21]. Other companies, like Netflix, have used AI to optimize the consumption of their videos, allowing them to halve their bandwidth consumption without losing broadcast quality [22].

2.3. A connected and sustainable agriculture

AI has the potential to greatly improve the sustainability and efficiency of agriculture [23, 24]. AI technology is reducing farming emissions by 20% and helping to manage the environment more effectively in food production [25]. By collecting and analyzing data from various sources, AI algorithms can help farmers make informed decisions about crop production, water usage, and pest management. This can help reduce the use of pesticides and other harmful chemicals, as well as increase crop yields and decrease water waste [26, 27]. Using AI to simulate changes in soil moisture, combined with real-time weather data to train the model, led to accurate predictions of soil moisture content and a 20% reduction in water use while maintaining sufficient soil moisture levels [28]. AI can reduce pesticide repetition by at least 20% compared to traditional methods and help protect non-targeted species from harm [29]. Improper irrigation and soil management can lead to crop loss and reduced crop quality. Examples of such systems include those that evaluate the design and performance of micro irrigation systems, recommend crops based on land suitability maps, and estimate soil moisture content [24]. AI-based systems have been found to be effective in improving irrigation and soil management practices. In arid climatic conditions, Al-Ghobari and Mohammad

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[3] Machine learning applications for data center optimization [White Paper] Google. https://static.googleusercontent.com/media/research.google.com/zh-CN//pubs/archive/42542.pdf

[30] assessed the efficacy of an irrigation controller based on evapotranspiration and concluded that applying AI resulted in water savings of up to 25% compared to the control method, while preserving crop yield. The agricultural industry has the potential to greatly benefit the environment and improve the sustainability of food production.

AI has been used to predict crop diseases and recommend control measures. Hybrid systems that integrate image processing with AI have also been developed. For example, "Dr. Wheat" is a web-based expert system that uses AI to diagnose wheat diseases [31]. AI used to forecast and prevent plant diseases with 90.79% accuracy by detecting and categorizing pathogens based on weather [32].

2.4. Anticipate natural disasters and adapt to climate change

The use of AI in anticipating natural disasters and adapting to climate change has the potential to greatly improve the way we respond to and prepare for such events [12, 33]. By analyzing large amounts of data and making predictions based on that data, AI can help us to better understand the likelihood of natural disasters occurring and what areas may be at risk. This information can then be used to develop plans and strategies for mitigating the impact of these disasters and reducing the potential for harm to people and property. Additionally, AI can help us to better understand and adapt to climate change by analyzing data on weather patterns, climate trends, and other factors that may be contributing to changes in our environment. This information can be used to develop strategies for adapting to these changes and minimizing their impact.

AI can help farmers improve weather forecasts and anticipate extreme weather events, which can be invaluable in protecting crops. By using its calculation power and the ability to process large amounts of meteorological data, AI can provide farmers with valuable information to help them prepare for and adapt to unpredictable weather. This can help farmers avoid losing entire harvests due to unexpected weather events.

Natural disasters can have significant impacts on global trade and agriculture. Tropical storms, known as typhoons, hurricanes, or cyclones, seem to be occurring more frequently and with greater strength, causing significant economic damage to agricultural products, shipping efficiency, property, and airline rerouting. Predicting the direction and likelihood of land impacts of tropical storms would greatly increase the chances of insuring against potential damage. According to Summers et al. [34], AI was able to identify the most severe storms with a success rate of 79% 24 h before impact and achieved an accuracy of 81% in categorizing storms on a six-point scale. Forecast-based financing is a financial mechanism that enables humanitarian actions in anticipation of floods by releasing pre-allocated funds based on the exceedance of flood forecast thresholds [35, 36].

2.5. Preserve Earth's ecosystem

AI has the potential to play a crucial role in preserving wildlife and flora. Through the analysis of large amounts of data, AI can help researchers better understand the effects of climate change on biodiversity and make predictions about which species are most at risk. AI can also be used to identify and monitor individual animals and plants, providing valuable information for conservation efforts. Additionally, AI can help detect and prevent illegal activities such as poaching and deforestation. By using AI to better understand and protect ecosystems, we can work toward preserving the rich diversity of life on our planet.

The application of AI in environmental conservation has immense potential, and an example of this is the monitoring of the Chesapeake Bay in the US. The use of ultra-fine image analysis through AI not only provides an accurate mapping of the area but also enables easier monitoring of the bay and its biodiversity, thereby enhancing efforts to protect and conserve it [37]. Another example is the partnership between Microsoft and the Nature Conservancy to map all ocean species using AI. This will help determine which areas can be used by humans without endangering the ecosystem [38]. Other initiatives using AI include the Ocean Cleanup project, which uses robots to clean up water on a large scale [39].

AI is being used to monitor terrestrial biodiversity and to help identify endangered species. The University of Southern California has set up a project called "Protection Assistant for Wildlife Security" (PAWS) that uses AI to predict where and when poachers are likely to strike [40]. This information can be used to arrest poachers and prevent the extinction of protected species. AI is also being used to help restore nature in areas damaged by human activity. In Massachusetts, an area destroyed by cranberry production has been rehabilitated and MIT Media Lab researchers are using microphones and AI to listen to interactions between species and determine the effectiveness of the restoration efforts [41].

2.6. Autonomous transport and sustainable mobility

AI can limit transport-related pollution by promoting fuel-efficient driving and optimizing engines to be more efficient. Companies in the automotive industry are heading toward innovation in autonomous and sustainable transport. The challenges related to autonomous transport include technical, safety, legal, ethical, and job displacement issues, while the policies necessary for their implementation include safety regulations, legal frameworks, infrastructure investment, data privacy, and public awareness. If 30% of vehicles become self-driving vehicles by 2030, the cost of congestion in cities could be reduced from $38 billion to approximately $26 billion [42]. Manufacturers are working on the development of shared, smart, and ecological transport. This is the ambition of the French company Transdev, a mobility specialist, which has partnered with ZF (a German automotive supplier) and e.Go (an electric car manufacturer) to develop its ecological and autonomous shuttle: the e.Go Mover [43]. With a capacity of 15 people, these electric shuttles aim to complement existing urban transport networks. Other manufacturers have also entered the innovation race to come up with their own shared transport solution, following the example of Transdev, which shows that the trend is heading toward autonomous mobility but within communities. It is also conceivable that an attractive public transport network, both ecological and personalized, could trigger the abandonment of individual cars, at least for daily commutes.

AI was used to detect real-time truck performance and driver behavior. This led to a 15% reduction in fuel costs and a decrease in delivery time [44].

2.7. Local and sustainable economy

Open data and AI can facilitate the shift to more sustainable and environmentally friendly production models. Recent health and geopolitical crises have highlighted the fragility of Western industrial policies. The current awareness opens the way to a reindustrialization model that combines ecology, resilience, social commitment, and economic performance. New dimensions are being embraced, such as environmental and social impact, securing essential goods, supply chain robustness, and distributed manufacturing, promoting local production. The recent release of economic and industrial data, combined with the emergence of AI, offers new perspectives for building a digital twin of countries' productive systems that combine both macroeconomic data and real observations of each company's activity [45]. This modeling allows the identification of industrial know-how, value chains, and potential synergies between companies to build a sustainable industrial symbiosis [46, 47]. AI could be used to identify synergistic pairings of one company's waste output with another company's input, facilitated by collaboration between companies through resource and information sharing [48].

3. Emergence of Green AI and Rebound Effects

3.1. An energy-consuming technology

In recent years, concerns about global warming and the depletion of resources have led to increased awareness of the environmental impact of the digital world. This has become a topic of public debate in many countries. After years of denial, the environmental impact of digital technology is now being recognized as a significant issue in research, including the environmental impact of terminal manufacturing, the energy required to use digital services, and the end-of-life analysis of equipment. Deep Learning is no exception to these concerns [49, 50]. In fact, due to the large amount of data and computational power required for Deep Learning, it has a significant impact on the environment. These increasing demands for computational power also contribute to the obsolescence of hardware and software.

Strubell et al. [51] measured the CO_2 emissions associated with the development of a natural language processing model, which generated the same amount of CO_2 as 5 cars over their lifetime, and the equivalent of 315 round trips by plane between New York and San Francisco. This study is significant because it considered the 3200 learning iterations that were necessary to develop the final model. This work has contributed to a growing awareness of the environmental impact of AI, although it should be noted that the evaluation of AI methods still often focuses on precision and accuracy, without considering environmental factors such as the energy efficiency of the models.

Rohde, Gossen, et al. [52] have detailed the different measures of energy consumption associated with tasks such as image classification, speech recognition, and strategy games. These energy consumption levels are correlated with the complexity of the computations required, expressed in Peta-FLOPS/s-days, or 1015 floating point operations per second in 1 day [53]. The more complex the AI models, the higher the associated energy consumption, CO_2 emissions, and resource requirements.

3.2. The importance of Ecodesign in AI development

Deep Learning is a powerful approach to AI that has achieved impressive results in a variety of tasks, such as image recognition, natural language processing, and medical diagnosis. However, one of the challenges of Deep Learning is that it requires large amounts of training data to achieve good performance. In contrast, the human brain can learn from relatively few examples and can generalize to new situations. This suggests that there is still room for improvement in the mechanisms of learning used in Deep Learning, and that new approaches may be able to learn more efficiently from less data [54].

One potential direction for improving the efficiency of learning in Deep Learning models is to draw inspiration from the mechanisms of learning in the brain. For example, the brain can learn from a small number of examples by making use of prior knowledge and by using mechanisms such as attention and memory. These mechanisms could be incorporated into Deep Learning models to make them more efficient and more effective at learning from small amounts of data.

Another approach to improving the efficiency of learning in Deep Learning models is to develop more sophisticated optimization algorithms. Many Deep Learning models are trained using gradient-based optimization, which can be slow and require a large amount of data to converge to a good solution. New optimization algorithms, such as evolutionary algorithms or Bayesian optimization, may be able to find good solutions more quickly and with less data [55–57]. A 2× improvement in energy consumption, model size, and inference time is observed with hyperparameter optimization [58].

Overall, there is still much work to be done to improve the efficiency of learning in Deep Learning models. By drawing inspiration from the mechanisms of learning in the brain and by developing new optimization algorithms, researchers may be able to develop Deep Learning models that are more efficient and more effective at learning from small amounts of data.

3.3. Optimized electronic components for AI

Deep artificial neural networks use principles of the brain's information processing to make breakthroughs in machine learning in many problem domains. Neuromorphic computing aims to create chips inspired by the form and function of biological neural circuits, so they can process new knowledge, adapt, behave, and learn in real time at low power levels [59]. Intel claims that the Loihi neuromorphic chip is 10,000 times more energy efficient than a CPU [60]. These chips are designed to handle the large amounts of data and complex calculations required by AI algorithms, making them more energy efficient and faster than traditional transistors.

3.4. Greening of data centers

Efforts to improve the efficiency of AI architectures must go hand in hand with a greening of the data center value chain [61]. Abts et al. [62] suggested an energy-saving mechanism for links in a flattened butterfly topology network, where the network links were downscaled based on traffic intensity at the expense of increased average latency, resulting in approximately 42% energy savings. Wang et al. [63] suggested a rate-adaptation solution for achieving network-wide energy proportionality through routing optimization, which could save up to 40% of energy with only a slight increase in network delay based on simulation results

The environmentally responsible hosting market is becoming more structured with the emergence of an energy performance indicator (called PUE) by the consortium The Green Grid [64]. This indicator has been supplemented by the European DCEM (Data Center Energy Management) indicator, which also considers reused and renewable energy. By using renewable energy, cooling servers with natural resources, or reusing the heat emitted, environmentally responsible data centers represent the most important lever in reducing the CO_2 emissions necessary for the operation of AI. According to Jahangir et al. [65], the use of free cooling systems could result in a reduction of up to 47% in cooling energy consumption and a 38% reduction in cost. For instance, we can cite the example of the Green Mountain data center in Norway, which, by cooling its servers with fjords and rivers, has been able to cut its energy costs by more than half.[4]

[4]Green Mountain: Setting the green standard in the data center industry. https://greenmountain.no/

3.5. The rise of hybrid AI

Hybrid AI combines multiple AI approaches or technologies, such as machine learning, rule-based systems, and expert systems, in order to achieve more accurate, efficient, or flexible performance [66, 67]. This approach allows AI systems to leverage the strengths of each individual method and overcome their limitations. One of the primary advantages of hybrid AI is that it enables the development of more sophisticated and capable AI systems that can handle more complex and nuanced tasks.

The DesCartes program is an ambitious initiative that seeks to develop a disruptive hybrid AI system to serve the smart city and enable optimized decision-making in complex situations involving critical urban systems.[5] The program brings together experts from a wide range of fields, including AI, engineering, data science, signal processing, formal methods, trusted AI, human–computer interaction, language processing, images, and the human sciences. The goal of the program is to develop an AI system that can handle complex and dynamic urban systems, such as transportation, energy, and environmental monitoring, in real time and provide decision-makers with accurate and timely information.

By combining different AI approaches, hybrid AI systems can achieve greater accuracy, speed, and efficiency.

3.6. Continuous improvement of the energy efficiency of deep learning and rebound effect

Although Deep Learning models have made remarkable progress in recent years, doubling their performance every 16 months [53, 68, 69], the significant increase in computational power required to train and operate these models has raised concerns about their energy consumption and environmental impact, as well as their economic cost when deployed at scale. However, there have been efforts to enhance the energy efficiency of Deep Learning, such as developing more efficient hardware and software, optimizing model architectures, and leveraging techniques like model compression and quantization.

However, it is crucial to recognize the potential occurrence of a “rebound effect” when enhancing the energy efficiency of AI. This means that as AI becomes more energy efficient, it becomes cheaper and easier to train and run more complex models. As a result, the growth of AI models has not followed Moore’s law, with models doubling every 3.4 months since 2012 [53]. The largest AI models published in 2020 used 600,000 times more computing power than the 2012 model that popularized Deep Learning, with some models requiring thousands of GPUs to train. The increased computing power of computers has made it possible to increase the number of parameters and layers (e.g., 530 billion parameters in the case of GPT3 “Megatron-Turing NLG” which required 4480 GPUs) [70, 71]. Training a model with one trillion parameters would require 42,000 petaFLOPS-days, costing $19.2 million on Google’s TPUs. Therefore, while improving energy efficiency in AI is important, it is crucial to also consider the potential rebound effect and its implications for energy consumption and environmental impact.

4. Perspectives

The need to address ecological issues of AI has been emphasized by the scientific community, just as ethical and transparency issues have been addressed [72]. Given the challenges posed by climate change, regulating AI will be necessary to determine the effectiveness of models in achieving the Sustainable Development Goals [73, 74].

Efforts such as the Carbontracker project, which focuses on optimizing energy use and increasing transparency on the environmental impact of AI solutions, are critical to achieving sustainability in AI [75]. While the European Commission’s proposed regulation of AI, the Artificial Intelligence Act (AI Act), aims to establish a uniform legal and regulatory framework for all AI in all sectors (except the military) and for all types of AI, it only regulates the providers of AI systems and entities that use them for professional purposes and does not address the environmental impact of AI [76].

To develop a set of sustainability criteria for AI-based systems and establish guidelines for sustainable AI development, the “Sustainability Index for Artificial Intelligence” project has been launched Rohde, Gossen, et al., [52]; Rohde, Wagner, et al., [77].

5. Conclusion

The growing use of AI technologies has raised concerns about their sustainability, as they rely on non-renewable resources and must be managed responsibly. To address this issue, there is a need to move away from energy-intensive AI technologies such as Deep Learning and toward more sustainable alternatives. This transition toward sustainable AI requires a concerted effort from the AI community, and by prioritizing sustainability, AI can continue to be a valuable tool in an ethical and responsible way.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Arnault Pachot: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Céline Patissier:** Methodology, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing.

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How to Cite: Pachot, A. & Patissier, C. (2023). Toward Sustainable Artificial Intelligence: An Overview of Environmental Protection Uses and Issues. *Green and Low-Carbon Economy*. https://doi.org/10.47852/bonviewGLCE3202608