

# Evaluation of Utilization of Artificial Intelligence (AI) to Combat Climate Change for Ecological Balance and Challenges: Global Perspective

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## Abstract

AI is a powerful tool for fighting climate change, providing advanced capabilities in climate modeling, optimizing renewable energy systems, and monitoring biodiversity in real-time to restore ecological balance. However, its high energy use during training and a “digital rebound effect” where efficiency gains lead to increased activity, stance challenges. In 2017, at the UN AI Summit in Geneva, the UN recognized AI as a potential facilitator of sustainable development, emphasizing its role in peace, prosperity, and human dignity. The UN proposed refocusing AI applications to support global efforts to eradicate poverty and hunger, protect the environment, and conserve natural resources. Addressing environmental sustainability is crucial. With AI’s rise, many environmental issues can now be tackled by prioritizing human interests. Sustainability involves the interconnectedness of environment, society, and economy. Sadly, Earth faces severe impacts from global warming and climate change, requiring immediate action to promote environmentally friendly, sustainable products. AI research supporting environmental sustainability spans various disciplines and addresses regional and global issues across the energy, transportation, biodiversity, and water sectors. These sectors are continually evolving and integrating into society. In some developed nations, AI applications are already active in biodiversity, health, industry, finance, and transportation—examples include sophisticated e-waste collection routes, AI-driven ocean-pollution cleanup, and species-protection efforts. While some research exists on AI’s role in transportation, health, agriculture, and industry, comprehensive studies on AI’s potential to enhance sustainability in water, energy, and biodiversity remain limited. This article explores how AI can be utilized to combat climate change and restore ecological balance, examines potential chal-

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allenges, and offers recommendations.

## Keywords

AI, ML, GHG, IPCC, SDGs, Climate Change, Environmental Sustainability

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## 1. Introduction

Scientific evidence confirms that our climate is warming at an accelerated rate. Since 1880, global average temperatures have increased by 1.20°C, with most of the rise occurring in the late 20<sup>th</sup> century. Greenhouse Gases (GHGs), chiefly atmospheric CO<sub>2</sub>, are responsible for over two-thirds of the global warming. The Intergovernmental Panel on Climate Change (IPCC) emphasizes that human activities have caused warming across the atmosphere, oceans, and land, resulting in widespread and rapid changes in these systems, as well as the cryosphere and biosphere. These climate shifts have led to a fivefold increase in weather, climate, and water-related disasters over the last 50 years, causing over 2 million deaths and \$3.64 trillion in damages. The IPCC warns that warming exceeding 1.5°C could lead to irreversible and permanent damages. Nonetheless, effective and fair strategies for adaptation and mitigation can considerably reduce risks and strengthen climate resilience. To keep global temperature rise below 1.5°C above preindustrial levels, countries committed to the Paris Agreement, which represents a historic milestone in international cooperation against climate change and is the first legally binding climate treaty. Accelerating action against the climate crisis involves targeted measures that produce real benefits while minimizing trade-offs across multiple domains. The 2030 Agenda and Sustainable Development Goals (SDGs) provide a global framework for sustainability and resilience, closely connected to climate action. Strengthening the link between the 2030 Agenda and the Paris Agreement by combining climate and SDG efforts offers an opportunity to achieve both goals and build a sustainable future for generations to come, making sure no one is left behind. In fact, enhancing measures to limit the increase in global temperatures could significantly progress toward many other SDGs, such as reducing poverty and hunger, increasing water availability, and protecting terrestrial and marine ecosystems. Additionally, many SDGs and their targets can be reached through initiatives that promote adaptive responses to climate change [1].

The role of artificial intelligence (AI) in environmental sustainability has rapidly expanded, becoming a vital component in addressing pressing ecological challenges. From combating climate change to the effective management of natural resources, AI is regarded as a transformative instrument that fosters innovation and enhances environmental outcomes. Developments within this domain demonstrate how technological advancements can underpin sustainability initiatives. Machine learning (ML) algorithms analyze extensive datasets, such as satellite imagery and meteorological data, to generate more precise climate forecasts. These

predictions inform policies and decision-making processes for governments and organizations, facilitating targeted resource allocation. Furthermore, AI augments renewable energy production: ML models forecast weather patterns to optimize the integration of solar and wind energy into power grids, thereby increasing efficiency and reliability. The transition to sustainable energy sources is imperative, given the variability and unpredictability of wind and solar power. AI also provides immediate pollution reduction by analyzing air and water quality data in real-time. Sensors and AI-controlled drones monitor pollution levels, identify emissions from manufacturing facilities, and track illegal waste disposal activities. These systems support law enforcement and public health initiatives through the provision of timely, accurate data, including the monitoring of water quality in rivers, lakes, and oceans [2]. Overall, AI enhances the capacity to detect contamination and environmental hazards more efficiently than traditional methods.

AI promotes ecosystem health by aiding local governments in securing clean water and vital resources, essential for human survival. Traditional resource extraction methods often waste resources and harm the environment, but AI can optimize these processes to enhance sustainability. In agriculture, AI-driven precision farming reduces use of water, pesticides, and fertilizers, lowering environmental impact [3]. Countries like Japan, the USA, China, Switzerland, and Norway successfully implement AI in agriculture and industry. AI also supports the achievement of Sustainable Development Goals (SDGs), especially those related to environmental sustainability, such as Goal 13. By 2030, the European Parliament's Think Tank estimates AI could help reduce global greenhouse gases by 1.5% - 4%, contributing directly to Goal 13. At the AI for Good Global Summit 2024, over 80 demonstrations showcased AI's potential in space exploration and environmental conservation, featuring innovations like AI-powered weather forecasting, water management, and waste tracking. The UN's SDGs include specific AI projects exemplifying AI's transformative impact across sectors including healthcare, conservation, education, disaster response, and agriculture, advancing global sustainability and societal progress. However, deploying and maintaining AI systems involves significant environmental costs, such as energy consumption during training and operation. Addressing these issues involves improving AI energy efficiency, utilizing renewable energy, and developing water-saving cooling technologies for data centers. A trend in sustainability is deploying large AI models on edge devices like smartphones, smart speakers, and wearables, which helps reduce environmental impact.

Edge devices, due to their limited processing power, cannot operate large models with billions of parameters. This limitation reduces both operational costs and energy consumption during data transfer in cloud computing. Besides training, end-users also care about the environmental impact of GenAI. For instance, picture synthesis uses more energy and emits more carbon than text generation, and large general-purpose language models consume more energy than smaller, task-specific ones [4]. Understanding when, why, and how companies utilize GenAI is

becoming crucial for building a sustainable AI ecosystem. AI holds great potential to support eco-friendly solutions in environmental research [5]. By employing AI technologies such as advanced algorithms, predictive modeling, and machine learning, we can detect, monitor, and manage pollution, including heavy metal contamination [6]. AI can identify pollution sources, assess risks, and assist in cleanup operations [7]. Moreover, AI-powered solutions can be integrated into sustainable practices in agriculture, industry, and urban planning to reduce heavy metal emissions [8]. Realizing AI's full potential in environmental sustainability requires interdisciplinary collaboration [9]. Merging expertise from environmental science and AI enables comprehensive approaches to address global environmental challenges.

Integrating AI into our socio-technical-ecological landscape presents both opportunities and challenges across social, environmental, and economic spheres. The link between AI and sustainability is intricate and multi-layered. While AI can aid sustainability efforts, it also raises concerns about worsening environmental damage or social inequalities [10]. This complexity requires a comprehensive view that considers the entire lifecycle of AI systems, from creation to deployment and beyond. Instead of solely emphasizing AI's role in sustainability, there's a growing focus on the sustainability of AI itself. This perspective evaluates the broader socio-economic and ecological impacts of AI, encouraging stakeholders to weigh both its benefits and risks. Today, AI's dual nature is evident: it boosts efficiencies and drives innovation to address environmental and social challenges, yet it also increases resource consumption, raising energy use concerns. AI is often seen as a dilemma—offering new applications that could lessen environmental impacts but also risking additional harm due to higher resource needs. Research indicates that current frameworks and laws often lack detailed guidance for companies to assess and implement AI sustainability measures. Evaluating and reporting on AI's sustainability remains complex because existing methods do not fully capture its overall environmental impacts chain. ML algorithms utilize data from on-site sensors to identify optimal levels of water, nutrients, and pesticides for specific systems, promoting healthier plants and reduced resource consumption. Additionally, AI improves waste management by forecasting waste materials, streamlining recycling processes, and uncovering opportunities for circular economy initiatives. These functions are vital for tackling increasing pressures on natural resources and reducing human ecological impacts. A key question persists: how can AI enhance long-term environmental quality [11]? Researchers should explore the integration of AI models into natural environments to advance sustainability. In the age of smart technology,

AI offers substantial opportunities for environmental protection through optimized resource use, biodiversity preservation, and climate change mitigation. Its applications in agriculture, energy, water, and waste management illustrate AI's potential to promote sustainable practices. However, challenges related to ecological footprints, ethics, data handling, and governance also arise. This pa-

per critically analyzes AI's dual role in the environment, highlighting both its benefits and the hurdles involved risks. The increase in AI technologies and their adoption in various industries has raised concerns about their impact on natural ecosystems. A major issue is their potential to disrupt wildlife habitats and migration routes. AI infrastructure projects, like building data centers and communication networks, often need large land areas, leading to habitat fragmentation and loss. These changes can harm wildlife by limiting access to resources and disrupting migration paths, thus threatening biodiversity and ecological balance. While AI can assist in environmental monitoring and conservation by enabling efficient data collection, analysis, and insights—enhancing our understanding of biodiversity, climate change, and ecosystem health—it also poses challenges. It may reduce field research and human involvement, risking the oversight of subtle ecological processes best understood through direct observation, as noted by Koh & Wich.

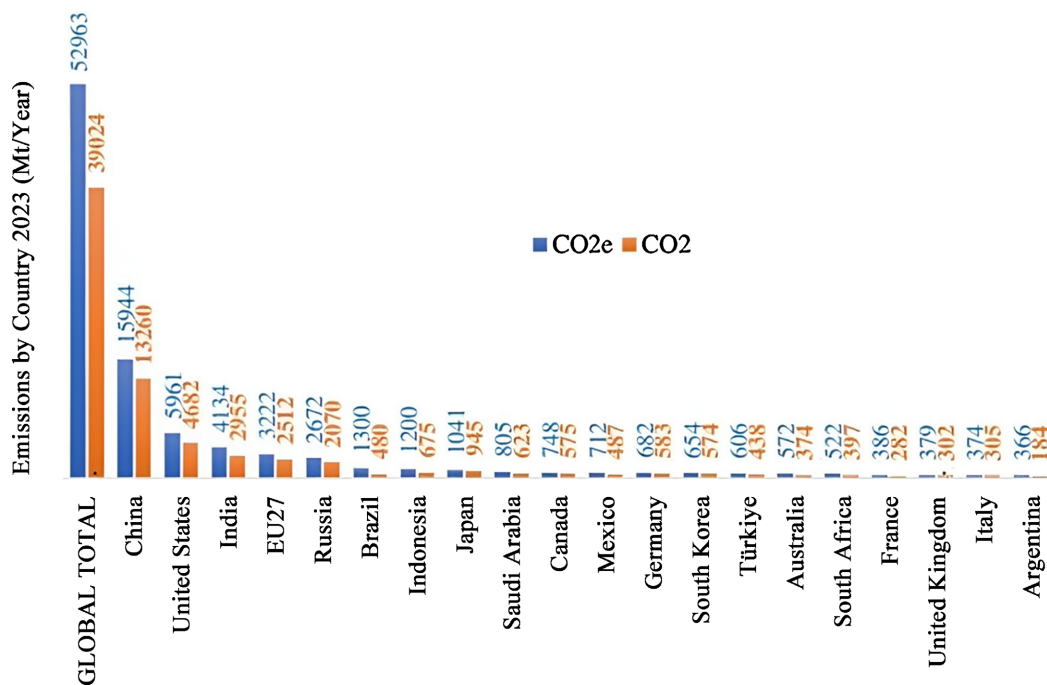
In 21<sup>st</sup> century, in the era of smart technology, humanity meets two primary challenges: rapid technological development and an escalating environmental crisis. Today, AI is increasingly acknowledged not only as an instrument for the digital revolution but also as a pivotal entity in reshaping environmental paradigms. Currently, AI possesses the potential to underpin a novel sustainable development framework founded on data-driven approaches, transparency, and predictive regulatory systems. Nevertheless, it is imperative to scrutinize the ethical and environmental risks associated with this technology, particularly the substantial energy consumption attributed to the Internet of Things (IoT), machine learning (ML), and other intelligent systems. The author evaluates AI's capacity to address environmental concerns, including monitoring, climate change prediction, resource management, and energy system optimization. This study endeavors to explore AI's role in promoting an environmentally sustainable future by analyzing its applications in ecology, its contribution to combating climate change, and its ethical and energy-related limitations. In this regard, AI emerges not merely as a technological breakthrough but as a renewed form of environmental consciousness, wherein digital and intelligent systems extend human cognition to safeguard the planet. By integrating scientific knowledge, ecological principles, and technological innovation, a pathway toward a balanced future is established, with artificial intelligence supporting nature rather than exerting dominion over it. In this analytical discourse, the author investigates the potential of AI to assist in combating climate change and maintaining Earth's ecological equilibrium, while duly considering potential challenges and proposing recommendations. Considering this backdrop there are few research questions as follows, which will be answered in this paper.

- 1) How AI is useful and beneficiary for sustainability strategies?
- 2) What is the prospect of Green-AI?
- 3) What are the problems and risks of AI use in contest of ecological balance?
- 4) Does AI have substantial carbon footprint?

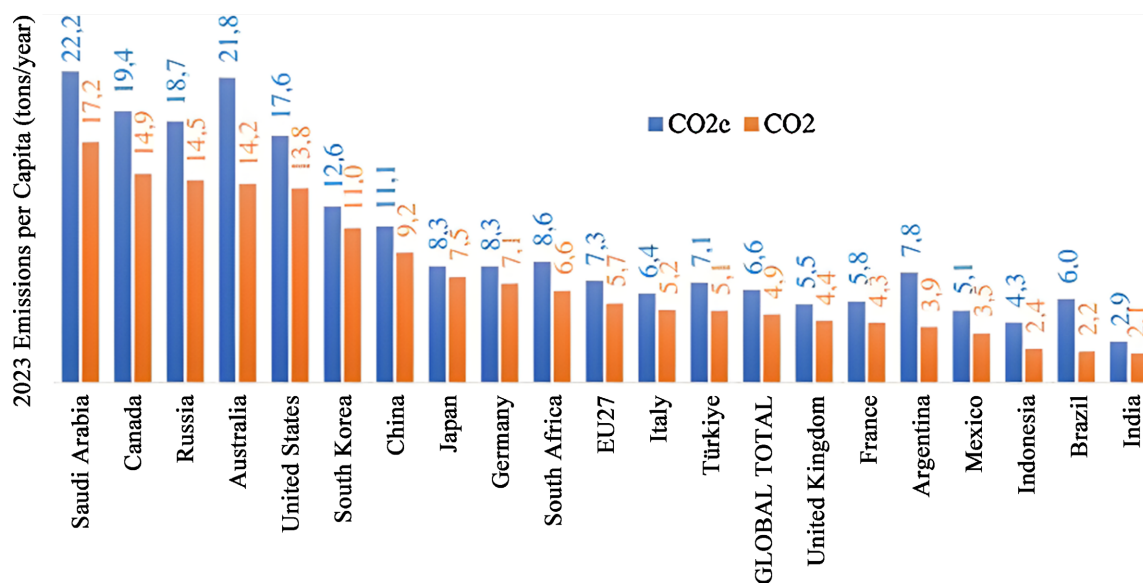
- 5) What are the probable challenges of use AI to achieve environmental sustainability?
- 6) How to fight against AI's challenges?
- 7) What is the long-term practicability of AI?
- 8) How to combat against problems raises due to AI use?

## 2. Literature Review and Methodology

Global temperatures are raising continuously since civilization (more specifically industrial era) stated. Now, the predicted of increase of the global temperatures has estimated by 5 °C by 2100, if measures are not taken. **Figure 1** has been shown the annual carbon emissions of G20 countries in 2023. Therefore, the highest per capita emissions in countries like China, the US, India, Russia and Brazil. However, the global total emissions are 52.96 Gt for CO<sub>2</sub>e, and 39.02 Gt for CO<sub>2</sub> generated from fossil fuels. The China emission is 15.94 Gt for CO<sub>2</sub>e and 13.26 Gt for CO<sub>2</sub> emission from fossil fuels. On the other hand, the US emission is 5.96 Gt for CO<sub>2</sub>e and 4.68 Gt for CO<sub>2</sub> emission from fossil fuels. Whereas, the EU emissions are 3.22 Gt for CO<sub>2</sub>e and 2.51 Gt for CO<sub>2</sub> emissions from fossil fuels and which are shown in **Figure 1** below. **Figure 2** shows the annual CO<sub>2</sub>e and CO<sub>2</sub>emissions per capita from fossil sources for the Global. The annual emissions per capita among G20 countries are ranked from largest to smallest as KSA, Canada, Russia, Australia, USA, South Korea and China. While EU27 countries are in 11<sup>th</sup> place and that has been shown in **Figure 2** below [12]. As a result, for a sustainable human and living life in the globe the world temperature increase must be kept below 1.5°C. So, to safeguard this, very noteworthy and urgency



**Figure 1.** Annual carbon emissions (both CO<sub>2</sub>e and CO<sub>2</sub>) of G20 countries in 2023.



**Figure 2.** Annual CO<sub>2</sub>e and CO<sub>2</sub> emissions per capita from fossil sources for the Global [14].

measures need to be taken by the global leader. If the present state remains unbothered, by 2030 an additional Earth twice the size of the World will be required to eliminate emissions and waste. If carbon emissions are reduced by 30% by 2030, this needs to decrease to 1.5°C world sizes. In addition, to carbon dioxide, some other Greenhouse Gases (CHG) also have a significant impact on the equivalent carbon emission calculation [13].

Recent technological progress has uncovered a paradox as our technologies become more sophisticated, our environmental challenges intensify. Issues such as climate change, resource depletion, and pollution in oceans and air cannot be solved solely through policy or economic solutions. New intellectual tools are necessary to analyze, predict, and manage natural processes on a planetary scale [15]. AI is increasingly becoming a vital candidate for this role. Its capacity to process large datasets and learn natural patterns supports the development of intricate climate models, natural disaster forecasts, and resource management with unmatched accuracy [16]. Essentially, AI is shifting from a simple analytical tool to a digital intermediary between humans and the earth and that composed to sustain ecological balance via an algorithmic understanding of natural systems processes. The smart technology like AI in ecology bring into line with a shift toward a new scientific paradigm of sustainable development, where the goal is not just growth but harmony with nature. Today ML algorithms are used to monitor pollution, optimize energy networks, forecast weather anomalies, and manage agricultural systems [17] [18]. AI technologies are key to smart city models, forming the foundation for energy-efficient urban planning where digital data supports ecological balance [19]. As AI is not environmentally neutral, so training neural networks demands massive energy and computational power, which increases the carbon footprint of data centers [17]. This creates a paradox as a tool meant to help save the planet also causes environmental costs. Therefore, along with tech-

nological progress, developing a “green AI” ethic is essential to focusing on reducing energy consumption, adopting renewable sources, and ensuring transparent algorithmic decision-making [20] [21].

Rendering to researchers like Poole, the intelligence of advanced machines, comparable to innate intelligence in animals and humans, and that can be considered AI and which referring to scientific and technical data that enable devices to imitate human cognition [22] [23]. AI systems have the ability to learn from experience to deliver artificial services and to adjust inputs in response to environmental changes [24]. Today, AI has surpassed human intellectual limits by creating a new reality where intelligent machines with artificial brains communicate with humans [25] [26]. AI is a powerful tool that supports environmental sustainability by allowing analysis of large datasets, pattern recognition, and prediction analytics. As new environmental challenges emerge, AI becomes a crucial tool for creating sustainable solutions to protect our planet’s future. Managing environmental sustainability remains a complex and challenging task. So AI integration, many of these issues can be tackled more effectively through strategic use of human resources [23] [27]. The economy, ecology, and society are interconnected when discussing sustainability. In the United Nations study ‘Sharing Our Future’ and which also known as the Brundtland report sustainability is described as development that meets the needs of the present without compromising the ability of future generations to meet their own needs. It can also be seen as a plan to supply future generations with essential products and services, as long as human goals do not harm ecological health of environment [28]. AI can help us understand how our activities impact the environment and assist in developing long-term solutions to preserve the Earth for future generations. Effective management of environmental sustainability and addressing current and future demands require AI, which is becoming increasingly vital in the face of critical environmental challenges. Climate change, one of the most complex concerns, is being addressed through new AI solutions. To reduce global warming and environmental risks, producing eco-friendly, sustainable products is essential [29]. AI plays a key role in developing sustainable solutions despite ongoing environmental degradation. Its applications include four main areas: sustainable agriculture, natural resource preservation, waste and pollution management, and pollution control and removal.

In the last fifty years, AI has been dynamic in promoting environmental sustainability efforts. Several environmental challenges—such as climate change and degradation require innovative AI-driven solutions. The AI and sustainability field covers several sectors, including energy, water, biodiversity, and transportation, which continue to grow [30]. Nevertheless, there remains a significant gap in research on how AI can actively support environmental sustainability across different domains. Numerous leading corporations, including Tesla, Google, and Microsoft, have achieved significant advancements in the development of environmentally sustainable AI systems that address innovation limitations. For in-

stance, Google's DeepMind AI has contributed to a 40 percent reduction in energy consumption within its data centers, thereby improving operational efficiency and reducing overall greenhouse gas emissions. Data centers account for three percent of the global energy demand. Progress in these AI technologies enhances energy efficiency and supports marginalized populations through the construction of microgrids and the integration of renewable energy sources. Unlike traditional power grids, which can be inefficient due to suboptimal design, urban smart grids utilize AI to manage and optimize local power distribution in accordance with specific demands [31] [32]. As AI-driven autonomous vehicles become available, strategies like eco-driving algorithms, optimized routing, and ride-sharing are expected to lower carbon footprints and reduce traffic congestion. As these technologies gain wider adoption, smart buildings and urban development can leverage sensors to enhance energy efficiency and advanced materials for roads and structures. Drawing inspiration from natural patterns, researchers have created sustainable materials from natural resources, like bacteria-made bricks, CO<sub>2</sub>-absorbing concrete, and solar systems powered by wind and sun [33] [34]. Cities worldwide are increasingly utilizing solar energy to power infrastructure, representing initial steps toward affordable, eco-friendly growth [35].

Managing industrial emissions and waste benefits from advanced ML and IoT-enabled captive grids that can detect leaks, hazards, and regulatory deviations. IoT devices are now integrated into many industries, including thermostats, refrigerators, and retail operations [26] [32] [36]. Microsoft's AI for Earth, a \$50 million initiative launched in 2017, aims to combat climate change, enhance agriculture, address water scarcity, and preserve biodiversity [37]. Currently, researchers are urgently developing algorithms to turn environmental data into practical solutions. AI applications like "iNaturalist" and "eBirds" gather expert observations on species, helping monitor populations, ecological health, and migration patterns. These tools are vital for identifying and protecting marine and freshwater ecosystems [38]. Many companies, NGOs, and start-ups are adopting artificial fuzzy neural networks to produce creative agricultural solutions. They utilize bio-sensor-driven and AI algorithms to monitor soil health and crop yields, as well as construct predictive models to foresee variables impacting yields. The Berlin-based agricultural tech start-up "PEAT" has built a deep-learning application termed "Plantix", which supposedly can identify potential shortfalls and inadequacies in the soil. An examination is conducted employing software algorithms that relate various leaf patterns to troubles with soil, pests, and diseases [39]. "AWhere" and "FarmShots", both United States-based firms, apply satellite ML algorithms to anticipate the weather, assess farms' viability, and research them without disease and pests. Farmers are paying special attention to the adaptive irrigation system because of its crucial function in water management. This device autonomously irrigates the land based on data acquired from the soil via sensors powered by artificial intelligence technologies. AI has practical applications in biodiversity. To simulate ecosystem services, rules-based systems like ARIES are among the most

popular and recognized [40]. These systems employ ML models that help researchers identify numerous connections through analytical tools [40]. Additionally, several AI examples demonstrate how AI can improve biodiversity monitoring and conservation efforts [41]. It is essential to emphasize avoiding resource overuse, which can cause environmental issues, and to recognize that access to AI-related data depends on the ecosystem's biodiversity. This biodiversity has developed effective methods [24] for estimating land services, similar to ML or natural language processing (NLP).

It has observed that, the most AI-related biodiversity research aims to predict ecosystem services [42]. AI offers a new approach to addressing biodiversity challenges across different geographic and temporal scales. Studies using AI for sustainability, like those involving Genetic Algorithms and popular ML models for biodiversity and artificial neural networks (ANN), as well as Bayesian networks, which are established ecosystem models [24], showcase this potential. AI has applicability and can be effectively implemented in the energy industry. AI is considered [22] to help minimize the use of natural resources and reduce energy needs from human activities. The main research areas include pattern recognition, expert systems, neural networks, and fuzzy logic [24], which are relevant to energy research [43]. This covers energy distribution, production, maintenance, and operations, which are key focus areas in energy [44]. Computer-aided learning is used to make predictions [45], and NC algorithms may also be employed to solve complex problems [46]. Most of the algorithms used by scientists are implemented in fuzzy logic systems that assist in making judgments based on forecasts [22]. Moreover, using multiple models, such as the area neural network, produces better results and broader combinations. AI has applications and can be used competently in the transport sector. Research on AI applications is available for sustainable transportation, health care, banking system, and industry. Most published works focus on the machine learning process [47]. Applications of AI research are also crucial for sustainable transportation. Learning through machines has been the main focus of most published studies [48]. Furthermore, the use of computer vision to assist in making judgments has been found in safety and traffic management, urban mobility, and public transit [48]. AI applications in transportation include ML and other time series and statistical models used to manage traffic [24]. Computer vision algorithms were extensively applied for road markings. AI has practical uses and can be effectively applied in water management.

Since 2015, remarkable research efforts have progressively focused on leveraging AI to improve water protection and management. Common techniques include artificial neural networks, especially neuro-fuzzy adaptive sequence systems, and support vector machines (SVMs) for machine learning. Models like decision trees (notably random forests), multiple regression, autoregressive displacement models (ARMS), regression splines, and adaptive neuro-fuzzy inference are utilized in this area [49]. Among these, genetic algorithms are considered particularly effective. Additionally, popular machine learning methods encompass regional

networks like ANNs, ANFIS and genetic algorithms [50]. For example, machine learning algorithms can be used to predict river flow and evaluate water quality parameters [51]. The modern understanding of AI significantly extends beyond engineering and computer science. Originally, AI aimed to formalize human cognition through algorithms, but it has since evolved into an interdisciplinary field that incorporates mathematics, neurophysiology, philosophy, linguistics, and the social sciences [52] [53]. In an ecological perspective, AI is seen not just as a collection of computational techniques but as an intelligent system capable of engaging with natural processes, analyzing biosphere interactions, and proposing solutions to support the sustainability of living systems. This perspective aligns artificial intelligence more closely with the noosphere concept proposed by V. I. Vernadsky, in which the human mind acts as a powerful geological force shaping the planet. This role is increasingly being assumed by AI [54]. Additionally, AI plays a vital role in ecosystem modeling and biodiversity preservation. ML based mathematical models enable predictions of population trends, assessments of species extinction risks, and the development of ecosystem restoration plans [55].

In 21<sup>st</sup> century, AI facilitates the monitoring of animal migration and the identification of poaching zones through the utilization of thermal imaging drones and acoustic sensors. Initiatives by the World Wildlife Fund (WWF) and Google Earth Engine employ sophisticated algorithms to analyze auditory data from tropical forests, thereby assisting in the detection of illegal logging and hunting activities. These technological advancements contribute significantly to the development of a comprehensive global digital biomonitoring network, which enables the precise recording and evaluation of ecosystem processes [15]. Therefore, the application of AI in ecology adopts the emergence of an innovative strategy for planetary governance founded on data-driven insights and predictive analytics. Today, AI is increasingly integral to intelligent systems tasked with monitoring climatic phenomena, regulating resource equilibrium, and protecting the biosphere from harm. This transition signifies humanity's evolution from merely observing natural environments to actively engaging with them, wherein technological integration occurs within ecosystems rather than counter to them. This discourse examines the transformative potential inherent in the integration of AI with environmental sciences to confront pressing global challenges and advance sustainability objectives. It focuses on critical sectors such as environmental monitoring, climate change forecasting, conservation efforts, biodiversity preservation, and sustainable resource management, thereby underscoring AI's pivotal role in innovative solutions for issues including climate change, biodiversity decline, and resource exhaustion [56]. Simultaneously, the discourse recognizes the challenges associated with employing AI to more effectively address environmental and climate concerns. In this investigative and analytical work, author will first depict the usefulness of AI to develop sustainable environment and prospect of Green-AI on the basis of secondary information and literature discussed above. As AI possesses distinct carbon footprint, so there are probable challenges of AI's use to fight cli-

mate change and to develop sustainable environment on the basis of available literature and previous work done on this subject as mention above. Author has taken effort to suggest the combat strategy to face the challenges and plan to fight against the problem arises to use AI for the development of sustainable environment by analytical output.

### **3. Benefit to Use AI as Sustainability Strategies**

While AI's application in sustainability is still emerging, it offers promising benefits for improving processes and increasing efficiency. Organizations can leverage AI to handle large volumes of environmental data, automating data collection once they establish the necessary data flows for analyzing sustainability metrics. This approach saves time and cuts costs, enabling companies to gather precise, actionable data to inform their sustainability strategies. When a sustainability team defines how to analyze data to assess environmental footprints while including relevant assumptions for accuracy, AI's ability to rapidly analyze data and detect hidden patterns can surpass human capabilities [38]. Nonetheless, human oversight remains essential to validate results and interpret insights. The faster pace of data analysis can help organizations make quicker, data-driven decisions. AI also holds potential to optimize complex supply chains and resource management, identifying more efficient methods for energy, water, and waste management—thus improving operational sustainability and decreasing environmental impact. Currently, AI presents significant opportunities for advancing sustainability, but meaningful outcomes depend on strategic, organization-specific implementation needs.

#### **3.1. Today AI Is Effective to Fight Climate Change**

AI technology has been successfully applied in Japan during major natural disasters to monitor deforestation in the Amazon and to develop more sustainable, intelligent urban environments in China. AI can also optimize building efficiency, enhance electricity storage, and upgrade wind and solar energy within the grid as needed. On a smaller scale, this helps households reduce energy use by automating lights when not in use or managing electric vehicle network demands to meet expectations. A recent study by PricewaterhouseCoopers, in partnership with Microsoft—specialists in ML solutions for climate change—revealed notable findings [57]. The research indicates that by 2030, AI implementation could reduce global greenhouse gas emissions by up to 4%, highlighting AI's significant potential to combat climate change.

AI's capabilities, especially its ability to analyze vast amounts of unstructured data such as shapes, images, graphs, and maps, are breaking new ground in climate modeling. This opens up unparalleled opportunities to deepen our understanding of sea-level rise and ice cap dynamics. Such potential highlights AI's role in elucidating the impacts of human activities on Earth and in developing sustainable solutions. Moreover, AI helps us better comprehend the consequences of our

actions and develop long-term strategies to address the climate crisis. Its contribution to combating climate change and reducing GHG emissions is significant [58]. The partnership between Microsoft and PwC exemplifies the importance of collaboration between the private sector and researchers in finding solutions. Continued investment in AI research and development is essential to tackle environmental sustainability challenges and secure a sustainable future planet.

The high costs of AI computing have led much research to be driven mainly by private industry. For instance, “Climavision” is a cutting-edge super-resolution radar system that uses satellite data and high-altitude weather balloons to address the “hundreds of gaps” in current weather forecasting networks [59]. This technology enables transportation, energy companies, businesses, and military personnel to access real-time weather data updated every second. As the world shifts towards low-carbon energy, the demand for AI-powered tools that predict market trends, balance transactions instantly, and optimize energy from networks to smart devices is expected to grow rapidly. Investing in AI research to unlock its environmental potential and help achieve Sustainable Development Goals is crucial. Such investment is vital for the future of our planet and upcoming generations.

Modern AI-powered technologies of agricultural pesticide spraying boost precision by recognizing weeds in real-time. Research suggests that these localized applications can lead to a large reduction in pesticide use, albeit the amount of savings varies depending on specific field conditions and weed density. Technology like John Deere’s “See & Spray” use computer vision, a subtype of AI that enables machines to understand and analyze visual inputs, to recognize weeds and activate nozzles tailored to the weed spot. This method has demonstrated to considerably cut input costs, with university experiments across many states indicating reduction of non-residual pesticide use by more than 50 percent. ML models may make predictions using previous meteorological data, satellite imagery, and soil sensor readings, directing annual planning and resource optimization. This not only helps farmers identify perfect periods for sowing and reaping crops to enhance quality and production, it also offers chances to conserve vital resources and their associated expenses. Smart systems have exhibited a 28 percent reduction in both water and energy use, with certain precision irrigation frameworks reaching water savings of up to 50 percent [60].

AI is transforming agriculture by enabling precision farming, optimizing resource use, boosting crop yields, and improving livestock management. As AI becomes more widespread and discussed globally, many industries are exploring ways to leverage this fast-developing technology to increase profits and productivity. Surprisingly, AI also plays a role in what many consider a “traditional” industry. The AI in agriculture market is expected to reach nearly \$5 billion by 2028, as producers adopt features like autonomous systems and predictive analytics. This major shift aims to replace traditional broad-scale management with more precise oversight, allowing farmers to better monitor and treat individual plants and animals. Such optimization of care and inputs like water, fertilizer, and labor

can offer benefits such as increased productivity and improved animal welfare, especially amid volatile market conditions [61].

### 3.2. The Influence of AI on Energy and Climate Resilience

AI in energy and climate is driving a new high-tech era of interaction between humans and nature. It serves as an intelligent tool that optimizes energy production, reduces carbon emissions, enhances urban system efficiency, and lessens human impacts on ecosystems. Essentially, AI connects technological advancement with sustainable development, fostering what is often called “smart energy” through predictive algorithms and efficient resource management [15] [62]. A key focus is AI’s role in optimizing energy generation, storage, and use within the energy sector. Currently, machine learning algorithms analyze weather data, consumption patterns, equipment conditions, and market trends to boost energy system efficiency and support the integration of renewable energy sources (RES) like solar, wind, and hydro power [63]. These intelligent models forecast peak load demands and automatically allocate energy among consumers, reducing losses and operational costs.

Examples of such solutions include Google’s DeepMind Energy Management system, which decreased data center energy use by 40%, and Siemens Mind-Sphere, which optimizes wind farms and solar power plants [18]. AI also plays a crucial role in lowering carbon dioxide (CO<sub>2</sub>) emissions. Advanced industrial and transportation process control systems analyze production cycles, spot inefficiencies, and suggest emission reduction strategies [64] [65]. In metallurgy and chemical industries, ML algorithms control reaction temperatures and pressures to save energy. In transportation, AI helps optimize routes, forecast traffic jams, regulate traffic lights, and manage electric vehicle networks, significantly lowering urban carbon footprints [66]. The idea of “smart cities” combines technology and ecology. Here, AI is embedded in transportation, lighting, water supply, and waste systems, transforming urban areas into self-learning ecosystems [19].

Projects in Singapore, Helsinki, Zurich, and Dubai have integrated algorithms that analyze traffic, air pollution, and building temperatures to automate ventilation, energy, and lighting controls. These innovations cut energy use by 20% - 30% and enhance urban environmental quality [66]. AI plays a crucial role in balancing technological development with environmental sustainability, transforming cities from pollution sources into active agents of climate recovery. In agriculture, AI helps minimize ecological impact and promotes sustainable practices. Machine vision identifies plant health, and analyzes soil moisture, temperature, and nutrients, enabling precise application of water, fertilizers, and pesticides [18]. This reduces environmental chemical loads and conserves resources. Autonomous farms in Japan and the Netherlands illustrate this, where AI manages greenhouses, lighting, and microclimates to achieve high yields with low carbon footprints [16]. Consequently, digital farming is part of a global “smart ecology” approach, where precision replaces excess, and data becomes vital for maintaining natural har-

mony.

### 3.3. AI Is Useful for Sustainability

Across all SDGs and the spectrum of sustainable development, a more detailed overview of AI's current use by various actors has been provided. This includes evaluating AI experts' perspectives in application areas for research purposes, offering insights into specific situations. Today, AI is employed by businesses to engage, identify opportunities, and support progress toward sustainable development. Because of the unpredictability of potential causes and the roles of different actors—including industries, agriculture, transportation, healthcare, education, NGOs, the scientific community, and local producers—these factors must be clarified in many AI-related hypotheses. These elements are likely to significantly influence progress toward the SDGs. Additionally, they represent channels through which AI can have a positive impact on sustainable development. The ideal outcome is that SDGs are able to reach their full potential, which is facilitated by a hierarchical structure—like a pyramid—where actors can influence or elevate other levels through better strategies and actions. AI can foster social cooperation among these actors and support a broad level of sustainable development.

Each SDG can potentially benefit from AI, as shown by a McKinsey Global Institute study that identified up to 135 AI use cases supporting the SDGs by November 2018. These cases represent definite, partial, or hypothetical opportunities for AI application. Different use cases entail various domains, capabilities, restrictions, and risk levels based on how AI is implemented. Successful examples of deep learning (DL) applications in medical imaging have grown, especially since 2015, when a surge of economic activity emerged around this field. AI startups focusing on imaging and diagnostics have raised funds since January 2015 [67]. Additionally, IBM researchers predict that by 2026, medical images will make up at least 90% of all medical data, becoming the largest source of healthcare information data.

With the growth of big data, deep learning (DL) is increasingly used in fields like blood flow visualization, medical diagnosis, cancer therapy, and diabetic retinopathy treatment. Today, AI is making significant advances in business sectors, including startups and tech giants such as IBM, Google, and Samsung. A notable example is Argus, a project by SAP Labs China, which developed an ML-based solution to detect lung cancer signs on CT scans. Argus allows for testing more patients in less time with higher accuracy. These AI applications contribute to the SDGs, particularly in “Nutrition, Health, and Well-Being”, and the “Trade and Industry” sector, as per the UN. SAP exemplifies how businesses can leverage AI responsibly for sustainable development. Evidence indicates AI can support 134 of the 169 SDG targets (about 79%), mainly through technological innovations addressing limitations. However, around 59 goals, roughly 35% of all SDGs, could be adversely affected by AI, according to the UN and Stockholm Resilience Centre research [68].

### 3.4. Utilization of AI in Environment Results

The final set of sustainability goals focuses on the environment. Among these, three targets relate to climate change, life underwater, and life on land as described in SDG goal 13, 14, and 15. However, these three goals are profoundly interdependent. As example, forests (SDG 15) and oceans (SDG 14) act as carbon sinks, and which unswervingly support climate action (SDG 13). Contrariwise, climate change (SDG 13) exacerbates biodiversity loss (SDG 15) and ocean acidification (SDG 14). Environmental organizations identified 25 goals (93%), where AI can serve as a facilitator [68]. Again, based on the 2018 report from PwC and the Stanford Woods Institute for the Environment, AI has the capability to facilitate 93% or 25 out of 27 identified of the targets within the SDGs. It acts as a key accelerator for environmental sustainability, including in climate action and resource management. AI's advantages include analyzing large, interconnected databases for collaborative curation. Regarding SDG 13 on climate change, AI advances are improving our understanding and modeling of climate impacts. AI also supports developing low-carbon energy systems crucial for combating climate change, as they utilize renewable resources and enhance energy efficiency. Additionally, AI can boost ecosystem health; for instant, AI-based automated oil spill detection helps achieve goal 14.1 by preventing and significantly reducing marine pollution [69].

15.3 illustrates the need to combat desertification and restore degraded lands and soils. AI techniques such as artificial neural networks (ANN) can enhance land cover classification from satellite images, enabling rapid processing of large datasets [70]. These tools can identify large-scale desertification patterns, supporting decision-making, planning, and environmental management, and can help prevent or reverse desertification by pinpointing underlying causes. However, as mentioned earlier, efforts to achieve SDG 13 on climate change might be hindered by the high energy demands of AI, especially when relying on carbon-free energy sources. Additionally, increased access to AI-related environmental data could lead to resource overexploitation, despite growing evidence of AI being used for biodiversity conservation and monitoring [41]. Although these AI misuse cases are not yet widespread, and potential deficiencies in AI need to be considered research.

### 4. Prospects and Development of Green-AI

The current stage of AI development is marked by a shift from merely increasing computing power to rethinking how environmentally efficient AI can be. A new scientific and technological paradigm, Green-AI, focuses on reducing energy use, enhancing algorithm resilience, and integrating AI into environmentally responsible planetary management [20]. As digital infrastructure's energy consumption rivals that of the aviation industry, developing energy-efficient algorithms has become both a technical and an ethical priority. Green AI involves creating and deploying AI systems that are sustainable, energy-efficient, and resource-conscious, addressing the high energy consumption and carbon footprint associated with Red-AI, which prioritizes accuracy at all costs. The aim of Green AI is to lessen

AI's environmental impact without sacrificing performance results. The core principle of the Green-AI concept is to develop algorithms that operate with minimal computing resources while delivering high accuracy and functionality. Techniques like reducing data sizes, employing hybrid architectures, using energy-efficient processors, and shifting to distributed learning enable AI's carbon footprint to be lowered without compromising performance [17] [62]. Leading tech companies such as Google, IBM, and Microsoft are already deploying automatic server cooling systems powered by renewable energy, while research centers are advancing Tiny ML technologies that train models directly on low-power devices. Consequently, Green AI is evolving not just as a scientific discipline but as a future ethical standard focused on reducing the environmental impact of digital transformation. One promising approach involves biomimicry, where AI algorithms draw inspiration from natural systems. In nature, self-organization, adaptation, and energy efficiency are essential for survival. These principles guide the development of neural architectures that learn efficiently with minimal energy and computational demands [55] [71]. For instance, evolutionary algorithms that imitate natural selection enable AI models to find optimal solutions, similar to biological evolution. This approach is part of neuro-ecological design, where artificial systems emulate nature's resilience and adaptability balance.

Green-in-AI focuses on making the AI models themselves more efficient through strategies like algorithm optimization, smaller models, and better hardware use. On the other side, Green-by-AI focuses on applying AI to solve environmental concerns, such as optimizing energy grids, smart mobility, and climate modeling. Lifecycle concentrate on addressing the full life of an AI model—from initial training to deployment and disposal—to save carbon emissions, water usage, and e-waste. Whereas transparency is the actively tracking and reporting the carbon footprint and energy usage of AI applications. To accomplish Green-AI requires to apply sparse training approaches, quantization, and energy-aware pruning to reduce model size and complexity. It also requires to use specialist hardware like Tensor Processing Units (TPUs) or energy-efficient GPUs that offer higher performance per watt. There should be process data closer to the source (on-device) rather than in big, energy-intensive central data centers. There need to be power data centers with solar, wind, or hydroelectric energy. There should be reuse pre-trained models instead of training from scratch, which saves tremendous amounts of energy. There are several examples and tools like CodeCarbon and CarbonTracker are used to measure the energy consumed and CO<sub>2</sub> emitted during model training. Or DistilBERT and MobileBERT are supposed to be speedier and lighter. Another example is Google's AI-powered data center cooling, AI-driven precision agriculture, and smart grid optimization [72]. However, smaller, greener models may sometimes sacrifice a tiny degree of accuracy. Sometime, creating and implementing sustainable infrastructure might be pricey upfront. Moreover, there is a need for globally agreed measures to quantify "greenness" across the sector [73].

The development of green-AI relies on international support. Global initiatives

aim to integrate AI into sustainable strategies. UNESCO's 2021 recommendation highlights "ecologically responsible AI", focusing on energy efficiency, equitable access, and biosphere protection. UNEP's AI for the Planet project uses AI for climate data, resource management, and disaster prevention. The European Green Deal advocates digitalization and decarbonization, certifying algorithms for energy and emissions. These efforts aim to establish a global standard for ecological intelligence, evaluating technology by both speed and sustainability. AI's role grows in renewable energy, optimizing solar and wind operations, forecasting supply and demand, reducing losses, and stabilizing grids. Combining AI with energy storage, smart grids, and distributed sources builds a future energy ecosystem, ensuring ecological balance.

However, the ultimate goal of producing "green AI" extends beyond technical efficiency. It is tied to developing a neo-ecological society, a model where intelligence, nature, and culture coexist in mutual harmony. Neo-ecology is a megatrend signifying a fundamental societal and economic movement toward sustainability, frequently defined as "Environmentalism 2.0". It pushes from individualized, guilt-driven efforts like recycling to a systematic, proactive strategy that blends ecological stewardship with economic activity. In this paradigm, AI is considered not as a tool for dominating nature, but as a mediator capable of coordinating human activity within the boundaries of the biosphere [54] [74]. The neo-ecological approach blends scientific rationality, philosophical morality, and artistic perception of the world, creating the framework for a new civilization—one of symbiotic intelligence. In the future, the development of green AI will become a significant aspect of worldwide sustainable development initiatives. Transitioning from exploitative technologies to life-sustaining ones will help humankind to transcend beyond the "human vs nature" paradigm toward a "human with nature" concept. AI inspired by the principles of the biosphere could become a tool that, instead of destroying the world, helps maintain its equilibrium quietly, precisely, and intelligently.

AI also brings new risks like high energy costs, ethical dilemmas, and the threat of technological inequality. These challenges are forcing humanity to rethink the very concept of progress. So, the concept of Green AI is becoming not just a research area, but a moral compass for a digital civilization striving to minimize its carbon footprint and harmonize its interactions with nature. The prospects for the development of green-AI are linked not so much to the improvement of computing technologies as to the formation of a neo-ecological society and that is a synthesis of intelligence, culture, and nature. AI should not be above nature, but at its service, becoming a mediator between the Biosphere and the Technosphere, and a tool for the conscious management of planetary processes [75]. In this high-tech era humanity stands on the threshold of a new paradigm and that is a paradigm of intelligent coexistence with the Earth, where AI and smart technology become a partner with nature. Its true mission is not to control, but to understand; not to consume, but to preserve. Definitely, there is a hope for sustainable, har-

monious, purposeful, effective and meaningful future for the planet is natural.

## 5. Problems and Risks of Using AI in Ecological Balance

Despite the immense potential of AI for sustainable development, its use is plagued with several inconsistencies and constraints. While AI is supposed to assist humanity tackle the environmental dilemma, the technology that enable it are itself becoming the source of new challenges including energy, ethical, social, and philosophical. These dangers demand a full understanding, as their resolution will determine whether AI may become a tool for ecological balance or become yet another mechanism for aggravating global disparities and human-induced pressure on the earth [21] [76]. One of the most important challenges is the high energy usage and carbon footprint of data centers that run machine learning algorithms. Modern AI models, especially those based on deep neural networks is require massive computational resources. Researchers at the University of Massachusetts Amherst estimate that training a single GPT model generates up to 300 tons of CO<sub>2</sub>, which is similar to operating dozens of cars throughout their entire life cycle [17]. The data centers where these models are taught consume billions of kilowatt-hours of electricity annually, frequently from non-renewable sources. As a result, AI created to prevent climate change, is itself becoming an extra factor in global warming. A solution may lay in the realization of the Green-AI concept and that is the development of energy-efficient designs, quantum computing, and the utilization of renewable energy in data center infrastructure [20].

The ethical and legal issues of using autonomous systems without human oversight are equally significant. In environmental projects, AI often makes autonomous decisions, such as controlling emissions, reallocating resources, or operating equipment at mining and processing sites [77]. Still, questions about liability for errors or unexpected results remain unresolved. Who bears legal and moral responsibility for damage to ecosystems caused by flawed algorithms—the developer, operator, or government? The lack of international standards heightens these concerns. As a result, the UN and UNESCO stress the need for a code of ethics for autonomous systems interacting with the biosphere [21]. Another concern is digital inequality and limited access to “green” technologies in developing countries. Creating AI requires substantial investments, computing resources, skilled experts, and reliable communication infrastructure, which many nations in the Global South lack [15]. Consequently, a new form of environmental inequality linked to technology is emerging. Countries with advanced AI can influence natural processes, while others depend on external digital solutions. This imbalance threatens global environmental justice and could lead to technological colonialism, where control over environmental data becomes a new form of dominance power.

Simultaneously, the reliance on artificial intelligence in strategic decision-making grows riskier. Algorithms are increasingly used to evaluate natural risks, design infrastructure, plan land use, and even develop climate policies [55]. How-

ever, overdependence on these algorithms can diminish human critical analysis skills. AI models reality through data, but data is often limited and prone to distortion. This poses a risk that environmental strategies based solely on algorithmic predictions might overlook social and cultural factors in human-nature interactions. Therefore, maintaining a human-centered approach is essential; AI should support human decision-making, not replace moral responsibility [76]. Amid these challenges, a fundamental contradiction exists between technological progress and the biosphere's limits. History shows that each technological surge initially gives an illusion of mastery over nature, then increases dependence. AI is no different: as it automates more processes, managing its repercussions becomes tougher. The widespread adoption of digital systems raises concerns about increased consumption of rare earth metals, electricity, and water for server cooling [62]. There's a risk that Ecological-AI could accelerate hyper-technological growth, conflicting with sustainability principles. Recognizing these risks is the first step toward addressing them. The future of AI in ecology should follow principles of ethical digital responsibility, energy efficiency, and social justice. Only through strict regulation, international cooperation, and integrating philosophical and ethical insights into technology policy can AI truly serve its initial purpose—to aid nature, not dominate it preservation.

One major factor in AI's energy use is the training process. Training a deep learning (DL) model involves inputting large amounts of data into neural networks, which then fine-tune their internal settings through repeated cycles to improve performance. This process often needs multiple passes over big datasets, using powerful hardware like graphics processing units (GPUs) or specialized tensor processing units (TPUs) [78]. These devices are energy-hungry, consuming lots of electricity to handle the complex calculations needed for training AI models. Energy use during training can vary from a few hundred to several thousand kilowatt-hours (kWh), depending on the model's size, complexity, dataset size, and hardware [79]. Besides training, deploying and running AI models also consume energy. After training, models are deployed on various devices or cloud servers to make predictions or perform tasks in real-time. Although inference generally requires less computational power than training, large-scale deployment can still lead to significant overall energy consumption [78].

AI system hardware also presents a major environmental challenge through electronic waste. The fast pace of technological progress and the demand for more powerful hardware cause frequent replacements, resulting in a growing amount of electronic waste [80]. Components like GPUs, ASICs, and other specialized parts have short lifespans due to ongoing technological advancements. As newer hardware is released, older models quickly become obsolete and are discarded, worsening electronic waste issues [81]. Improper disposal releases hazardous substances into the environment, contaminating soil, water, and air, which threatens human health and ecosystems. Additionally, valuable resources in discarded hardware are wasted, and toxic materials like lead, mercury, and flame retardants can

cause further pollution when not managed correctly [82].

## 6. AI Have Substantial Carbon Footprint

AI has a rapidly expanding carbon footprint due to the high energy requirements of training and deploying large models, along with the growth of physical data center infrastructure. Although AI presents opportunities for environmental sustainability, its current ecological impact—such as carbon emissions, water use, and electronic waste—is considerable and often surpasses management capabilities. Training Large Language Models (LLMs) demands vast computational resources, typically involving thousands of GPUs for weeks, resulting in high electricity use. Notably, inference—the daily deployment phase—often accounts for over 60% of AI's energy consumption. For example, training GPT-3 can emit over 500 metric tons of CO<sub>2</sub>, comparable to the emissions from driving across the US multiple times. Data center emissions are comparable to those of the aviation sector. By 2025, the AI industry's carbon footprint might rival that of a small country like New York City. Data centers, housing AI servers, currently consume about 1% - 1.5% of global electricity, with expectations of a significant increase by 2030 due to AI workloads. The construction of data centers, including steel, concrete, and GPU manufacturing, contributes substantial “embodied” emissions, often overlooked. AI data centers also require large water quantities for cooling; a 2023 study estimates training GPT-3 used around 700,000 liters of freshwater. Additionally, energy consumption by AI could rise by up to 300% within five years.

AI-based systems demand immense computational power and large data processing, leading to more servers and higher energy use to cool data centers, significantly increasing overall energy consumption. A study shows that the energy needed for data processing and storage to develop complex algorithms can emit as much CO<sub>2</sub> as driving a car for five of its lifetimes or making 300 round trips between New York and San Francisco [83]. Data centers handling online activities like streaming and emailing contribute around 1% to global energy consumption [84]. Projections indicate that by 2030, computing could account for up to 8% of worldwide energy demand [85], raising concerns about the continued reliance on fossil fuels.

The most common training tasks produce relatively low carbon emissions. While current AI techniques do not generate massive emissions, their contribution could become significant in the near future. Few studies are available to help companies estimate AI's carbon footprint. AI can both aid and hinder efforts against climate change. The need for rare earth materials for hardware manufacturing could have negative environmental impacts, and AI is not infallible—it can make mistakes during computation or output generation. Additionally, logging individuals' energy use raises privacy concerns, as it can potentially track personal data [59]. Ultimately, climate change should primarily impact those who contribute most to emissions and cause substantial life changes. Relying solely on technology now is insufficient to solve the problem and preserve integrity in the short

and medium term [59].

## 7. Challenges of Using AI to Achieve Environmental Sustainability

Using AI for environmental sustainability creates a paradox: while AI provides significant tools for resource optimization and addressing climate change, its creation and use demand large amounts of energy, water, and raw materials, which might increase environmental damage. The key concerns entail managing this resource intensity, maintaining data quality, and addressing ethical and legal constraints. A significant hurdle is the lack of suitable success measures and unpredictable human behavioral responses to AI interventions [24]. To enhance sustainability, it is necessary to measure and assess the effects of actions made. Since measurement methods are complex and often ineffectual, adopting a combined analytical and technical standard metric is crucial for AI to support environmental goals. Though AI software resembles human decision-making, their methodologies differ from human replies. Understanding behavioral responses is crucial to avoiding feedback traps, a typical challenge in technology growth [24]. Furthermore, the rebound effect is an intrinsic hazard associated to many smart devices. High upfront costs remain a major obstacle. While AI technology shows promise, the necessary capital investment can discourage many, especially small family farms. Many AI tools depend on high-speed data transmission to analyze imagery and sensor data. In many rural U.S. areas, limited 5G or broadband infrastructure hampers the real-time use of these tools. Another key issue is “vendor lock-in”, which occurs when data from one manufacturer’s system cannot be easily transferred to another’s. This new landscape also prompts questions about who owns the agronomic data generated on private land.

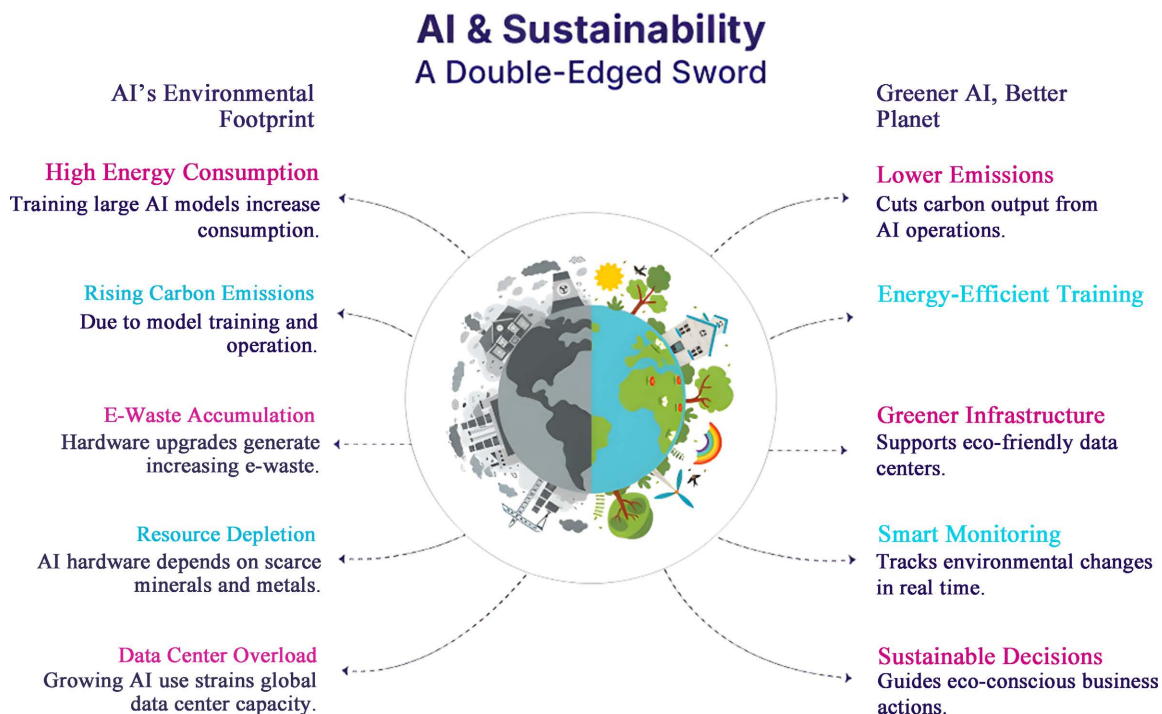
AI effectiveness depends on quality data; models trained in the Midwest may produce inaccurate recommendations if used in the Pacific Northwest without local calibration, risking crop loss, input waste, or safety concerns. The USDA’s 2025-2026 AI Strategy highlights that as AI is integrated and developed, clear objectives are needed to ensure risk management and human oversight for ethical, equitable, and responsible implementation of AI. However, AI can effectively address environmental issues; however, it also faces challenges because it depends on historical data used for machine learning (ML). ML models struggle to account for AI’s unpredictable nature and the constantly changing traits of human behavior. Therefore, data from the past, such as age groups and climate cycles, can help reflect conditions before major human activities, but predicting climate change remains difficult. Additionally, incorporating historical data into models complicates modifications, as many computer scientists focus closely on it. This can lead to overgeneralized data, resulting in inaccurate predictions, a problem known as variance bias shift [24]. In today’s era of smart technology, cybersecurity risks are an ongoing challenge. When deploying AI solutions, resilience comes into question. Managing cybersecurity risks is crucial when integrating data into AI appli-

cations. However, the increasing number of threats from hackers presents a significant obstacle to addressing environmental sustainability, especially since third parties often access vital data, and disparate security methods are less effective risks.

Developing and deploying complex AI models, especially generative AI, demands vast computational resources, resulting in significant energy consumption during both training and inference. While AI can enhance energy efficiency, this often encourages greater usage and adoption, which can negate efficiency gains and increase overall energy demand. Most data centers supporting AI rely on non-renewable energy sources, leading to considerable greenhouse gas (GHG) emissions. Acquiring reliable, real-time environmental data is challenging, particularly in developing countries. AI models trained on incomplete or biased data may produce inaccurate predictions, undermining effective sustainability efforts. Additionally, ML models depend on historical data, which might not accurately reflect rapid ecological changes. The complexity of AI systems also makes it difficult to interpret their decision-making processes, reducing trust in AI-driven environmental solutions. Furthermore, many users find it hard to assess the full carbon and water footprint of AI tools due to proprietary or confidential methods [86]. Existing environmental frameworks often lack comprehensive and standardized metrics to fully gauge AI's environmental impacts across its entire supply chain.

The progress by use of AI comes with a heavy environmental cost. AI models usually grow larger and more complex; they demand massive amounts of energy and water for training and operation. Experts also warn, as AI use continues to rise, data centers alone could consume up to 1,580 TWh of energy by 2034 and which is almost equal to round 10% the energy used by world today. Again, AI technology evolves, old servers and devices become electronic waste. This waste contains harmful substances like mercury and lead, which can pollute land and water. Managing growing e-waste is becoming a major challenge worldwide. If we look to the **Figure 3** below, we found today AI and sustainability become double-edge sword [87]. Large-scale AI data centers use significant amounts of water for cooling, often in regions already experiencing water shortages. The hardware supporting AI, like GPUs and servers, relies on critical minerals, mining of which damages ecosystems, pollutes water and soil, and harms biodiversity. Rapid AI development results in short hardware lifespans, leading to increased electronic waste containing hazardous chemicals. Currently, less than 25% of global e-waste is properly collected and recycled, allowing toxic substances to seep into the environment. This waste, generated by AI, poses a serious environmental risk, as it contains hazardous chemicals such as lead, mercury, and cadmium that can contaminate soil and water and threaten health and ecosystems. By 2050, the World Economic Forum predicts e-waste will surpass 120 million metric tons. To prevent environmental damage and reduce chemical pollution, effective e-waste management and recycling are essential. Stronger legislation and ethical disposal practices are required to ensure safe processing and significantly minimize the environ-

mental impact of AI-related electronic waste [88].



**Figure 3.** Today AI and sustainability become double-edge sword [87].

AI applications like driverless cars and delivery drones pose risks to animals and the environment. Automation driven by AI may lead to increased consumption and waste, especially in sectors like e-commerce, where rapid and frequent delivery has become standard. In agriculture, the growing use of AI could cause overuse of pesticides and fertilizers, contaminating soil and water and harming biodiversity [89]. Employing AI to boost crop yields at the expense of ecosystem health could result in monocultures and biodiversity decline. AI in environmental management also raises ethical concerns, as decisions may be biased if based on incomplete or inaccurate data. For example, an AI system prioritized for economic growth over environmental protection might favor short-term profits over sustainability. To ensure a balanced coexistence of technology and nature, people must develop sustainable practices and make informed decisions by considering AI's environmental impacts [90]. The benefits of AI should be weighed against the need to protect our natural ecosystems.

The hidden nature of AI development and use leads to a lack of transparency and accountability about its environmental effects. Some companies prioritize profit and competitive advantage over potential environmental harm caused by AI technologies. Because AI systems are complex, users often struggle to fully understand their environmental footprint. Accurate assessments of carbon emissions or other environmental impacts are difficult due to secretive practices and undisclosed data used in training AI models. To address this, more transparent processes and regulations are needed to ensure AI development and deployment

align with environmental sustainability. Promoting responsible AI that emphasizes sustainability can improve accountability. Frequently, the environmental impacts of AI, such as pollution from data centers, affect vulnerable or marginalized communities. Meanwhile, the benefits of AI solutions tend to go to wealthy nations, while poorer nations bear a larger share of environmental costs. Reliance on AI for quick technological fixes might also distract from deeper political and socio-economic reforms necessary for genuine sustainability. Experts suggest adopting “Green AI” (focusing on energy efficiency), enhancing transparency in data reporting, and enforcing strict environmental standards on AI infrastructure [91].

## 8. Fight against Challenges and AI's Role in Sustainable Development

Currently, AI applications are increasingly supporting Sustainable Development Goals (SDGs), including autonomous vehicles, AI-enhanced smart grids [92], and healthcare [93]. These systems must be more resilient and beneficial to minimize disruptions. As the role of AI expands across sectors such as agriculture, healthcare, and education, it becomes imperative to invest in AI security research to prevent mishandling, misleading, or damage. A key aspect of AI security research involves understanding potential disasters and system failures within AI systems. For example, a recent study by the World Economic Forum [94] expressed similar concerns regarding AI in banking. Given the increasing reliance on such technology, it is essential to raise awareness about the risks associated with AI system failures and to fund research addressing these issues. Consequently, it is necessary to develop and deploy AI and related intelligent technologies in ways that promote safety, efficiency, and sustainability. As society continues to evolve and adapt to the impacts of AI and other technological advancements, the relationship between society and technology remains dynamic. This ongoing interaction generates a feedback loop wherein societal influence shapes the development and utilization of AI, and AI, in turn, influences societal structures and functions society.

Despite the great potential of AI to reduce carbon emissions, the usage of AI itself also emits CO<sub>2</sub>, and that is the other side of the coin. For example, from 2012 to 2018, the estimated amount of computation used to train deep learning models has increased significantly [95]. Hence, research, training, and deployment of AI models require an increasing amount of energy and hardware, of course. Both produce carbon emissions and thus contribute to climate change. There are very few study that estimates the overall carbon emissions of AI. Still, there are some estimations of the CO<sub>2</sub> or CO<sub>2e</sub> emissions of some Natural Language Processing (NLP) models that have become increasingly accurate and hence popular during recent years [96]. According to the following **Table 1**, the final training of Google's BERT model roughly emitted as much CO<sub>2e</sub> as one passenger on their flight from New York to San Francisco. Of course, the training of other NLP models like Transformer<sub>big</sub> is emitted far less, but the final training of a model is only the last part of finding the best model. Prior to the final training, many different models

are tried to find the best parameters. Accordingly, this neural architecture search for the Transformer<sub>big</sub> model emitted about five times the CO<sub>2e</sub> emissions as an average car in its lifetime. Now, you may look at the estimated CO<sub>2e</sub> emissions of GPT-3 and imagine how much emissions resulted from the related neural architecture search [97].

**Table 1.** Comparison of selected human and AI carbon emissions [96].

Emissions by Humans		Emissions by AI	
Example	CO <sub>2e</sub> Emissions (Tons)	Training of NLP Models	CO <sub>2e</sub> Emissions (Tons)
A passenger on a flight from New York to San Francisco	0.90	Transformer <sub>big</sub>	0.09
Average human per year	5.00	BERT <sub>base</sub>	0.65
Average American per year	16.40	GPT-3	84.74
Average car during lifespan including gasoline	57.15	Neural architecture search for Transformer <sub>big</sub>	284.02

Several studies indicate that AI has the potential to support various SDG goals and calculations. However, much of this research is limited by data constraints and cannot be tested in controlled environments or laboratory prototypes [98]. As a result, it's challenging to translate these findings to real-world impacts, especially when considering larger temporal and geographic scales. Conducting controlled experiments is crucial to understanding how AI tools perform in specific settings. Some evidence suggests society may resist changes introduced by AI. To properly evaluate new technologies in terms of efficiency, ethics, and sustainability, innovative methodologies should be adopted prior to widespread AI deployment. Errors in AI systems pose significant risks, making it vital to research their causes and develop integrated human-machine analysis tools. This approach will support responsible AI development and application [99].

Although evidence generally indicates that AI supports rather than hinders SDG achievement, several important points deserve attention. The AI research community and industry are often motivated to report positive results due to conflicting interests. Detecting AI shortcomings may require long-term studies, but limited assessment tools make this challenging. This positive reporting trend is particularly pronounced in environmental SDGs, such as coastal and marine protection, objective 14.5, highlighting this bias [100]. ML and DL algorithms tend to offer optimal solutions because they consider many parameters in selecting safety measures. However, deliberate, goal-driven research is essential to assess the long-term effects of these algorithms on fairness and justice. Funding frequently targets profit-driven projects, which can skew focus toward economic interests, potentially increasing inequality, as noted by some researchers in 2018 [101].

Economic benefits should not be the sole criterion for prioritizing AI solutions

to meet SDGs. It is crucial to evaluate the social, ethical, legal, and environmental consequences of emerging AI technologies. Funding should prioritize projects that assess and address these critical aspects while demonstrating commercial viability. This strategy ensures AI progresses serve all communities equitably. One method to leverage AI for SDGs involves in-depth research and application of machine learning and data mining on the growing datasets, from analyzing historical weather patterns to predicting future events [102]. A significant challenge is the difficulty governments face when integrating AI into decision-making effectively [103]. Institutions encounter obstacles such as establishing cybersecurity, safeguarding privacy—especially concerning surveillance—and preventing data breaches or internal negotiations. Furthermore, automating processes without strict ethical and legal standards risks perpetuating bias [104].

Currently, the applicability of artificial intelligence (AI) technologies is relatively limited, as many initiatives address problems predominantly encountered in developed nations. For instance, mechanized harvesting and the optimization of its timing are more effectively executed by systems in these countries, owing to their access to infrastructure such as robust energy networks and high-end processing capabilities required for such activities. Conversely, less developed regions may lack the comprehensive infrastructure necessary, rendering their AI applications less effective—unless they are designed from the outset using locally available components, thereby eliminating the reliance on international trade agreements that often place a disproportionate burden on economies with low income. Recent advancements in AI also engender concerns regarding the exacerbation of inequality both within and among nations. Such disparities could potentially hinder progress toward the achievement of the Sustainable Development Goals. Consequently, it is imperative for researchers and funding agencies to focus on developing solutions that are tailored to the specific requirements of less developed countries or regions where AI adoption faces significant challenges [105]. Ultimately, each initiative must be carefully adapted to suit the customs and needs of the local community. In fact, AI technology is utilized to promote equality and contribute positively to the welfare of all societal segments.

## 9. The Long-Term Practicability and Sustainability of AI

Today, AI offers noteworthy potential for environmental sustainability as well as its rapid advancement and the training of large-scale models create a substantial ecological footprint. However, beside considerable environmental benefits of AI use, also poses significant challenges. Balancing digital progress and AI's carbon footprint is crucial. Training large neural networks consumes vast computation, raising energy usage in data centers [17]. AI's influence on energy and climate sustainability is complex: it can foster an eco-friendly future with accurate data but also demands rethinking energy costs and establishing ethical guidelines for growth. Only by balancing technological innovation with environmental care can AI shift from a potential burden to an agent of sustainable energy and climate

solutions, laying the groundwork for a resilient global civilization. AI technology is increasingly recognized not as a luxury but as a practical response to labor shortages and climate challenges. To mitigate AI's environmental footprint, a comprehensive approach is essential. This starts with investing in energy-efficient hardware and AI algorithms, which can significantly cut energy consumption while maintaining performance. Additionally, establishing ethical AI standards—such as minimizing unnecessary data collection and considering end-of-life issues—is crucial. Fostering a culture of transparency and responsibility is also vital. Stakeholders should focus on providing relevant data about AI models and data sources to properly assess their environmental impact.

To ensure the ethical development, use, and disposal of AI technologies, governments and regulatory agencies should establish clear standards and restrictions. Collaboration among businesses, academics, and policymakers is also vital. Researchers ought to develop solutions that emphasize technological advances and environmental sustainability by encouraging multidisciplinary research and knowledge sharing. The environmental impact of AI's rapid growth is a genuine concern that requires urgent attention [106]. While AI's potential is undeniably attractive, we must directly address its negative effects. By exposing the hidden environmental challenges related to AI, people can promote informed discussions and encourage the adoption of responsible practices. Policymakers should broaden federal broadband efforts to focus on delivering high-speed internet to agricultural lands, not just rural residential areas. Without this “last-acre” connectivity, autonomous machinery and precision sensors cannot perform real-time processing over much of American farmland. Additionally, state frameworks should require industry-wide open-source data standards to guarantee interoperability among various equipment manufacturers and software providers.

This approach helps prevent “vendor lock-in”, enabling farmers to transfer their historical field data smoothly across brands and keeping digital assets as the property and priority of the producer [107]. Funding should also support research into regional AI datasets that adapt machine learning models to local soil, pest, and climate conditions, with physical field verification to prevent AI inaccuracies or hallucinations. To tackle issues like climate change, environmental damage, pollution, biodiversity decline, and associated injustices, we urge policymakers, industry leaders, and all stakeholders to acknowledge the real environmental costs of AI, end fossil fuel use across the entire tech supply chain, reject misleading solutions, and dedicate all necessary resources to keep AI systems within planetary boundaries. Achieving this is vital to prevent AI from further harming the planet and to support a sustainable, equitable transition. We call on policymakers, industry leaders, and everyone involved in AI to recognize AI's environmental effects, dismiss ineffective remedies, and provide the resources needed to ensure AI aligns with planetary limits [108].

It is crucial to recognize that AI and its infrastructure incur costs, as they consume significant resources and place pressure on our finite natural reserves. The

advantages and drawbacks of AI are not shared equally. Vulnerable nations and communities most impacted by climate change are the first to face AI's adverse effects and high computational needs, yet they hold less influence over its development. There is an urgent need for a fundamental shift. We must change our view of technological progress, moving away from the idea that it is always beneficial or limitless, and instead focus on AI projects that create societal value while reducing environmental and human harm. This involves redefining expectations, establishing new standards, and making conscious choices to lessen AI's ecological impact and develop technology sustainably [109]. Only through deliberate action can AI be used as a tool for sustainability rather than a source of further planetary harm.

Research and reflection are crucial for understanding the complex interconnections and entanglements of sustainability impacts in AI systems. As socio-technical-ecological entities, these systems display interdependence across multiple impact levels. To develop a comprehensive assessment approach, a deeper understanding of these dependencies is necessary. For instance, moving computation to cloud data centers might boost ecological sustainability but could also increase market concentration concerns. Future studies should examine these trade-offs and synergies within the socio-technical-ecological framework thoroughly. Moreover, describing interdependent impacts requires societal negotiation to address trade-offs in AI sustainability. As AI becomes more prevalent, managing these trade-offs through critical discussions, organizational sensemaking, and societal dialogue will be vital. Prioritizing and focusing on diverse sustainability impacts will depend on ongoing research and societal involvement. A holistic framework for evaluating AI sustainability is essential to guide future research and policy-making [110]. Ensuring sustainability across the AI lifecycle calls for a multi-dimensional approach, emphasizing continuous research and societal negotiation to set priorities and address trade-offs effectively. The sustainability assessment of AI systems involves four key impact levels.

- **The AI System Level.** This level mainly concentrates on the AI systems themselves, covering the full lifecycle from developing models to deploying them. It includes aspects like data collection, management, conceptualization, training, testing, and inference. Throughout the AI lifecycle, diverse social, technical, and hybrid elements interact to shape the system. The AI system is integrated within and interacts with both the broader social context and the ecological environment, forming a socio-technical-ecological system [111].
- **The Application Level.** This level relates to the specific contexts and use cases for AI applications. It includes criteria concerning ecological sustainability and labor market impacts within the application setting. Grasping the application level is crucial for evaluating the real-world effects and implications of AI systems [112].
- **The Macro-Social Level.** AI systems are integrated into broader social frameworks, both influencing and being influenced by societal norms, laws, and cul-

tural values. Factors such as regulations, legal structures, and cultural expectations play a role in shaping how AI is developed and applied [113].

- The Ecological System Level. AI systems are linked to ecological systems and the environment. This connection is evident in resources used to produce hardware and in how nature is monitored. Recognizing the ecological impact of AI is crucial for assessing their sustainability [114].

These conceptual foundations provide a comprehensive approach that transcends disciplines and recognizes the complexity of AI systems and their impacts. The Sustainable AI Assessment Framework (SCAIS) is developed not only to foster academic discussion but also to serve as a practical tool for enterprises to develop and sustain AI systems in the long run. By thoroughly examining these impact levels, we seek to stimulate beneficial contributions to the development and deployment of sustainable AI solutions. Such a Sustainable AI Assessment Framework (SCAIS) can address different effect levels and offer practical advice for enterprises [115]. To explain how this self-assessment tool can be utilized in practice, we give a hypothetical example. The tool, built based on the criteria described previously, assists enterprises involved in AI development or use to evaluate their sustainability policies and find areas for improvement.

An organization might find that creating a Code of Ethics, covering principles like transparency and nondiscrimination, is a good first step. The tool could then suggest improvements, such as setting up an internal oversight body to monitor compliance and ensure effective governance in AI development. It may also recommend ways to increase transparency about AI models and datasets for stakeholders. When AI systems directly affect individuals through automated decisions, the self-assessment tool scores well if the organization consults marginalized groups throughout the system's lifecycle. On the other hand, it might point out the need for improvement if the organization lacks diversity management or has a uniform workforce. For environmental issues, the tool recognizes efforts like using carbon-efficient methods and eco-certified hardware and data centers. However, it might advise forming partnerships with recycling or re-manufacturing companies to dispose of old hardware responsibly [116]. This self-assessment tool, based on the SCAIS framework, offers practical insights for organizations developing or deploying AI systems. It supports a thorough review of sustainability practices and helps guide organizations toward more sustainable AI development deployment.

## 10. Combat Against Problems Raises due to AI Utilization and Suggestions

Today, efficient ML approaches have received attention in the research community, but are generally not interested by being green. However, a substantial amount of work in the computer vision community has addressed competent interpretation, which is essential for real-time processing of images for applications like self-driving cars [117]-[119], or for placing models on devices like mobile phones

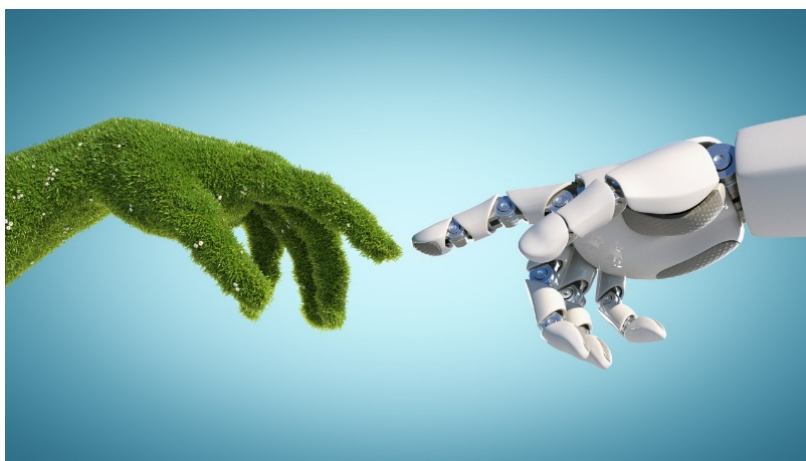
[120] [121]. Recent work has analyzed the carbon emissions of training deep NLP models and concluded that computationally expensive experiments can have a large environmental and economic impact. With modern experiments using such large budgets, many researchers (especially those in academia) lack the resources to work in many high-profile areas. Again, the conclusions are the result of long-term trends, and are not isolated within NLP, but hold true across machine learning [122]. The energy-heavy nature of AI calculations raises concerns about their environmental impact and sustainability. As AI tools spread across various industries, the need for computational resources will grow, leading to higher energy use. It is essential to explore energy-efficient computing designs, develop algorithms that lower computational demands, and use renewable energy to power AI systems [123]. Efforts are ongoing to tackle these issues. Researchers and industry professionals are focusing on creating more energy-efficient algorithms and hardware, using techniques like model compression, quantization, and distributed training. These methods aim to lessen the computational load of AI models while maintaining performance [123]. There is also a rising emphasis on optimizing data center operations and increasing renewable energy use to cut down the carbon footprint of AI computations [78].

To tackle the problem of electronic waste in the AI sector, adopting sustainable practices is crucial. One effective approach is promoting reuse and recycling of AI hardware. Refurbishing and remanufacturing older devices can help extend their lifespan, reducing the constant demand for new equipment [80]. Additionally, establishing take-back programs and recycling centers ensures that discarded hardware is properly managed and valuable materials are recovered for reuse. When designing and producing AI hardware, prioritizing eco-friendly principles is essential. This includes using environmentally less-impactful materials, designing for recyclability, and reducing hazardous substances to support a more sustainable hardware lifecycle. Modular designs that allow for component replacement and upgrades can further prolong the usefulness of AI hardware, decreasing the need for full device replacements [80].

Researchers are exploring techniques to improve AI energy efficiency. Model compression reduces neural network complexity by pruning connections or lowering weight precision [83], cutting energy use and inference time without harming performance. Quantization, representing values with fewer bits, saves energy by lowering memory and compute needs [124]. Efforts also target training energy, with gradient compression like smartification and quantization reducing communication overhead during distributed training [125]. Improved algorithms and learning schedules also cut training iterations, saving energy [126]. Researchers are investigating new hardware, such as neuromorphic devices mimicking the brain, for energy efficiency gains [127] [128].

AI hardware technologies are progressing rapidly, driven by continuous innovation that results in more potent and efficient AI systems [130]. A notable development is the transformation of GPUs into indispensable components for AI pro-

cessing. Originally designed for graphics rendering, GPUs are now extensively employed in AI due to their capability for parallel processing [130]. Their high throughput and computational power render them ideal for training and deploying AI models. Furthermore, specialized hardware known as Application-Specific Integrated Circuits (ASICs) has emerged to manage particular AI tasks. ASICs enhance performance and energy efficiency by customizing hardware architecture to optimize AI algorithms [130]. These dedicated AI chips provide greater computational density and faster processing speeds compared to general-purpose processors. The swift advancement of AI hardware has been instrumental in enabling significant breakthroughs across various AI fields. For instance, in computer vision, high-performance hardware facilitates complex image recognition and object detection with exceptional accuracy [130]. Similarly, in natural language processing, powerful hardware accelerates both the training and inference processes of language models, supporting applications such as machine translation and sentiment analysis as shown in **Figure 4**.



**Figure 4.** Use of AI to combat climate change [129].

The rapid advancement of AI technologies has led to an increase in the number of electronic devices, resulting in a concerning rise in electronic waste, or e-waste, which presents serious environmental and health risks. The lifecycle of AI hardware is pivotal in determining the volume of e-waste generated and its environmental impact [131]. It commences with raw material extraction and manufacturing, involving the procurement of precious metals, rare earth elements, and other valuable substances—many of which are non-renewable and require substantial energy to produce [80]. The extraction and processing of these materials can cause environmental degradation and often involve hazardous chemicals that are detrimental to ecosystems and human health. As AI hardware advances rapidly, device lifecycles tend to diminish, leading to more frequent replacement of obsolete models. This phenomenon, known as planned obsolescence, worsens e-waste challenges, with outdated AI devices being discarded, thereby causing a significant accumulation of electronic waste [132]. E-waste contains toxic substances

such as lead, mercury, and flame retardants, which can contaminate soil, water, and air if not disposed of responsibly.

Improper disposal and inadequate recycling of e-waste aggravate the issue. Many electronic devices end up in landfills or are burned, releasing hazardous compounds and contaminating air and soil [133]. Ineffective recycling also results in the loss of valuable resources that could be recovered and reused. Policymakers play a vital role in creating legislation and incentives to enhance e-waste management. For example, extended producer responsibility (EPR) makes manufacturers accountable for their products' environmental impact throughout their lifecycle, encouraging sustainable practices and investments in recycling infrastructure. Initiatives like improved collection systems, recycling programs, and refurbishment projects can help prevent AI gadgets from ending up in landfills and promote reuse [134]. The circular economy offers a promising alternative, focusing on reuse, refurbishment, and recycling of electronics to reduce resource consumption and environmental damage [80]. By applying circular economy principles, AI hardware can be designed and managed to prolong lifespan and reduce the need for upgrades, thereby decreasing e-waste. Embracing these principles improves resource efficiency and product reuse, helping to limit waste generation [135]. Strategies such as refurbishing, repurposing AI hardware, and establishing secondary markets for used devices can further extend the lifespan of AI systems and reduce the need for new production.

To address environmental concerns related to electronic waste from AI hardware, various techniques have been developed to encourage responsible e-waste management throughout the AI product lifecycle. Incorporating Design for Disassembly (DfD) and Design for Recycling (DfR) in AI hardware design and production can facilitate easier separation and recycling of components. Designing gadgets for simple disassembly and recyclability helps reduce e-waste. The concept of Extended Producer Responsibility (EPR) makes producers accountable for their products' entire lifecycle, including proper disposal [136]. Implementing AI-specific EPR standards can motivate producers to create recyclable products and assume responsibility for their environmentally sound disposal and recycling. Establishing effective take-back and recycling programs is crucial for ensuring responsible disposal of AI hardware. Manufacturers can collaborate with professional e-waste recyclers or establish collection points to promote proper recycling and prevent devices from ending up in landfills or informal recycling sites. Ongoing research and development of better recycling technologies are essential to improve the efficiency and effectiveness of e-waste recycling [137].

Data centers have expanded significantly in recent years due to rising demand for digital services, leading to increased environmental impacts. Building and operating these centers require large amounts of land and resources, which contribute to land use changes and habitat degradation [138]. Additionally, their growth in urban areas raises concerns about effects on local communities and infrastructure. Data centers are known for their high energy use, as maintaining servers,

networking equipment, and cooling systems consumes substantial electricity. Cooling these centers presents specific challenges; the heat generated by IT equipment must be dissipated efficiently to maintain optimal conditions. Traditional cooling methods, like air conditioning, are energy-intensive and inefficient. This has driven research into innovative cooling solutions such as liquid cooling and advanced airflow management to improve energy efficiency and reduce environmental impact [139]. However, the vision of Green AI raises many exciting research directions that help to overcome the inclusiveness challenges of Red AI. Progress will reduce the computational expense with a minimal reduction in performance, or even improve performance as more efficient methods are discovered. Also, it would seem that Green AI could be moving us in a more cognitively plausible direction as the brain is highly efficient. It's important to reiterate that we see Green AI as a valuable option not an exclusive mandate—of course, both Green AI and Red AI have contributions to make. We want to increase the prevalence of Green AI by highlighting its benefits, advocating a standard measure of efficiency [122].

The total number of experiments run to get a final result is often underreported and underdiscussed. The few instances' researchers have of full reporting of the hyperparameter search, architecture evaluations, and ablations that went into a reported experimental result have surprised the community [122] [140]. Water constitutes an indispensable resource for cooling in data centers; however, their substantial water consumption can place pressure on local water supplies, especially in regions experiencing water scarcity or competing demands. Cooling towers, which depend on evaporation, may utilize considerable quantities of water. To mitigate environmental impacts, stakeholders within the industry are implementing sustainable practices. These include energy-efficient design strategies such as optimizing server utilization, improving power distribution, and employing energy-efficient hardware to considerably reduce energy consumption and carbon emissions [141]. The transition to renewable energy sources, such as solar and wind power, reduces reliance on fossil fuels and diminishes greenhouse gas emissions. Water-efficient cooling technologies, including closed-loop systems and water-saving cooling towers, further assist in minimizing water usage. Moreover, recycling and reusing water during operations can alleviate pressure on local water resources.

AI algorithms heavily depend on training datasets to inform decision-making processes; however, these datasets frequently contain biases that can result in inequitable outcomes within environmental decision-making. Such biases may originate from sources such as historical data that mirror societal inequalities and systemic prejudices [142]. Addressing these biases is essential to guarantee fair and equitable environmental processes. When AI systems exhibit bias, they can intensify disparities experienced by marginalized communities. For instance, if datasets predominantly represent affluent areas, decisions regarding resource allocation or policy formulation may disregard the needs of vulnerable groups [143]. Biases

against specific demographics or geographic locations can also lead to unequal access to benefits such as clean air, water, or green spaces. Incorporating diverse perspectives into datasets and accurately reflecting the affected communities are fundamental steps. This entails curating data to mitigate underrepresentation and to prevent the reinforcement of existing biases [144]. Developing transparent and explainable AI systems facilitates stakeholder understanding and bias identification, enabling impacted communities to challenge unjust decisions [134]. Continuous monitoring and evaluation of AI systems are imperative to detect and rectify biases that may emerge over time. Regular assessment of AI's influence on various populations ensures its alignment with principles of fairness and equity 2016.

To minimize the ecological damage caused by AI, it is important to adopt ethical deployment practices. This involves conducting thorough environmental impact assessments before deploying AI technologies, assessing potential risks to ecosystems, and identifying appropriate mitigation strategies. Additionally, it is vital to integrate AI into existing conservation efforts and include local communities in decision-making. This participatory approach encourages a comprehensive understanding of ecological systems and supports the development of AI solutions that improve biodiversity and human well-being. The rise of AI has led governments and regulatory agencies to consider its potential environmental effects. Some countries and regions have already taken measures to reduce the ecological costs of AI. In the European Union, the EcoDesign Directive [145] has been updated since March 2020 to cover servers and data storage devices. This regulation establishes minimum energy efficiency standards for these products, including those used in AI hardware. Its aim is to cut energy consumption and decrease the environmental impact of data centers and other AI infrastructure components.

In conjunction with the EcoDesign Directive, the Waste Electrical and Electronic Equipment (WEEE) Directive assumes a pivotal role in the sustainable management of electronic waste, inclusive of AI hardware components. The WEEE Directive provides guidelines for the appropriate management and disposal of electronic waste, ensuring that discarded AI technologies are handled in an environmentally sustainable manner. The responsibilities for the collection and recycling of e-waste are designated to producers and consumers, thereby promoting the circular economy and mitigating the environmental impact associated with the disposal of AI hardware [146]. As part of the review of the WEEE Directive, a public consultation was scheduled for June 2023 to solicit feedback regarding its efficacy and potential enhancements. Furthermore, the European Union has promulgated Regulation [147] pertaining to eco-design standards for servers and data storage equipment, aimed at reducing energy consumption and diminishing the environmental footprint of data centers and other AI infrastructure components [147] [148]. Through the adoption of energy efficiency standards and the promotion of responsible e-waste management, the EU endeavors to cultivate a more sustainable and environmentally conscious approach to AI development deployment. Using digital and smart technologies like AI, IoT, ML and advanced

sensor applications in agriculture, carbon emissions can be reduced by saving water, fertilizer, pesticides, and fuel. Using advanced and smart technologies and process, harvest storage and transportation losses can be meaningfully reduced. Additionally, noteworthy efficiency can be attained in livestock and aquaculture production with the use of new methods and technologies like AI and other smart technology [149] [150].

## 11. Conclusion

The modern development of AI signifies not just a technological revolution, but also marks the beginning of a new ecological era, where both natural and artificial intelligence become the primary tools for preserving the planet. AI, integrated into the ecological system, can analyze and predict processes as well as shape a new way of thinking, combining scientific rationality with ethics of sustainability and respect for the biosphere. Today, AI is increasingly central to the transition toward sustainable development. Its potential lies in its ability to see the world as a connected network of systems, where every mistake has global consequences and every decision can influence the environment's future. The domain of AI is a vast and expanding frontier, with the potential to revolutionize industries across the board. The possibility of using this technology to protect the world's natural resources is particularly exciting. Although the environment is not an industry, it forms the foundation for human life. Therefore, it has become a top priority for governments worldwide to safeguard it for future generations. As we strive for a more sustainable future, the importance of AI in environmental conservation becomes ever more evident. AI technologies and algorithms are continually advancing to monitor pollution, lessen energy use, and better understand the complex effects of climate change. Governments worldwide can recognize AI's potential to protect the environment and incorporate it into their policies and programs. With its ability to rapidly gather, analyze large data sets, and learn to adapt, AI is a valuable tool against pollution and climate challenges. Today, combining AI with IoT, or smart technology, can boost environmental sustainability in innovative ways. Connecting devices, sensors, and machines to the internet lets us gather vast data for real-time analysis and action.

Using AI's capabilities with IoT connectivity helps reduce carbon footprints, improve air and water quality, and safeguard natural habitats. Currently, AI actively supports sustainability efforts, from evaluating its own carbon footprint to advancing conservation initiatives. As reliance on technology grows, it's vital we harness AI and ML for the benefit of our planet and future generations inhabitants. In recent years, the merging of artificial intelligence (AI) and environmental science has become a promising area for tackling urgent global issues related to sustainability and environmental management. As the world faces complex challenges such as climate change, biodiversity loss, pollution, and resource depletion, there's increasing awareness of the need for innovative methods that utilize AI to better understand the environment and develop effective solutions. This interdis-

disciplinary approach combines the strengths of two fields: AI, capable of analyzing large datasets, spotting patterns, and making predictions, and environmental science, which offers deep knowledge of natural systems and processes. By applying AI techniques like machine learning, data mining, and predictive modeling within environmental research, scientists are gaining valuable insights into ecological dynamics, environmental risks, and mitigation strategies. A holistic approach is essential for ensuring AI systems' sustainability. This might involve adopting various sustainability criteria and using an indicator-based method, which offers a practical way to implement sustainable AI practices. Nonetheless, this assessment highlights significant challenges that need tackling to promote sustainability in AI development, research, and policy. It underscores the importance of regulations and industry standards to guide sustainable practices, such as mandatory reporting and embedding sustainability into policies, standards, and certification schemes. Addressing all sustainability aspects can help steer AI's growing impact toward societal and environmental benefits. Additionally, ongoing research and reflection are needed to better understand the complex, interconnected impacts of AI systems, which are socio-technical-ecological entities. Achieving a thorough sustainability assessment requires understanding these interdependencies and engaging in societal negotiations to balance the inherent trade-offs.

The idea that technology could be harnessed to improve our globe was once just a dream, but with the advent of AI, it has become a tangible reality. Green AI is more than a sustainable technology and it's a mindset change. It challenges us to build smarter, safer, cleaner, and more responsible AI systems that drive progress without damaging the planet. By putting sustainability at the heart of AI development, we move toward a future where innovation and environmental care go hand in hand. Considering the hidden ecological costs of AI reveals the importance of addressing its environmental impacts. The energy needed for AI computations, electronic waste, disruption of ecosystems, and potential biased decisions highlight the need for proactive measures. Embracing sustainable practices like energy-efficient algorithms, renewable energy, responsible e-waste management, and ethical standards can foster a more environmentally friendly integration of AI. It is everyone's responsibility to ensure AI benefits both humanity and the planet. By prioritizing environmental sustainability and taking steps to reduce AI's ecological footprint, we can develop a future that leverages AI's strengths while conserving natural resources. Through collaboration, research, and policy development, we can steer AI's evolution toward sustainability and ethical responsibility. There is an urgent need for regulations and industry standards to steer sustainable AI practices. A key challenge is the absence of comprehensive data and documentation during AI development and deployment, often due to limited awareness in AI communities and organizational limitations. Having some sustainability criteria provides a useful resource for companies working on AI, raising awareness of wider sustainability effects. Policy initiatives, standards, and certification programs are increasingly integrating sustainability factors, emphasize-

ing the importance of adopting new practices and enforcing mandatory reporting. Effective policy strategies should cover all sustainability aspects to ensure AI systems' growing influence benefits society and the environment.

## Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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