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ARTIFICIAL INTELLIGENCE AND BIODIVERSITY

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Abstract

Biodiversity is essential for ecosystem balance, yet it faces growing threats from human activities and climate change. To address these challenges, Artificial Intelligence (AI) is emerging as a powerful tool for promoting biodiversity conservation and sustainable practices. This article examines how AI technologies are being combined with the Internet of Things to improve the identification of species in danger, protect habitats, and optimize resource management. It also explores real-world applications of AI in areas such as wildlife protection, environmental monitoring, and precision agriculture, with a focus on the shift from traditional farming methods to more sustainable and regenerative approaches in Agriculture 3.0 to 5.0. The article also highlights obstacles such as limited accessibility for smaller organizations. Overall, this work underscores the growing impact of AI in fostering ecological preservation and advancing sustainability efforts.

Keywords

Biodiversity, Sustainability, Artificial Intelligence, Machine Learning, Deep Learning, Internet of Things, Agriculture 5.0

1. *Introduction: Biodiversity*

Biodiversity, the variety of life on Earth, is essential for keeping ecosystems in balance and supporting human survival. However, protecting it has become increasingly challenging. In recent years, Artificial Intelligence (AI) has proven to be a game-changer, offering innovative ways to address these challenges.

AI's ability to analyze massive datasets and uncover hidden patterns makes it an invaluable tool for biodiversity conservation. From monitoring ecosystems to finding new solutions for preserving species, AI can make a difference.

This article takes a closer look at how AI is helping to protect biodiversity, focusing on both the scientific breakthroughs and practical applications that are shaping the future of conservation.

Following this introduction, Section 2 provides a simple overview of some aspects of AI. Section 3 reviews the current scientific literature to explore how researchers are leveraging AI to address biodiversity-related challenges. It then focuses on commercial AI systems specifically designed for biodiversity applications, highlighting their innovative features and real-world impact. Section 4 discusses policy initiatives related to biodiversity and sustainability. The article concludes by reflecting on the broader implications of these advancements, as well as the opportunities and challenges of integrating AI into biodiversity initiatives.

Through this exploration, we aim to provide a comprehensive overview of the intersection between AI and biodiversity, emphasizing the importance of leveraging technological innovation to ensure a sustainable future for all life on Earth.

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1.1 Biodiversity and sustainability

Biodiversity, or biological diversity, is a term coined in 1988 to describe the richness and variety of life on Earth. It encompasses the millions of species of plants, animals, and microorganisms, the genetic material they contain, and the intricate ecosystems they create within the biosphere. This incredible diversity plays a vital role in maintaining the delicate balance of our planet, performing essential functions such as climate regulation (especially through CO_2 absorption), air and water purification, and the production of food and other critical resources.

Biodiversity forms the foundation of life as we know it, creating an equilibrium that is both fundamental and fragile. However, this equilibrium has been severely disrupted in recent decades due to unsustainable activities. Deforestation, pollution, and probably anthropogenic climate changes are among the primary culprits that have led to a significant reduction in biological diversity.

To counter these alarming trends, sustainability has emerged as the key approach to preserving biodiversity and ensuring a healthy, thriving environment for current and future generations. Sustainable actions include reducing pollution, conserving natural resources, adopting responsible agricultural and industrial practices, and protecting ecosystems from further degradation.

The preservation of biodiversity is not merely an environmental concern; it is an essential strategy for maintaining the resilience of our planet and the well-being of humanity. By fostering sustainable practices, we can work towards a more balanced relationship with nature, safeguarding the rich tapestry of life that supports us all.

2. *What is Artificial Intelligence?*

AI can be broadly defined as the simulation of human intelligence in machines. It enables them to perform tasks that require cognitive skills comparable to those of humans, such as learning, reasoning, and problem-solving. In recent years, AI has emerged as a powerful tool in various fields, including the preservation and safeguarding of biodiversity. By leveraging advanced technologies like data analysis, machine learning algorithms, sensors, drones, and intelligent devices, AI offers innovative solutions to address pressing environmental challenges.

AI processes data through sophisticated algorithms to deliver valuable outputs such as diagnostics, detailed insights, alerts, and recommendations. Moreover, it facilitates automated actions that optimize and accelerate interventions. These capabilities are particularly critical for biodiversity preservation, where timely and data-driven decision-making can make a significant difference in mitigating threats to ecosystems and species.

By harnessing the power of AI, it becomes possible to not only monitor and analyze environmental changes but also to implement proactive strategies for conservation. This technological approach offers the potential to enhance our understanding of complex ecological systems and to act with greater precision and effectiveness in protecting the natural world.

2.1 Different types of Artificial Intelligence

AI encompasses various approaches and techniques, each suited for specific applications and challenges. Among the most notable are Machine Learning (ML), Deep Learning (DL), and Generative AI (GAI). These diverse AI technologies provide the foundation for transformative tools and strategies that can be applied to complex environmental and biodiversity challenges, paving the way for more efficient, innovative, and impactful solutions.

2.2 Machine Learning and Deep Learning

ML involves creating models that learn from data to make predictions or decisions by identifying patterns within datasets. These models rely on algorithms such as artificial neural networks or binary decision trees and require measurable or calculated variables that act as "discriminators" (referred to as "features"). By analyzing these features, ML models can make informed decisions, demonstrating their adaptability to changing inputs without requiring explicit instructions.

In ML, the task of identifying relevant features from data, such as images, relies heavily on the expertise of the programmer, usually supported by a domain expert. The programmer must determine which specific measurements or characteristics should be extracted from the images to enable accurate classification of the object depicted. For instance, when classifying a diseased leaf or an insect, the programmer might define features such as texture, color, or shape to differentiate one category from another. This process, known as feature engineering, requires a deep understanding of both the domain and the dataset to ensure the selected features effectively capture the variability needed for classification.

DL is a subset of ML, distinguished by its ability to identify discriminative features automatically, eliminating the need for preliminary calculations. Through iterative training, the system learns to discern which patterns or characteristics in the dataset are most useful for distinguishing one class from another, such as identifying whether a leaf is healthy or diseased. These automatically determined features, often referred to as learned features, emerge from the hierarchical structure of DL models, such as neural networks, which progressively refine their understanding of the data from low-level patterns to high-level concepts. This shift from manual to automated feature extraction represents one of the key advantages of DL, enabling it to excel in tasks involving complex data like images, audio, and video, where identifying the optimal features is challenging or even infeasible for human programmers. These capabilities make DL essential for analyzing biodiversity data, where insights often depend on interpreting visual or complex ecological patterns.

ML and DL share a common foundation in "supervised learning", where models are trained on labeled datasets. In this approach, the algorithm learns to map inputs to desired outputs (classes or categories) by minimizing errors during training. In this way, ML/DL systems become able to make predictions or classifications about new, unseen data. For example, in image classification, both ML/DL systems are provided with labeled images and iteratively adjust their internal parameters to correctly identify categories. At the heart of this process lies the classifier, a key component of the ML/DL system that is responsible for distinguishing between different categories within the data.

The classifier achieves this by calculating the placement of decision boundaries—imaginary lines that divide the data space into distinct regions based on the characteristics of the labeled examples provided during training (the "learning set"). Each point in the dataset corresponds to a specific example, such as a flower with features such as petal length or sepal width. By analyzing these features, the classifier determines the optimal separation boundaries to distinguish between categories (e.g., different flower species).

Once these boundaries are established, the ML system can classify new, unlabeled data by identifying the region of the data space in which it falls. For instance, when presented with a new flower, the classifier evaluates its position on the graph relative to the decision boundaries and assigns it to the most likely category. While this process is highly effective, it is not infallible and operates within a margin of error, particularly when data points are ambiguous or overlap between categories.

This foundational concept of supervised ML is widely applicable, from recognizing handwritten digits to identifying patterns in biodiversity datasets, enabling actionable insights and informed decision-making across numerous domains.

2.3 Generative AI and Large Language Models

GAI focuses on creating new content based on its knowledge base and contextual understanding. Unlike traditional predictive models, GAI produces entirely new outputs, such as images, text, or music. Well-known examples include Large Language Models (LLM), which can generate coherent and contextually relevant text responses to questions. These models are increasingly being applied in creative fields, scientific research, and environmental monitoring, offering innovative solutions to generate actionable insights or creative content.

LLMs are specifically designed to "understand" and generate natural language. These models have become indispensable tools for handling tasks related to natural language processing, such as summarizing content, translating text, and generating human-like textual responses.

The training process for LLMs involves analyzing vast quantities of text data from diverse sources, including books, websites, and journal articles. This extensive exposure allows the models to learn the structure, patterns, and nuances of language. The core mechanism behind their functionality lies in their ability to predict the next word in a sentence based on the context of the preceding words, enabling them to produce coherent and contextually appropriate outputs.

One notable example of an LLM is GPT (*Generative Pre-trained Transformer*), which has gained recognition for its ability to generate text that closely resembles human communication. ChatGPT, a popular chatbot application, is built on the GPT framework and demonstrates the practical utility of LLMs in creating conversational agents capable of engaging in realistic and meaningful interactions.

These capabilities make LLMs powerful tools for a range of applications, from simplifying complex information to providing language-based

Fig. 1: Data integration from various sensors or locations helps gain deeper ecological insights. Image courtesy of the U.S. Geological Survey, also in Tuia, Kellenberger, Beery, et al. (2022).

support in fields such as education, customer service, and environmental monitoring. Their ability to process and generate language effectively holds significant potential for advancing solutions in biodiversity conservation and beyond.

3. How can AI support biodiversity preservation?

AI holds great potential for enhancing biodiversity conservation by addressing critical challenges in monitoring, decision-making, and intervention. By leveraging advanced tools such as sensors and Internet of Things (IoT) connectivity, AI can collect and interpret extensive data on endangered species, habitats, and meteorological conditions. This capability enables informed and timely responses to threats to biodiversity.

One important application of AI is in the recognition of animal and plant species. Sensors deployed in natural environments—such as video cameras or audio recognition devices—use AI to monitor at-risk species. This technology plays a significant role in protecting biodiversity by helping prevent deforestation and the extinction of vulnerable species.

AI also assists in the development of projects aimed at improving environmental efficiency. For instance, it can help design strategies to enhance energy efficiency, reduce greenhouse gas emissions, and combat plastic pollution.

Moreover, AI can optimize production processes by improving waste management systems and, more broadly, reducing the human impact on ecosystems. By addressing these challenges, AI offers transformative solutions for sustainable biodiversity preservation and the protection of our planet's natural resources.

The role of IoT in biodiversity and environmental protection is fundamental. IoT represents a network of interconnected physical devices and machinery equipped with sensors, enabling seamless communication between devices, computers, and users via the Internet. This technology, integrated with satellites and Unmanned Aerial Vehicles (UAV), facilitates continuous remote monitoring and control of animal health, soil productivity, and pathogen spread, unlocking numerous possibilities across various sectors, including agriculture and environmental conservation (Figure 1). These insights are essential for proactive biodiversity protection, ensuring early detection of ecological imbalances and enabling targeted interventions.

In agriculture, IoT plays a critical role in fostering sustainability. Sensors can monitor soil quality, optimize water usage, and track crop health, leading to more efficient resource management and reduced environmental impact. By bridging real-time data collection with decision-making processes, IoT contributes significantly to the reduction of human-induced environmental pressures.

When combined with Artificial Intelligence, IoT becomes even more powerful. The data collected through IoT sensors can be analyzed by AI algorithms to generate actionable insights, such as identifying endangered species' habitats, predicting climate impacts, or suggesting sustainable farming practices. This synergy between IoT and AI marks a pivotal step toward more intelligent, data-driven biodiversity conservation strategies.

3.1 AI for Biodiversity: insights from scientific literature

The intersection of AI and biodiversity has become a thriving area of research, with a growing body of scientific literature exploring how advanced technologies can contribute to the preservation and restoration of ecosystems. AI has proven to be a valuable ally in addressing the complex challenges of biodiversity conservation, offering tools that enable data collection, analysis, and intervention at unprecedented scales.

Scientific studies highlight the application of ML and DL techniques in various biodiversity-related tasks. These include species recognition through image and sound analysis, predicting habitat loss, and monitoring changes in ecosystems over time. Research has also demonstrated how AI-powered systems can analyze vast datasets to detect patterns and trends, providing critical insights into species behavior, migration, and the impact of human activities on natural environments.

Moreover, AI has been employed to support conservation strategies by creating predictive models that inform policy decisions. For instance, models trained on environmental and climate data can forecast the spread of invasive species or identify areas most vulnerable to habitat destruction. Such applications underline the importance of leveraging AI to develop proactive measures for biodiversity preservation.

In addition, studies emphasize the role of AI in enhancing collaboration among researchers and practitioners. Platforms that integrate AI tools facilitate data sharing and joint analysis, fostering a multidisciplinary approach to solving biodiversity challenges. The literature thus underscores the transformative potential of AI in making conservation efforts more effective and scalable. By synthesizing findings from this extensive body of work, AI offers a powerful toolkit for understanding and protecting the natural world. The continued exploration of AI applications in biodiversity conservation remains a vital area of research, poised to address the pressing environmental challenges of our time.

In August, Pescott, Joly, et al. (2020), the authors examine the application of newly developed AI image classifiers to large social media image datasets, evaluating their potential for generating new biodiversity observation datasets. They analyze biases present both in the image datasets and in the performance of AI classifiers in making accurate identifications. Additionally, the authors propose a checklist of key considerations for researchers contemplating this approach to data generation. A related topic is discussed in Roy, Alison, August, et al. (2024), where the authors present a framework for automated, image-based monitoring of nocturnal insects, emphasizing the potential of sensor technologies to standardize and expand insect monitoring on a global scale (Figure 2). The system includes sensors that attract insects with light, a camera for image capture, and a computer for data scheduling, storage, and processing. The authors discuss the importance of metadata to balance ecological data capture with power and storage limitations. Given the large volumes of data generated, the paper outlines scalable computer vision methods for detecting, tracking, and classifying insects, emphasizing the need to address biases in species occurrence and abundance estimates. The authors propose ten priorities to advance automated insect monitoring, recognizing its critical role in combating biodiversity loss caused by global environmental threats.

In Silvestro, Goria, Sterner, et al. (2022), the authors address the critical challenge of biodiversity conservation amidst the alarming threat of extinction faced by over a million species. They introduce “Conservation Area Prioritization Through Artificial Intelligence” (CAPTAIN), a novel framework leveraging reinforcement learning to optimize spatial conservation prioritization (Figure 3). CAPTAIN demonstrates superior performance compared to state-of-the-art conservation software, using both simulated and

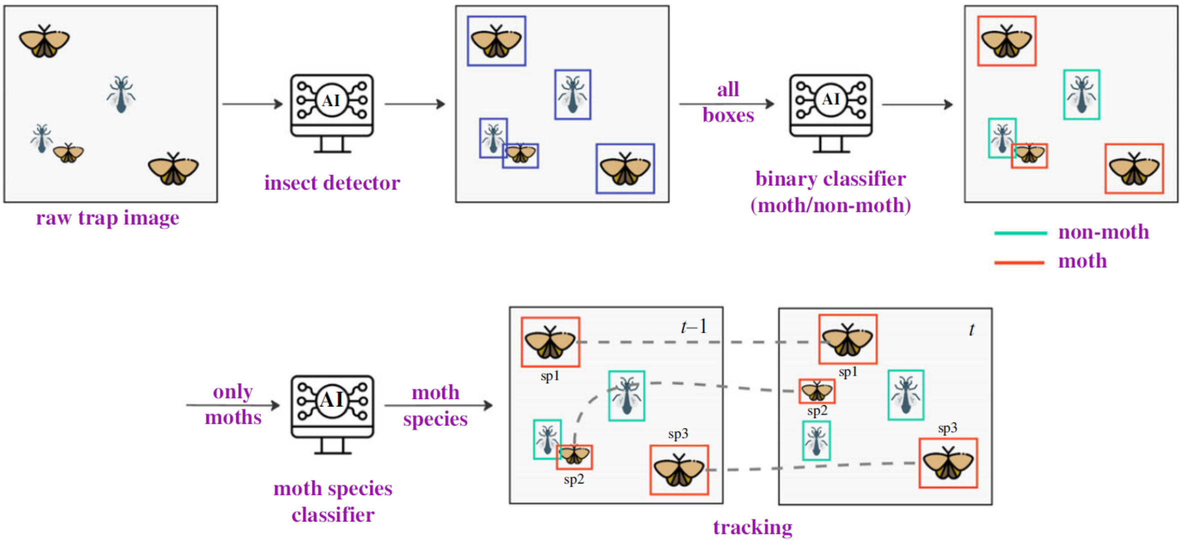

Fig. 2: Machine learning workflow to analyse moth camera trap data (Roy et al. 2024). License: http://creativecommons.org/licenses/by/4.0/).

empirical data. The methodology evaluates trade-offs between costs and biodiversity protection benefits, incorporates multiple biodiversity metrics, and delivers significantly better outcomes under budget constraints. The framework reliably meets conservation targets, protects more species from extinction, and generates interpretable prioritization maps. The study underscores AI's transformative potential in supporting sustainable ecosystem management in resource-limited and rapidly changing environments.

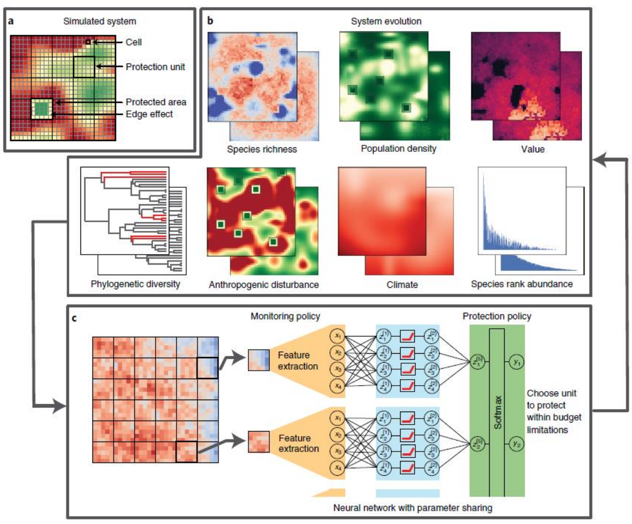

Fig. 3: The CAPTAIN reinforcement learning framework. For details see Silvestro et al. (2022). License: http://creativecommons.org/licenses/by/4.0/.

The work by Tuia, Kellenberger, Beery, et al. (2022) explores the growing potential of inexpensive and accessible sensors in accelerating data acquisition in animal ecology. While these technologies enable large-scale ecological studies, they highlight the limitations of current processing methods, which fail to efficiently transform data into actionable insights. The authors propose that animal ecologists can leverage large datasets generated by modern sensors by integrating ML techniques with domain-specific knowledge. This integration could enhance ecological models and contribute to the development of hybrid modeling tools. The paper emphasizes the need for interdisciplinary collaboration to ensure the quality of new approaches and the training of a new generation of data scientists in ecology and conservation.

In Mo, Zohner, Reich, et al. (2023), the authors assess the global carbon storage potential of forests by combining ground-sourced data with satellite-derived approaches. They highlight the significant role of forests as carbon sinks, noting that anthropogenic land use and climate change have reduced their capacity. The study finds a 12% difference between ground-based and satellite estimates of global forest carbon, indicating consistency in predictions despite regional variations. The results show that current global forest carbon storage is significantly below its

Fig. 4: Sampling devices to test soundscapes and metabarcoding for monitoring of restoration success in tropical forests; left: sound recorder, right: light trap. From Müller et al. (2023), partial figure, license: http://creativecommons.org/licenses/by/4.0/).

natural potential, with a deficit of 226 Gt (ranging from 151–363 Gt). Most of this carbon potential (61%, or 139 Gt) is in areas with existing forests, where ecosystem protection could allow for recovery. The remaining 39% (87 Gt) is found in areas where forests have been cleared or fragmented. While forests cannot fully replace emission reductions, the authors argue that the conservation, restoration, and sustainable management of forests are crucial for meeting global climate and biodiversity targets.

The paper by Delavaux, Crowther, Zohner, et al. (2023), investigates the drivers of non-native tree invasions using global tree databases. The authors explore how factors such as the phylogenetic and functional diversity of native tree communities, human pressure, and environmental conditions influence the establishment and severity of these invasions. The study finds that anthropogenic factors are crucial in predicting whether a location will be invaded, while native diversity plays a key role in determining invasion severity, with higher diversity leading to lower severity. Temperature and precipitation are identified as strong predictors of invasion strategies, with non-native species thriving in areas with cold or dry extremes, like the native community. However, the authors also observe that human activities, particularly proximity to shipping ports, can obscure ecological patterns, highlighting the complex interplay between human drivers and ecological forces in shaping tree invasions.

In Ma, Crowther, Mo, et al. (2023), the authors investigate the global variation in tree leaf types and the factors influencing this variation, which are crucial for understanding their role in ecosystem functions like carbon, water, and nutrient dynamics. Using ground-sourced forest inventory data, they assess the global distribution of needle-leaved, broadleaved, evergreen, and deciduous trees. The study finds that leaf habit is mainly driven by isothermality and soil characteristics, while leaf form is influenced by temperature. The authors estimate that 38% of global tree individuals are needle-leaved evergreen, 29% are broadleaved evergreen, 27% are broadleaved deciduous, and 5% are needle-leaved deciduous. Additionally, the paper projects that, depending on future emissions pathways, up to 34% of forested areas may experience climate conditions that could alter their current forest types. The findings provide valuable insights into the distribution of tree leaf types and biomass, with implications for understanding future ecosystem functioning and carbon cycling under climate change.

The paper by Müller, Mitesser, Schaefer, et al. (2023) explores tropical forest recovery in Ecuador, focusing on both biodiversity and carbon sequestration. The authors use bioacoustics and metabarcoding (a technique employed to identify multiple species within a mixed sample of DNA) to assess forest recovery after agricultural use (see Figure 4). The study demonstrates that community composition of vocalizing vertebrates, rather than species richness, best reflects the restoration gradient. Two automated measures (the acoustic index model and bird community composition derived from a Convolutional Neural Network) show strong correlations with restoration progress. Notably, both measures also align with the composition of non-vocalizing nocturnal insects identified through metabarcoding. The authors argue that these new technologies, including automated monitoring tools, can provide reliable and reproducible data to effectively track forest recovery success.

In Ullah, Saqib, & Xiong (2024), the authors study the transformative role of AI in enhancing traditional biodiversity conservation methods, which are often limited by scaling challenges and outdated data. The study examines the growing use of AI technologies, such as ML and data analytics, in improving species identification, habitat monitoring, and threat assessment with greater precision and efficiency. Through case studies, the authors highlight successful applications of AI in areas like data management, predictive modeling, and resource allocation. The findings emphasize the importance of combining traditional conservation techniques with modern AI approaches to create more resilient and effective conservation solutions. The paper also discusses the potential implications for future research and the practical integration of AI in conservation efforts, suggesting that such synergy can enhance both scientific outcomes and conservation practices.

Chatbots have been the focus of numerous studies, which explore both the potential benefits and the challenges, including biases, of LLMs. Here are some examples.

In Haghighi, Saqalaksari, Johnson (2023), the authors examine the potential of AI, particularly ChatGPT by OpenAI, to transform ecological research and education. The paper discusses the use of AI-driven chatbot services in ecology education, academic writing, and research, highlighting both the opportunities and challenges associated with these technologies. AI can significantly reduce the workload of researchers, generate new insights, and assist students in learning, but it also presents several limitations. These include AI's inability to fully capture the complexity of ecological systems, its reliance on high-quality data, and the ethical concerns of using AI in research. Additionally, the environmental impact of AI technologies, including the construction and operation of such services, is addressed, with both potential negative and positive outcomes. The authors emphasize that while AI, particularly AI chatbots, can be a valuable tool in ecological research by automating tasks and analyzing large datasets, it is crucial to adopt a responsible, sustainable, and transparent approach. Ethical considerations, as well as the environmental and societal implications, should be carefully evaluated to ensure that AI contributes positively to the field of ecology.

The research by Manik, Rini, Priyanti, et al. (2024) examines the factors influencing the adoption of *Chatsicum*, a Knowledge-Based Chatbot (KBC) designed to enhance species literacy for biodiversity students (Figure 5). The study aims to bridge the gap between technology, education, and biodiversity conservation by providing innovative solutions to empower individuals with species knowledge for natural world preservation. Using a quantitative approach and Partial Least Square Structural Equation Modeling (PLS-SEM), the study analyzed responses from 145 university students. The research model combined the Task-Technology Fit (TTF) framework and elements from the Diffusion of Innovation (DOI), such as relative advantage, compatibility, complexity, and observability, while introducing perceived trust as a variable. The study found that TTF influenced all DOI factors positively, except for complexity, which had a negative impact. While TTF significantly affected usage intention indirectly, compatibility and trust were found to strongly influence the intention to use the KBC. The findings provide insights for developers, educators, and policymakers in enhancing biodiversity education. It is recommended that developers prioritize KBCs aligned with user needs and build trust through accurate information. Educators should design interventions that cater to diverse learner preferences, and conservation organizations can use these findings to improve outreach efforts. Future research should delve deeper into the relationships between TTF, DOI, and trust, exploring mediating and moderating variables. Longitudinal studies could examine the evolving user behavior and investigate how species literacy, augmented by chatbots, impacts real-world conservation actions.

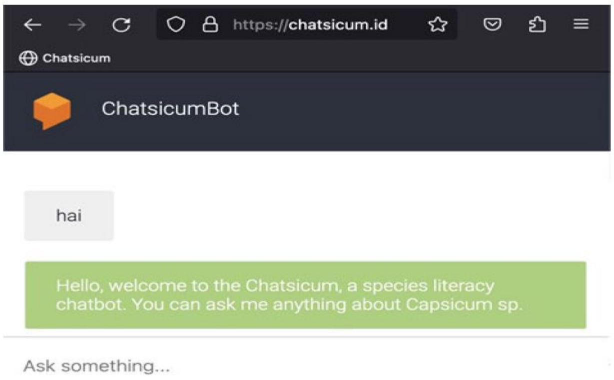

Fig. 5: Chatsicum user interface

Urzedo, Sworna, Hoskins, et al. (2024) examine the impact of AI-driven language models, such as chatbots, on ecological restoration and conservation efforts, focusing on the potential biases in chatbot-generated content. By analyzing 30,000 responses from ChatGPT on topics related to ecological restoration expertise, stakeholder engagement, and techniques, the study reveals a heavy reliance on expertise from male academics in the United States, while significantly underrepresenting knowledge from low- and lower-middle-income countries (7%) and Indigenous communities (2%). The responses predominantly emphasize reforestation techniques (69%) and optimistic environmental outcomes (60%), while neglecting broader, holistic approaches that involve non-forest ecosystems (25%) and non-tree species (8%). The findings highlight how AI-driven content creation can reinforce Western-centric scientific perspectives and exclude diverse sources of ecological knowledge. The paper calls for the integration of more inclusive and just principles in the development of generative AI tools to address the global environmental crisis more equitably. In a recent paper (Sworna, Urzedo, Hoskins et al., 2024), the same group delves deeper into the ethical concerns surrounding the use of AI-driven chatbots, such as ChatGPT, in the context of conservation research and practices. The study examines the sources, biases, and representation of conservation evidence generated by two versions of ChatGPT, GPT-3.5-turbo and GPT-4, analyzing 40,000 responses related to ecological restoration. The findings reveal that while these AI models are improving the inclusion of diverse data sources and enhancing the accuracy of responses, they still exhibit significant ethical issues. The chatbots predominantly rely on evidence from high-income countries (88%), North American experts (67%), and male academics (46%), with minimal input from minority groups, Indigenous organizations (10%), and low-income countries (2%) (Figure 6). The paper emphasizes the need for human-centered negotiations to ensure fair representation and the equitable inclusion of diverse expertise and knowledge in the development and use of AI tools like chatbots.

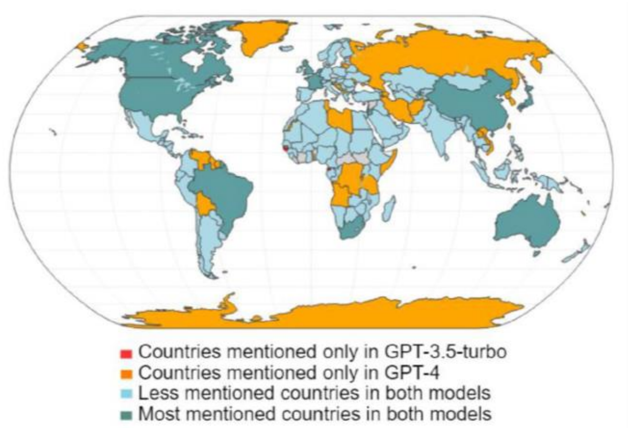

Fig. 6: Comparison of countries mentioned by GPT-3.5-turbo and GPT-4 model. Although the inclusion of more different countries is observed in GPT-4 model, both GPT models heavily rely on narrow expertise from the global north (from Sworda, et al. 2024). License: http://creativecommons.org/licenses/by/4.0/.

The literature also includes a few review papers.

The article by Nti, Cobbina, Attafuah, et al. (2022) is a systematic review in which the authors highlight the growing significance of AI in addressing environmental sustainability challenges, including biodiversity, energy, transportation, and water management. They discuss the development of machine learning and natural language processing solutions for predicting ecosystem services in biodiversity research. AI models are also explored for their role in predicting and optimizing water resource conservation. The review emphasizes key focus areas such as neural networks, expert systems, pattern recognition, and fuzzy logic in energy, while applications of computer vision and decision support systems are noted in transportation. The authors underline the importance of timely monitoring of interventions to enhance environmental sustainability.

The review by Shivaprakash, Swami, Mysorekar, et al. (2022) examines the recent advancements in data science and digital technology, particularly satellite technology, which have enhanced the potential for AI applications in the forestry and wildlife sectors. They focus on India, which shares 7% of the global forest cover and is the eighth most biodiverse region in the world. Despite this, the country's biodiversity is threatened by rapid urbanization, agricultural expansion, and developmental projects. The authors highlight how AI adoption in India's forest and biodiversity sectors could support effective monitoring, management, and conservation. A systematic literature review of AI applications in forestry and biodiversity conservation globally, including within India, is presented. The authors also explore the rise of AI-based startups and non-profits in these sectors, revealing slow adoption in India compared to developed and other developing nations. They identify challenges to AI adoption in India but emphasize that improvements in data access, cloud computing, and satellite technology could accelerate AI integration for forest management and biodiversity conservation. The paper aims to encourage Indian officials, scientists, and conservationists to adopt AI technologies for sustainable resource management.

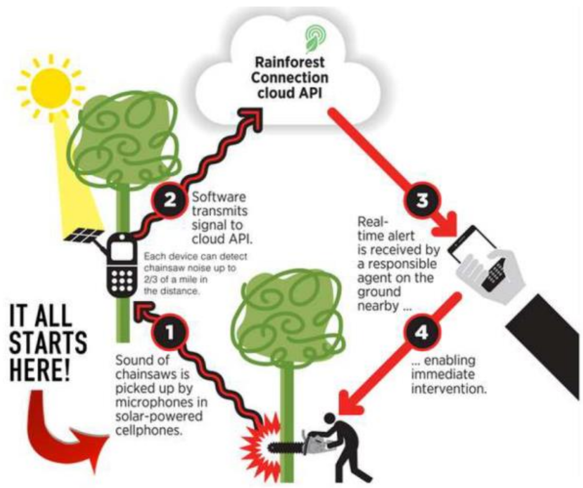

Fig. 7: Unauthorized loggers are detected and monitored using old mobile devices (Raihan, 2023), license: ttp://creativecommons.org/licenses/by/4.0/.

Raihan (2023) explores the recent advancements in data science, as well as the evolution of digital and satellite technology, which have significantly increased the potential for AI applications in forestry and wildlife conservation. The paper highlights the global threat to biodiversity posed by the rapid expansion of developmental projects, agriculture, and urban areas. The author argues that the integration of emerging technologies like AI can help in the efficient monitoring, management, and preservation of biodiversity and forest resources (Figure 7). A comprehensive review is provided on the use of AI algorithms in the forestry sector and biodiversity conservation worldwide. The research also examines the challenges faced when implementing AI in these fields. The paper suggests that improving access to large-scale data on forests and biodiversity, along with the use of cloud computing and satellite technology, can promote broader AI adoption. The author hopes that the findings will inspire forest officials, scientists, researchers, and conservationists to explore the potential of AI for sustainable forest management and biodiversity conservation.

3.2 AI for biodiversity and sustainability: examples of commercial companies and applications

The integration of AI in biodiversity conservation has not only captured the interest of researchers but also spurred the development of innovative commercial applications. Some of them are described in this section, listed in alphabetical order. Web sites were accessed in December 2024.

Aclima (https://www.aclima.io/), based in California, employs AI to create highly detailed maps of air pollution. Their network of sensor-equipped vehicles gathers real-time air quality data, enabling cities and organizations to make informed decisions that improve public health and environmental quality.

Agreena (https://agreena.com) (Denmark) supports regenerative farming by enabling farmers to sell carbon credits to companies seeking to offset emissions. This incentivizes sustainable agricultural practices, enhancing soil health and contributing to carbon sequestration while creating new revenue streams for farmers.

Agricolus (Italy) provides a comprehensive platform to optimize agricultural practices through AI-driven insights (https://www.agricolus.com). This system assists farmers in reducing their use of pesticides and fertilizers while maximizing crop yields. Agricolus integrates data from soil sensors, weather forecasts, and satellite imagery to offer actionable recommendations for resource-efficient farming. The platform not only boosts productivity but also minimizes environmental harm, contributing to sustainable food production.

Algapelago (https://www.algapelago.com/, UK*)* operates large-scale offshore kelp farms to capture CO2, enhance ocean biodiversity, and improve soil health. Already the UK's largest kelp cultivator, the company plans significant expansion to scale its environmental impact.

Apicoltura Urbana, an Italian company at the forefront of biodiversity and environmental innovation, exemplifies the practical integration of AI into sustainable practices (https://www.apicolturaurbana.it/). The company's specificities merit a thorough examination. By offering a unique service called "Bees as a Service" (BaaS), Apicoltura Urbana enables businesses and individuals to adopt beehives, with a data-driven approach for biodiversity monitoring and conservation. This innovative model leverages AI to transform traditional methods of ecological tracking into a system based on real-time data. By analyzing the movement of bees, their interactions with the environment, and the pollination process, the company provides unprecedented insights into biodiversity trends, which were previously understood only through theoretical models. Apicoltura Urbana's adoption of AI is central to its mission of addressing the growing challenges faced by pollinators. Advanced ML algorithms are used to identify patterns and detect anomalies related to environmental stressors such as pollution and diseases. This capability empowers businesses and environmental managers to make data-driven decisions about biodiversity conservation and their operational impacts on ecosystems. Key features of the AI-powered system include bee recognition and movement tracking, real-time monitoring and alerts, and combating the varroa parasite. ML algorithms can identify individual bees, track their movement, and analyze the pollen they carry. By categorizing the color of pollen and determining its plant origin, the system provides valuable information about local flora, flowering trends, and overall biodiversity health. The technology allows for the real-time detection of critical issues, such as bee poisoning from agricultural chemicals. By identifying such threats promptly, remote interventions can be initiated, such as restricting access to the hive to protect the colony's health. The Varroa mite, a parasitic threat to bee populations globally since the 1980s, can be controlled using AI: Apicoltura Urbana's system raises hive temperatures in a controlled manner, naturally eliminating the parasite without the need for chemical treatments. This method is not only effective but also promotes sustainable beekeeping practices. The implications of Apicoltura Urbana's approach extend beyond the health of individual hives. By providing tangible data about pollination patterns, plant biodiversity, and ecosystem health, this technology creates actionable insights for enhancing agricultural practices by understanding pollination dynamics, informing policy decisions for biodiversity conservation, and reducing reliance on chemical treatments, supporting organic farming methods. The integration of AI into beekeeping demonstrates a practical pathway for addressing the challenges of biodiversity loss. It bridges cutting-edge technology with age-old natural processes, highlighting how innovation can be a powerful tool in ensuring environmental sustainability. Apicoltura Urbana's work not only protects pollinators but also fosters a broader commitment to preserving ecosystems for future generations.

Blue River Technology, a John Deere company, is based in California. They integrate AI into agriculture to advance sustainable practices (https://www.bluerivertechnology.com). Their AI-powered machinery reduces dependency on pesticides and fertilizers, fostering environmentally friendly crop management.

Boston Consulting Group, based in US and Italy, (https://www.bcg.com/) uses AI to deliver deep insights into multiple aspects of a company's carbon footprint and quick cost-cutting, offering a promising route to accelerating sustainable transformation and reducing expenses.

Carbon Engineering in British Columbia (https://carbonengineering.com/) harnesses AI to enhance carbon capture and removal technologies. Their innovative approach extracts carbon dioxide from the atmosphere, a pivotal step in fighting climate change, with AI optimizing the efficiency of the process.

Conservation Metrics, based in California (https://conservationmetrics.com/), offers automated solutions to replace traditional, labor-intensive wildlife survey methods. By integrating advanced wildlife monitoring technology, remote sensing, robust statistical methods, and scientific expertise, it reduces costs while enhancing the scope and accuracy of wildlife measurements. For example, they apply AI to safeguard marine ecosystems. Their software automates the analysis of underwater footage, helping organizations such as The Nature Conservancy monitor marine life and accelerate conservation efforts.

Descartes Labs (https://descarteslabs.com/), Santa Fe (US), applies AI to interpret satellite images, delivering valuable information on deforestation, land use shifts, and carbon output. Their models support policymakers and conservationists in monitoring and mitigating deforestation, contributing significantly to forest preservation efforts.

Greeniant (https://greeniantold.weebly.com/) is based in The Netherlands. This company employs AI to identify and monitor human activities that negatively impact the environment. These activities include overexploitation of land, pollution, and other harmful practices. The system generates detailed reports and alerts, empowering governments, organizations, and environmentalists to address these issues effectively. By offering precise data, Greeniant plays a crucial role in mitigating environmental damage and promoting sustainable development.

GreenVulcano (Italy) leverages AI to monitor and reduce greenhouse gas emissions in industrial settings (https://www.greenvulcano.com/). By analyzing emissions data, their system identifies areas where energy efficiency can be improved, enabling industries to implement targeted interventions. This technology supports companies in reducing their carbon footprint while adhering to increasingly stringent environmental regulations.

Iceberg Data Lab from France (https://www.icebergdatalab.com) provides environmental analytics for financial institutions to evaluate the biodiversity impact of investments. It also determines whether entities align with global climate goals, including the Paris Agreement, supporting informed decision-making in the financial sector.

Leeana (https://www.leeana.io/) (Germany) helps businesses and financial institutions understand and address their biodiversity impact. The platform offers tools for risk assessment, data management, and mitigation planning, aligning business activities with conservation regulations to foster positive environmental outcomes.

Microsoft leverages artificial intelligence through its *AI for Earth* program to aid global biodiversity conservation. The initiative offers AI tools for ecosystem monitoring and management, empowering data-driven strategies to safeguard the planet's diverse biological heritage.

Nala Earth (https://www.nala.earth/) from Germany provides a platform for businesses to measure, report, and mitigate their biodiversity impact and risks. By analyzing data such as water stress and deforestation, the platform equips companies with tools to comply with biodiversity-related regulations and set impact reduction targets.

Spun out of Oxford University, *Natcap* (UK) (https://www.natcapresearch.com/) offers a platform to assist corporations in meeting nature-related reporting standards. It helps organizations assess and manage dependencies, risks, and impacts on nature, while setting actionable environmental targets.

Pivotal Earth (https://pivotal.earth/, UK) focuses on large-scale biodiversity regeneration by linking commitments to tangible outcomes. Using a detailed species-level biodiversity dataset, it connects gains in biodiversity to financial tools like biodiversity credits and sustainability-linked bonds, encouraging investments in restoration projects.

Focusing on soil biodiversity, *Soilytix* (Germany) monitors bacteria, fungi, and microfauna to help organizations optimize crop yields and measure soil's carbon removal potential (https://soilytix.com/). Currently, it collaborates with supermarkets to assess the regenerative practices of farms in their supply chains.

Single Earth (https://www.single.earth/, Estonia) bridges conservation efforts with financial backing by connecting landowners with investors. The platform allows enterprises to purchase tokens to balance their environmental impact while monitoring projects through digital twins that track carbon sequestration and biodiversity progress.

Stream Ocean (https://www.streamocean.io/) is based in Switzerland. They combine underwater cameras and real-time analytics to monitor the impact of offshore wind farms on marine biodiversity. This technology provides essential data for ensuring the growth of renewable energy projects without harming marine ecosystems.

V7 (https://www.v7labs.com/) is a UK-based startup co-founded by an Italian entrepreneur, which specializes in using AI-driven computer vision to address critical environmental and biodiversity challenges. V7's technology has been successfully applied across diverse scenarios, leveraging advanced AI algorithms to process data from cameras, drones, and satellites. By deploying cameras strategically placed on trees within the Chinko Nature Reserve in Africa, V7's AI system identifies endangered animals. The system processes vast amounts of footage to detect the presence of at-risk species, enabling conservationists to monitor their movements and implement timely protective measures. V7 employs drones equipped with cameras to identify smoke sources in forests. This capability facilitates early detection of potential wildfires, allowing authorities to respond quickly and mitigate damage to ecosystems. Through the analysis of satellite imagery, V7's AI can pinpoint areas affected by flooding or coastal erosion. These insights help environmental organizations and local governments take preventive actions to protect vulnerable ecosystems and nearby communities. In aquaculture settings, V7's underwater cameras and ultrasound imaging systems assess the health of farmed fish populations. The devices detect signs of disease or stress, enabling fish farmers to optimize care and reduce losses while promoting sustainable farming practices. In protected marine areas, V7's AI identifies the presence of plastic and other non-biodegradable waste. By analyzing images from drones and underwater cameras, the system supports clean-up efforts and enhances strategies to combat marine pollution.

Xylem (https://www.xylem.com/) head office is in Washington DC. They use AI to transform water resource management. By monitoring and optimizing water infrastructure, their systems reduce water waste and promote a more sustainable and reliable water supply.

Zulu Ecosystems is based in UK. (https://www.zuluecosystems.com/). This company connects landowners with corporations to implement nature regeneration projects, such as woodland and peatland restoration. The platform facilitates planning and execution to help businesses fulfill ecological commitments effectively.

Several other companies and commercial AI applications exist: the given list of examples is only a glimpse into the world of innovative companies and startups and exemplifies how AI can serve as a powerful ally in the fight for environmental sustainability. The commercial applications of AI systems demonstrate the potential of combining technological innovation with environmental stewardship. These solutions not only address specific conservation challenges but also pave the way for scalable and replicable approaches across different ecosystems. By harnessing the capabilities of AI, companies are contributing to a more sustainable future, where cutting-edge technology supports biodiversity protection on a global scale.

4. *Sustainable agriculture: from Agriculture 4.0 to Agriculture 5.0*

Since biodiversity and sustainability are closely interconnected, it is important in this context to explore how policy initiatives are promoting sustainability in agriculture.

The evolution of agriculture toward sustainability has led to the development of Agriculture 4.0 and Agriculture 5.0 (Fountas, Espejo-García, Kasimati, et al., 2024), marking significant milestones in the transformation of food production (Figure 8). These advancements integrate cutting-edge technologies and practices to enhance efficiency, sustainability, and consumer-centricity in the agricultural sector.

Agriculture 4.0 builds upon the principles of precision agriculture (Agriculture 3.0), which employed digital and information technologies for targeted agronomic interventions. It incorporates IoT, cloud computing, and data connectivity to create a networked, intelligent farming ecosystem. Key enabling technologies include:

- Sensors for real-time data collection on soil, weather, and crop health.
- Drones for monitoring and mapping agricultural land.
- Automation and robotics for planting, harvesting, and maintaining crops.
- AI and data analytics for optimizing production and resource management.

The benefits of Agriculture 4.0 are substantial:

- Increased efficiency in resource utilization.
- Reduced operational costs.
- Improved traceability throughout the agri-food supply chain.
- Enhanced collaboration among stakeholders, from farmers to distributors.

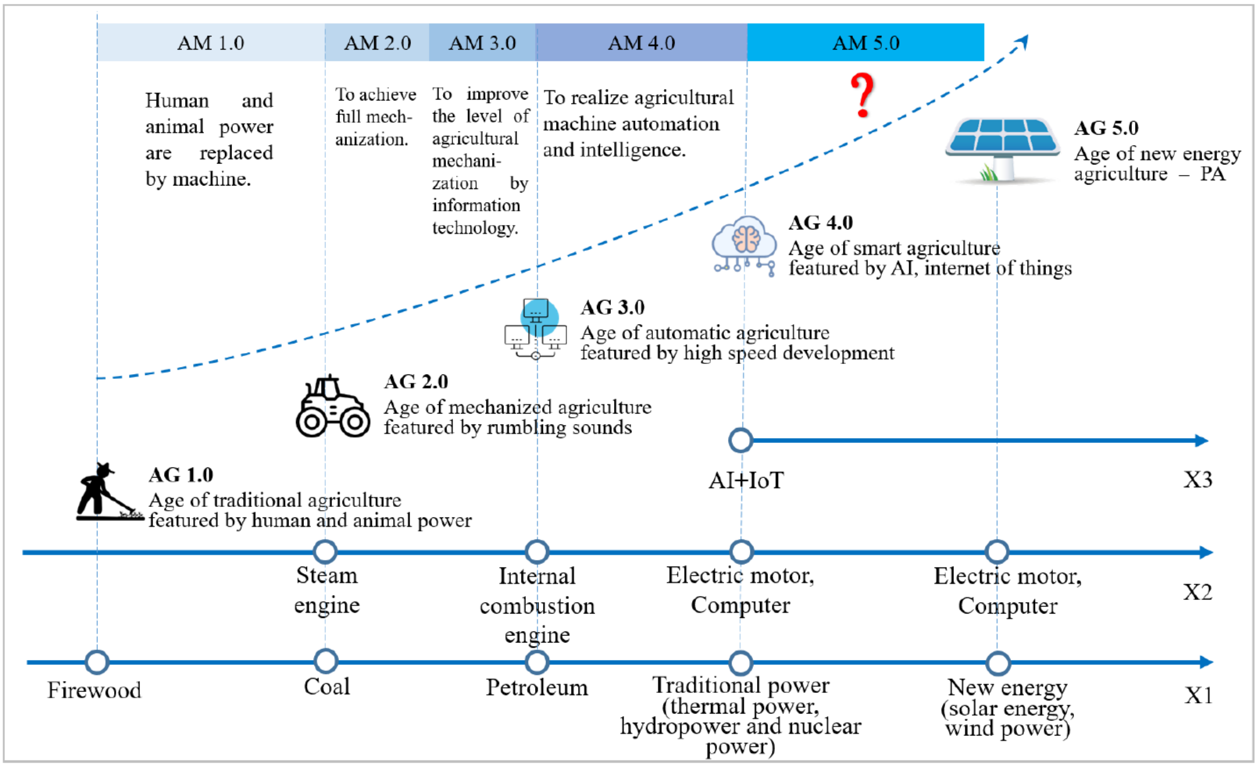

Fig. 8: The trend of agricultural development (AM: Agricultural Mechanization; AG: Agriculture). From Huang et al. (2020), license: http://creativecommons.org/licenses/by/4.0/).

Moving beyond the automation and digitalization of Agriculture 4.0, Agriculture 5.0 introduces a paradigm where human ingenuity is synergized with machine capabilities. This approach emphasizes flexible, personalized, and sustainable agricultural practices.

Core aspects of Agriculture 5.0 include:

- Personalization: Tailoring agricultural products to meet specific consumer needs, focusing on quality and individual preferences.
- Sustainability: Utilizing advanced technologies to minimize environmental impacts by reducing energy consumption, waste, and the use of pesticides and fertilizers. Initiatives include carbon reduction, reforestation, and wastewater reuse, aligning with green and digital transitions.
- Regeneration: Agriculture 5.0 aims not only to protect the environment but also to regenerate ecosystems, restoring degraded land and biodiversity.

In summary, while Agriculture 4.0 emphasizes digital transformation and resource optimization, Agriculture 5.0 goes further by integrating human creativity, AI, and robotics into the agricultural process. This collaboration facilitates sustainable and personalized farming practices, addressing both the demands of modern consumers and the urgent need for environmental stewardship. Together, these innovations represent a critical step toward a more sustainable and regenerative future for global agriculture.

4.1 European and Italian initiatives supporting Agriculture 4.0 and 5.0

The advancement of Agriculture 4.0 and 5.0 is underpinned by significant policy interventions and financial support aimed at driving the green and digital transformation of the agricultural sector. These initiatives not only promote sustainable farming practices but also provide businesses with the tools to achieve environmental and technological goals. Some of the key European policies and strategies are:

- Industry 5.0 Report by the European Union: The "Towards a Sustainable, Human-Centric, and Resilient European

Industry" report (European Commission, 2021) emphasizes the role of industry, including agriculture, in advancing sustainability and human-centered approaches. It highlights the importance of integrating resilience into industrial practices to address environmental and societal challenges.
- The Green Deal: The European Green Deal is a landmark initiative aiming to make the European Union carbon-neutral by 2050. With a budget of €1 trillion over ten years, this plan supports both the green transition and the digital transition, providing a robust framework for innovation and sustainable development across all sectors, including agriculture.

The initiative by the Italian government aligned with the directives issued by the European Union is the "Transizione 5.0" tax credit. Introduced under the National Recovery and Resilience Plan (PNRR), it supports businesses in their digital and green transformation efforts. This measure, enacted through Decree-Law No. 19/2024 and its subsequent conversion under Law No. 56/2024, is particularly relevant for the agricultural and agromechanical sectors. Funding allocation was a total of €6.3 billion for 2024-2025, with an additional €6.4 billion from the national budget, to support digital and green transitions across industries. Investments qualifying for the tax credit include interconnected machinery, equipment, and software, as well as robotics systems controlled by computerized mechanisms and equipped with sensors and actuators.

These technologies must also demonstrate a measurable reduction in energy consumption, aligning with the sustainability objectives of Agriculture 5.0.

These interventions provide agricultural businesses with significant opportunities to modernize operations and adopt sustainable practices. By leveraging financial support for advanced technologies, farms can enhance productivity while reducing their environmental footprint. Initiatives such as these also align with the broader goals of reducing greenhouse gas emissions and fostering a greener, more efficient agricultural landscape.

The synergy between fiscal policies, technological innovation, and environmental priorities paves the way for a resilient agricultural sector that embraces the principles of Agriculture 4.0 and 5.0, ensuring long-term sustainability and growth.

4.2 Challenges of innovation in the transition to Agriculture 5.0

The shift to Agriculture 5.0 represents a paradigm shift in the agrifood system, offering tremendous potential to revolutionize traditional practices. However, the transition also faces critical challenges rooted in the socio-economic and cultural framework of conventional agriculture.

The main challenge is that the agrifood sector operates within a system heavily influenced by the principles of conventional agriculture, which is characterized by:

- Dominance of large-scale retail chains: The preponderance of Organized Large Distribution (GDO) exerts significant influence on agricultural production and distribution practices.
- Market for proprietary technologies: Innovation is often driven by proprietary systems, which may limit accessibility and customization for smaller stakeholders.
- Reinforcement of long food supply chains: Conventional agriculture tends to prioritize extended supply chains, which can increase inefficiency and environmental impact.

While powerful technologies associated with Agriculture 4.0—such as predictive analytics, real-time operational insights, and business process redesign—hold significant potential to transform farming, their current implementation largely perpetuates the established practices and logic of conventional agriculture.

Other important questions are accessibility issues and scale bias. Many of the measures and innovations associated with Agriculture 4.0 and 5.0 are most readily applicable to medium-to-large enterprises. This creates a disparity where smaller farms, which often lack the financial resources and infrastructure to adopt these innovations, risk being left behind in the transition.

If these challenges are not addressed, the transition to Agriculture 5.0 may inadvertently exacerbate inequalities within the agrifood sector. Ensuring that technological advancements are inclusive and accessible to farms of all sizes is critical for achieving the broader goals of sustainability, equity, and resilience in agriculture. Solutions such as cooperative ownership of technologies, open-source innovation, and targeted support for smaller operations could help bridge this gap and foster a more equitable transition.

Addressing these systemic issues will be essential to unlocking the full potential of Agriculture 5.0, allowing it to move beyond the constraints of conventional agriculture and contribute meaningfully to a sustainable and inclusive future for the agrifood system.

5. Conclusions

The integration of AI in biodiversity conservation and sustainable agriculture marks a transformative step toward addressing critical environmental challenges. From monitoring endangered species and detecting environmental threats to optimizing agricultural processes and supporting regenerative practices, AI-driven technologies demonstrate immense potential for fostering sustainability. However, as highlighted, the transition to Agriculture 5.0 and similar innovations must ensure inclusivity, avoiding disproportionate benefits to larger enterprises while marginalizing smaller stakeholders. By combining technological advancements with supportive policies like those from the European Union and fostering equitable access, we can create a future where economic growth harmonizes with environmental preservation and social equity.

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