Politická ekonomie 2026

Volume 74 (4), Special Issue:
Confluence of Political Economics, Artificial Intelligence, and Environmental Policies: Tackling Pollution Issues in a Digital Era
https://doi.org/10.18267/j.polek.1507
Open Access

VŠE / PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

Unbreakable Trade-off Between Agricultural Development and Biodiversity Loss: Is There a Magical Role of Artificial Intelligence?

Siew-Pong Cheah, Ai-Lian Tan, Yan-Ling Tan, Thian-Hee Yiew, Chee-Loong Lee

Siew-Pong Cheah (email: siewpongc@sunway.edu.my), Sunway Business School, Sunway University, Petaling Jaya, Malaysia

Ai-Lian Tan (email: AiLian.Tan@taylors.edu.my), Taylor's Business School, Taylor's University Lakeside Campus, Subang Jaya, Malaysia

Yan-Ling Tan (email: tanya163@uitm.edu.my), Faculty of Business and Management, Universiti Teknologi MARA Cawangan Johor Kampus, Segamat, Malaysia

Thian-Hee Yiew (email: yiewth@utar.edu.my), Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia

Chee-Loong Lee (*corresponding author*, email: loongfx@gmail.com), Taylor's Business School, Taylor's University Lakeside Campus, Subang Jaya, Malaysia

Abstract

Artificial intelligence (AI) significantly enhances agricultural production by optimizing inputs, minimizing waste and improving management practices. However, the capability of AI to foster sustainable agriculture remains under scrutiny. This study investigates the impact of AI on the relationship between agriculture and biodiversity loss across 132 countries from 2013 to 2021. Employing a negative binomial (NB) regression model, our findings reveal that traditional agricultural practices contribute to an increase in the number of threatened species. Conversely, integrating AI in smart farming practices appears to mitigate biodiversity loss. Additionally, our analysis confirms that climate change plays a substantial role in species depletion. Strategic use of AI on agricultural land not only boosts productivity and reduces operational risks but also enhances environmental stewardship. It is crucial, therefore, that policies are crafted and refined to better align AI initiatives with sustainability objectives.

Keywords: Artificial intelligence, agriculture, biodiversity loss, negative binomial

JEL Classification: Q16, Q57, O33, Q54

Citation: Cheah, S.-P., Tan, A.-L., Tan, Y.-L., et al.: Unbreakable Trade-off Between Agricultural Development and Biodiversity Loss: Is There a Magical Role of Artificial Intelligence? *Politická ekonomie*, 2026, 74, (4), Special issue, 574–604, https://doi.org/10.18267/j.polek.1507

1. Introduction

In the 21st century, reconciling food security with biodiversity preservation emerges as one of the foremost global challenges. By 2050, the global population is projected to reach around 10 billion (UN, DESA, Population Division, 2017), necessitating a significant increase in food production to meet growing demands. The UN (2019) projects that food production must increase by 60% to support Sustainable Development Goals (SDGs) aimed at eradicating poverty, malnutrition and hunger. This requirement places significant demands on the agricultural sector to enhance crop yields, thereby bolstering the economic prosperity of countries. Consequently, expanding agriculture is crucial not only for creating employment and generating national income but also for strengthening the resilience of the food system. This study seeks to identify strategies for agricultural expansion that do not exacerbate biodiversity loss.

Agricultural expansion significantly disrupts natural ecosystems. Notably, land conversion for agricultural use has led to widespread deforestation, causing severe fragmentation and loss of natural habitats (Kubo *et al*., 2021). Moreover, traditional agricultural practices, especially livestock farming, account for nearly 25% of the world's greenhouse gas (GHG) emissions and are responsible for approximately 75% of biodiversity loss (Garske *et al*., 2021). The use of pesticides and fertilizers to boost crop production also poses risks, including soil erosion and water pollution. These chemicals can quickly run off or infiltrate, contaminating surface and groundwater, which adversely affects species diversity and richness. Consequently, the farming sector urgently needs to integrate new knowledge and technologies that enhance crop yields without compromising environmental health.

In recent years, approaches such as agricultural intensification, which focuses on increasing productivity on existing farmland through increased inputs and advanced technologies, and urban agriculture, which makes use of city spaces, can contribute to local food production and resilience. However, Foley *et al*. (2011) highlighted environmental issues arising from intensive agriculture, such as degradation of natural ecosystems and challenges of water scarcity. On the other hand, urban and peri-urban agriculture can enhance food security, but spatial limitations and productivity challenges are inherent in urban contexts (Opitz *et al*., 2016). The limitations of these approaches motivate farms and governments to seek methods that are more effective and environmentally friendly.

Artificial intelligence (AI) has become increasingly popular in the agricultural sector, primarily for its capability to provide real-time data that enhance agricultural efficiency. Smart farming technologies, which include high-performance information systems, gather data from fields to advance precision agriculture practices (Javaid, 2023). Farmers utilize these insights to not only boost crop yields and refine precision management but also to reduce labour, increase input use efficiency, minimize waste, produce higher-quality products and make environmentally conscious decisions (Vijayakumar, 2022). For example, an array of tools, such as sensors, drones and satellites, is employed to determine the optimal sowing periods, thereby maximizing yields and optimizing resource use. This includes judicious land utilization by selecting suitable crop types, precise application of fertilizers and pesticides for effective weed, pest and disease control, and efficient water management. Thus, AI technologies are instrumental in enhancing farming practices, enabling better monitoring and increasing the precision of agricultural operations.

Despite the role of AI in enhancing farming efficiency, concerns persist about its alignment with global biodiversity and climate objectives. The use of AI must go beyond merely providing sufficient food for the growing global population; it should also reduce environmental threats concurrently. This approach aligns with several Sustainable Development Goals, including zero hunger (SDG 2), responsible consumption and production (SDG 12) and life on land (SDG 15). Beyond agricultural productivity, AI offers significant opportunities for biodiversity conservation by enabling advanced data analysis to inform sustainable land management practices and support adaptive conservation strategies (Shivaprakash, 2022). AI-driven technologies enable precise monitoring of emissions, environmental impacts and biodiversity, serving as a crucial foundation for designing and implementing effective environmental and climate protection strategies (Garske, 2021).

On one extreme, implementation of AI in agriculture, involving tools such as drones, robots and sensors, has exposed risks, including fluid leaks, fume emissions and the release of toxic chemicals, which pose significant ecological threats. These risks can lead to soil degradation, water contamination and the fragility of biodiversity. For instance, the genetic modification of livestock, plants and crops to integrate AI technologies raises concerns about unintended consequences, such as reduced genetic diversity and increased susceptibility to plant diseases (Sparrow *et al*., 2021). Additionally, heavy reliance on AI systems increases vulnerabilities to sabotage and hacking, which can undermine the precision of predictions (Gao *et al*., 2024). To mitigate these risks, robust regulatory frameworks, regular maintenance protocols and eco-friendly technological innovations must be implemented to ensure that AI applications align with environmental sustainability goals. In light of these challenges, the present study aims to explore the mediating role of AI in balancing agriculture and biodiversity loss across 132 selected countries, offering insights into both its potential benefits and ecological risks.

This study enriches the academic discourse in several key ways: Firstly, it addresses a notable gap in the literature. To the best of our knowledge, the impact of AI on agriculture and its consequent effect on biodiversity loss has been underexplored. Our research advances this field by investigating the mediating role of AI, particularly as agricultural expansion typically poses irreversible threats to biodiversity. This approach is pioneering among existing studies. Secondly, the anticipated outcomes of this study will determine whether investments in and the application of AI technology are crucial for achieving sustainable agricultural development while simultaneously preserving biodiversity. By making a multi-country analysis across 132 countries, the study provides a comprehensive understanding of how AI applications vary across different socio-economic and environmental contexts. This research builds upon previous studies such as Zambrano-Monserrate *et al*. (2024) and Huang *et al*. (2024), which examined the relationship between economic development and environmental sustainability using global datasets and advanced econometric methods, thereby enriching the existing body of knowledge in environmental science.

Finally, to support the attainment of the SDGs, this research outlines a three-step framework aimed at informing policymakers: (1) elucidating the potential benefits of AI in enhancing agricultural sustainability and mitigating biodiversity loss; (2) highlighting the challenges associated with integrating AI in the agricultural sector and its impact on biodiversity; and (3) proposing the formulation of policies that equitably balance economic growth, ecological integrity and social sustainability.

2. Literature Review

Food production is escalating in response to population growth, which in turn fuels a rising demand for agricultural development. Abundant evidence suggests that this development is a primary driver of biodiversity loss (Dudley and Alexander, 2017). The impact of agriculture on species diversity is multifaceted and can be categorized into four main channels: (1) competition for land use, (2) adoption of monoculture farming practices, (3) release of pollutants through pesticide uses and greenhouse gas emissions and (4) impacts associated with the food value chain. The evidence from existing studies is reviewed and summarized in the following Table 1.

Table 1: Summary of reviewed articles: agricultural development and biodiversity loss

Key theme	Findings	Authors
Land use and deforestation	■ Agriculture drives ecosystem degradation, especially in tropical forests.	Barraclough and Ghimire (2000) FAO (2022)
	■ Farmland expanded by 12% globally, largely replacing natural ecosystems.	FAO (2022)
	■ Annual forest loss (2010–2020): 4.7 million hectares, totalling 94 million hectares since 2000.	FAO (2022) Gibbs *et al*. (2010) Taylor *et al*. (2015)
	■ Agriculture threatens grasslands such as the Paraguayan Chaco and Brazilian Cerrado.	Dal Pont and Longo (2007) Gibbs *et al*. (2015)
	■ Growing food demand will necessitate further land acquisition, increasing deforestation and biodiversity loss.	Obersteiner *et al*. (2014) Mujtar *et al*. (2019)
Intensive agriculture	■ Traditional farming has been replaced by monoculture plantations, reducing biodiversity.	Thomin *et al*. (2022) Raven and Wagner (2020)
	■ Expansion of cropland for soybeans, oil palms and biofuels.	Ghazali *et al*. (2016) WWF (2014) Pacheco (2012) Danielsen *et al*. (2009)
	■ Grazing lands transformed by non-native grasses, herbicides and fertilizers.	Musil *et al*. (2005) McLaughlin and Mineau (1995)
Use of agrochemicals	■ Fertilizer demand surpassed 200 million tonnes by 2022, but nutrient pollution harms biodiversity.	FAO (2019)
	■ Pesticides and systemic insecticides damage invertebrates, amphibians, birds and ecosystems.	Chagnon *et al*. (2015) Luzardo *et al*. (2014) Dudley *et al*. (2017) Geiger *et al*. (2010)
	■ Herbicide-resistant genetically modified crops increase glyphosate use, worsening environmental impacts.	Benbrooke (2016) Tanentzap *et al*. (2015)
Climate change impacts	■ Livestock production contributes 14.5% of global greenhouse gas emissions.	Gerber *et al*. (2013)
	■ Beef production is resource-intensive, amplifying land, water and emission challenges.	Eshel *et al*. (2014)
Renewable energy and agricultural practices	■ Underscore the intricate relationships among renewable energy adoption, globalization and agricultural practices.	Atasel *et al*. (2022) Rehman *et al*. (2021) Pata (2021)
Economic policies and environmental outcomes	■ Explore how economic policies and market dynamics influence environmental outcomes.	Andrew *et al*. (2024) Meo and Adebayo (2024) Özkan and Adebayo (2024)
Agricultural strategies and biodiversity	■ Study benefits and limitations of agroecological practices and conservation agriculture.	Kaur *et al*. (2025) Wezel *et al*. (2020)
Other biodiversity impacts	■ Salinization affects 20% of irrigated lands, reducing agricultural productivity.	Pitman and Läuchli (2002) Butcher *et al*. (2016)
	■ Food transportation and waste contribute significantly to pollution and emissions. ■ One-third of food is wasted annually, equating to 1.4 billion hectares of farmland and $750 billion lost.	Pretty *et al*. (2005) FAO (2013; 2021)

Source: Authors' own elaboration

The demand for extensive land use in food production is a critical driver of ecosystem degradation, particularly in tropical forests (Barraclough and Ghimire, 2000). Over recent decades, global farmland has expanded by 12%, largely at the expense of natural ecosystems (FAO, 2022a). During the 1980s and 1990s, forests were the primary targets for conversion into agricultural land (Gibbs *et al*., 2010), a trend that persists (Rojas-Downing *et al*., 2017; Tavares *et al*., 2019). Between 2010 and 2020, the annual loss of forest cover averaged 4.7 million hectares, resulting in a total loss of 94 million hectares since 2000 (FAO, 2022a). A study of 11 deforestation fronts identified agriculture as a major, often the predominant, driver of these changes (Taylor *et al*., 2015). Moreover, the expansion of agriculture continues to threaten remaining natural grasslands, including areas such as the Paraguayan Chaco (Dal Pont and Longo, 2007) and the Brazilian Cerrado (Gibbs *et al*., 2015). Projections indicate that the escalating global food demand will necessitate further land acquisition (Obersteiner *et al*., 2014; Mujtar *et al*., 2019). Consequently, this relentless development in food production is likely to continue driving widespread deforestation and exacerbating biodiversity loss.

Management practices have shifted significantly since World War II, with traditional farming methods – often conducive to high biodiversity – being largely supplanted by more intensive agricultural systems. These contemporary, large-scale monoculture plantations have led to considerable losses in both crop diversity (Thomin *et al*., 2022) and arthropod diversity (Raven and Wagner, 2020). The last few decades have seen a marked increase in cropland dedicated to soybeans, oil palms and various biofuels (Ghazali *et al*., 2016; WWF, 2014; Pacheco, 2012; Danielsen *et al*., 2009). Additionally, grazing lands have undergone transformations with the introduction of non-native grass species (Musil *et al*., 2005) and the application of herbicides and fertilizers (McLaughlin and Mineau, 1995). Collectively, the cited studies affirm that monoculture plantations not only lead to deforestation but also deteriorate soil health, yielding long-term detrimental effects on ecosystems.

The intensification of agriculture is closely linked to the increased use of agrochemicals, including fertilizers and pesticides. According to the FAO (2019), global demand for fertilizers is expected to surpass 200 million tonnes by 2022. While fertilizers have contributed to higher yields, their leakage has caused significant environmental harm. For example, nutrient pollution has triggered algal blooms that damage freshwater biodiversity and increasingly affect marine habitats, leading to over 500 oxygen-depleted "dead zones" worldwide. Recent metastudies indicate that systemic insecticides have severely harmed invertebrates, amphibians and birds (Chagnon *et al*., 2015). Similar detrimental effects are associated with other pesticides (Luzardo *et al*., 2014; Dudley *et al*., 2017), fungicides (Geiger *et al*., 2010) and herbicides (Chiron *et al*., 2014). Moreover, many pesticides drift far beyond their application sites (Martín-López *et al*., 2011). Herbicide-resistant genetically modified crops account for 56% of total glyphosate usage (Benbrooke, 2016) and with increasing tolerance, application rates are expected to rise further (Tanentzap *et al*., 2015). These findings elucidate why biodiversity continues to decline in and around agricultural landscapes (Donald *et al*., 2006).

Modern agriculture significantly contributes to climate change, which in turn affects biodiversity (Kang and Banga, 2013). Livestock production, for instance, is responsible for approximately 14.5% of anthropogenic greenhouse gas emissions (Gerber *et al*., 2013). Consumer preferences for meat and other animal-based products exacerbate these impacts. Specifically, beef production poses substantial challenges; it requires on average 28 times more land and 11 times more water than other livestock such as pigs and poultry, while generating five times more greenhouse gas emissions (Eshel *et al*., 2014). If current trends in this food value chain persist, biodiversity loss is likely to intensify.

Recent studies underscore the intricate relationships among renewable energy adoption, globalization and agricultural practices in influencing ecological footprints and CO_2 emissions across various geopolitical and economic scales. Pata (2021) elucidated these dynamics within BRIC countries, presenting a sustainability perspective that highlights renewable energy as a pivotal factor in mitigating environmental impacts associated with globalization and agricultural intensification. Similarly, Atasel *et al*. (2022) contributed to this discourse by empirically testing the agricultural-induced environmental Kuznets curve (EKC) hypothesis in major agricultural economies, suggesting that beyond a certain threshold, agricultural expansion adversely affects environmental quality. This narrative was complemented by Rehman *et al*. (2021), who investigated the role of diversified exports and cleaner energy consumption in curbing atmospheric pollution in Asia, employing advanced econometric techniques to reveal nuanced impacts across different economic activities.

In parallel, recent literature also explores how economic policies and market dynamics influence environmental outcomes. Meo and Adebayo (2024) delved into the impact of financial regulations and climate policy uncertainty on CO_2 emissions, utilizing a sophisticated bootstrap subsample rolling-window Granger causality approach to reveal the temporal dynamics of policy effectiveness. Additionally, Özkan and Adebayo (2024) examined the asymmetric effects of fossil fuel price volatility on clean technology investments, illustrating how economic uncertainties shape investment landscapes. Extending this analysis, Andrew *et al*. (2024) assessed the moderating roles of technological innovation and economic complexity in the nexus between financial development and environmental quality within BRIC countries, suggesting that technological advancements and complex economic interactions are crucial for achieving sustainable environmental outcomes.

Agroecological practices and conservation agriculture are key to promoting biodiversity within agricultural systems. Agroecology enhances resilience by diversifying species and reducing use of chemicals, which benefits the local environment and cuts costs, although it faces challenges with lower yields and high skill requirements (Wezel *et al*., 2020). Conservation agriculture improves soil health and reduces CO_2 emissions through practices such as minimal soil disturbance and crop rotation, offering long-term sustainability benefits (Kaur *et al*., 2025). However, both strategies come with significant initial costs and require adjustments in management practices that may delay benefits, presenting obstacles to widespread adoption despite their potential to integrate food production with ecological preservation.

A variety of side effects, both direct and indirect, significantly affect biodiversity due to agricultural activities. Salinization, primarily from irrigation practices, affects at least 20% of irrigated lands, leading to substantial agricultural losses (Pitman and Läuchli, 2002; Butcher *et al*., 2016). Additionally, emerging infectious diseases from fungi, exacerbated by human activities that intensify fungal dispersal, are posing increasing risks to food security (IOM, 2011; Fisher *et al*., 2012). The transportation of food over greater distances than ever before incurs significant energy costs and contributes to pollution (Pretty *et al*., 2005). Emissions from agri-food systems have increased globally by 16% from 1990 to 2019, totalling approximately 17 billion tonnes of carbon dioxide equivalent in 2019 (FAO, 2021). Furthermore, an estimated one-third of all food produced is wasted, corresponding to the output from 1.4 billion hectares. This waste also squanders 250 km^3 of water and $750 billion annually, contributing a carbon footprint of 3.3 Gt of CO_2 equivalent each year, positioning food waste as the third-largest emitter behind the United States and China (FAO, 2013). To mitigate these effects, agricultural development must integrate new technologies, shifting from practices that harm biodiversity to those that protect and sustain it.

With technological advancements, precision agriculture has become feasible through the integration of AI-based technologies in farm management (Bacco *et al*., 2019; Finger *et al*., 2019). Precision agriculture aims to optimize crop yields while minimizing the use of fertilizers, pesticides and herbicides through improved spatial management practices (Amato *et al*., 2015; Talaviya *et al*., 2020). Table 2 reviews and summarizes past studies that discussed the potential and challenges of adopting AI technologies in agricultural domains.

Table 2: Summary of reviewed articles: application of AI technologies in agriculture

Application of AI technologies in agriculture and food production		
Agricultural challenges	▪ Key challenges include crop disease detection, storage management, pesticide and fertilization process control, weed management and soil and irrigation management.	Jha *et al*. (2019) Talaviya *et al*. (2020) Mohamed *et al*. (2021) Holzinger *et al*. (2023)
Precision agriculture	▪ Precision agriculture utilizes AI to optimize crop yields and reduce fertilizer, pesticide and herbicide use.	Bacco *et al*. (2019) Finger *et al*. (2019) Amato *et al*. (2015) Talaviya *et al*. (2020)
AI solutions	▪ AI technologies effectively address comprehensive crop management issues. ▪ Promising potential in augmenting crop production, disease monitoring, fertilizer and irrigation management, optimized harvesting and post-harvest managerial efficiency.	Jha *et al*. (2019) Talaviya *et al*. (2020) Mohamed *et al*. (2021) Lioutas *et al*. (2021) Shen *et al*. (2022)
IoT applications	▪ IoT applications in agriculture enable remote and automated crop management, as well as smart irrigation system.	Banerjee *et al*. (2018) Mohamed *et al*. (2021) Jha *et al*. (2019) Tace *et al*. (2022)
Challenges in adopting AI technologies in agriculture	▪ Heavy capital requirements and lack of funding. ▪ Lack of expertise and training. ▪ Poor quality or unavailability of high-speed and stable internet. ▪ Data lacking in breadth and depth. ▪ Incompatibility of AI models to region-specific issues and agronomic practices. ▪ Regulatory gaps and risk of data breach.	Bhat and Huang (2021) Zha (2020) Whig (2023)

Source: Authors' own elaboration

Farmers face a variety of challenges throughout the agricultural cycle, from seed sowing to storage of harvested crops. These challenges include crop disease detection, storage management, pesticide control, fertilization process control, weed management and soil and irrigation management (Jha *et al*., 2019; Talaviya *et al*., 2020; Mohamed *et al*., 2021; Holzinger *et al*., 2023). AI technologies have proven effective in addressing these comprehensive crop management issues. The evolution of AI in agriculture from 1983 to 2017 was extensively reviewed by Banerjee *et al*. (2018), while Mohamed *et al*. (2021) and Jha *et al*. (2019) explored the applications of the internet of things (IoT) in agriculture, including the recent developments in remote and automated crop management systems (Tace *et al*., 2022).

While the body of literature on precision and smart farming largely supports the use of AI technologies in agriculture for enhancing operational efficiency and optimizing yields, the environmental benefits are found to be varied and highly dependent on specific cases (Finger *et al*., 2019). For instance, variable rate pesticide application has been shown to reduce herbicide use by 11% to 90% across different crop types compared to uniform spraying techniques (Dammer and Wartenberg, 2007; Balafoutis *et al*., 2017). Additionally, Dammer and Adamek (2012) demonstrated that this method could decrease insecticide use by 13.4% in wheat production, effectively controlling cereal aphids while preserving beneficial insects such as lady beetles. Similarly, Kempenaar *et al*. (2018) reported that variable rate applications could reduce pesticide and fertilizer use by an average of 25% in potato farming. Additionally, adoption and implementation of AI technologies in agriculture comes with its unique set of challenges (Zha, 2020; Bhat and Huang, 2021; Whig, 2023). These challenges (see Table 2) are particularly pronounced in developing and under-developed countries, which could induce questions on whether the benefits of adopting AI technologies in agriculture can outweigh the costs of overcoming the obstacles. Therefore, it is vital to assess the potential of AI technology in agriculture and, indirectly, biodiversity conservation, through an empirical lens.

Despite extensive research into the impact of agricultural practices on biodiversity, the role of advanced technologies such as AI in mediating these effects remains underexplored. Existing literature primarily focuses on the direct impacts of agriculture on biodiversity loss, with minimal attention given to how AI can influence these dynamics. Our study seeks to fill this critical gap by hypothesizing that AI, through precision and smart farming techniques, can serve as a crucial intermediary in mitigating the adverse effects of agriculture on biodiversity. Previous studies, such as Garske *et al*. (2021), have hinted at the potential of digitalization in supporting biodiversity objectives within agricultural frameworks but stopped short of empirically testing the mediating role of AI. By incorporating empirical analysis, our research not only contributes new insights into the integration of AI in agriculture but also explores its potential to enhance biodiversity conservation, largely overlooked in current discourses. This approach is particularly novel as it quantifies the indirect benefits of AI applications, thus providing a more comprehensive understanding of how technological advancements can alter traditional agricultural impacts on ecosystems.

3. Data and Methodology

3.1 Data

This study compiles an unbalanced panel of annual data from 2013 to 2021 to investigate the nexus between AI and biodiversity loss. It utilizes data on five major taxonomic groups of threatened species and three measures of AI, alongside other variables such as precipitation and agricultural land use. Given the scarcity of long-term AI data and to ensure robustness, the study adopts three alternative AI measures: patent applications (*PA*), research and development expenditures (*R&D*) and high-technology exports (*HT*). The data collection spans 132 countries for patent applications, 115 countries for research and development expenditures and 149 countries for high-technology exports. AI advancements are often indicated by increased expertise in employing new technologies for wildlife monitoring and management (Singh and Mayanglambam, 2022). Detailed descriptions of each variable can be found in Table 3.

Table 3: Description of variables

Variable	Measures	Abbrev.	Units of measurement	Source
Biodiversity loss	Threatened mammals	*MAMM*	Number of species	IUCN Red List (IUCN, 2022)
	Threatened birds	*BIRD*		
	Threatened reptiles	*REPT*		
	Threatened amphibians	*AMPH*		
	Threatened plants	*PLANT*		
Habitat size	Agricultural land	*LAND*	km^2	FAOSTAT (FAO, 2022b)
Precipitation	Average precipitation	*PR*	Millimetres (mm)	Climate Change Knowledge Portal (WB, 2022a)
Artificial intelligence	Resident patent	*PA*	Number of applications	World Development Indicators (WB, 2022b)
	Research and development expenditures	*R&D*	% of GDP	
	High-technology exports	*HT*	% of manufactured exports	

Source: Authors' own elaboration

3.2 Methodology

Several studies have been developed to examine the factors affecting biodiversity loss. The common factors include habitat size, climate condition, income level and institutional determinants (Asafu-Adjaye, 2003; McPherson and Nieswiadomy, 2005; Naidoo and Adamowicz, 2001). The term "artificial intelligence" came into use very recently (Nguyen and Vo, 2022). Subsequently, this study incorporates the novel information of artificial intelligence on biodiversity loss across 132 countries for *PA*, 115 countries for *R&D* and 149 countries for *HT*. The baseline specification can be written as the following equation:

$$B_{it} = \beta_1 + \beta_2 LAND_{it} + \beta_3 AI_{it} + \beta_4 PR_{it} + \varepsilon_{it} \tag{1}$$

where i = 1, …, N and t = 1, ..., T and ε is the error term, B represents the biodiversity loss, which is measured by the threatened plants and four common land vertebrates, namely threatened mammals, threatened birds, threatened reptiles and threatened amphibians. *LAND* is agricultural land, *AI* is artificial intelligence and *PR* is precipitation. The expected sign of β_2 is positive because a higher level of habitat loss through land conversion to intensive agriculture may result in greater biodiversity loss. Artificial intelligence is expected to reduce biodiversity loss, $\beta_3 < 0$. This is because artificial intelligence improves and optimizes human activities and experiences and thereby reduces species loss. Furthermore, climate change is a primary reason for biodiversity decline and β_4 is expected to be positive. Heavy precipitation will probably cause a widespread rise of species loss.

Next, this study continues to analyse the impact of the introduction of artificial intelligence along agricultural land on biodiversity loss. For this reason, we add an interaction term by interacting agricultural land with the artificial intelligence variable ($LAND \times AI$) in Equation (2). It is believed that the impact of agricultural expansion on biodiversity loss can be reduced by incorporating artificial intelligence in agriculture. Such an interaction term is expected to reduce species loss ($\theta_3 < 0$).

$$B_{it} = \theta_1 + \theta_2 LAND_{it} + \theta_3 LAND \times AI_{it} + \theta_4 AI_{it} + \theta_5 PR_{it} + \varepsilon_{it} \tag{2}$$

where all the variables are as defined above.

Poisson-based regressions are commonly employed to model count response variables. However, due to the presence of overdispersion in ecological data, the negative binomial (NB) regression model is often preferred. This preference arises because the Poisson regression model operates under the restrictive assumption of equidispersion, where the conditional mean and variance are assumed to be equal – a condition frequently violated in ecological studies (Osgood, 2000; Winkelmann, 1999). Consequently, the NB model is utilized, as it accommodates variability by allowing the mean and variance to differ, which is expressed in the distribution for y as follows:

$$\mathrm{P}(Y = y_i | \mu_i, \alpha) = \frac{r\left(\frac{1}{\alpha} + y_i\right)}{r\left(\frac{1}{\alpha}\right) r(y_i + 1)} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \mu_i}\right)^{\frac{1}{\alpha}} \left(\frac{\mu_i}{\frac{1}{\alpha} + \mu_i}\right)^{y_i} \tag{3}$$

where y_i is the occurrences of threatened species, r(.) is the gramma integral that specializes to a factorial for an integer argument, α is a random parameter, μ is the mean incidence rate of y per unit of exposure, $\mu_i = \exp(\boldsymbol{x_i \delta})$, $\boldsymbol{x_i}$ is the vector of independent variables, and $\boldsymbol{\delta}$ is the vector of parameter estimates.

4. Results

Table 4 presents the descriptive statistics for the key variables of interest in this study. Over the analysis period, the average number of threatened plant species is 101, while the averages for the four groups of threatened land vertebrates are: mammals at 18, birds at 24, reptiles at 11 and amphibians at 14. The study includes three measures of artificial intelligence: research and development expenditures, patent applications and high-technology exports. Annually, patent applications average 15.9 thousand, with the highest count recorded in China at 1.4 million. The average *R&D* expenditures between 2013 and 2021 accounted for 1.03% of GDP, ranging from a minimum of 0.01% in Madagascar to a maximum of 5.44% in Israel. High-technology exports from 149 countries constituted approximately 10.56% of total manufactured exports. Additionally, the average agricultural land across these countries is 285,068 km^2, with a range from 3 km^2 to 5,300,000 km^2. Annual average precipitation is approximately 1,136.38 mm, varying from a low of 10.88 mm to a high of 4,578.7 mm per annum.

Table 4: Summary statistics

	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***	***LAND***	***PR***	***R&D***	***HT***	***PA***
Mean	18	24	11	14	101	285,068	1,136.38	1.03	10.56	15,892.54
Maximum	211	172	139	289	2,850	5,300,000	4,578.70	5.44	78.48	1,400,000.00
Minimum	0	0	0	0	0	3	10.88	0.01	0.000081	1.00
Std. dev.	24	26	19	36	236	702,003	780.60	0.99	11.39	109,163.90
N	1,412	1,412	1,412	1,412	1,412	1,240	1,413	696	1,219	926

Source: Authors' own calculations

Based on Equation (1), the baseline results of the NB estimator, which incorporates three measures of artificial intelligence (research and development, patent applications and high-technology exports), are detailed in Tables 5–7. Models 1–5 in each table display the regression outcomes for the number of threatened mammals (*MAMM*), birds (*BIRD*), reptiles (*REPT*), amphibians (*AMPH*) and plants (*PLANT*), respectively. Using likelihood ratio tests, the null hypothesis that $\alpha = 0$ is rejected at the 1% significance level (*i.e.*, all p-values < 0.01), indicating strong evidence of overdispersion. Consequently, this study prefers the NB model over the Poisson model for analysing count data related to threatened species, aligning with the methodology used in prior studies (Clausen and York, 2008; Naidoo and Adamowicz, 2001; Tan *et al*., 2022).

Across all the models presented in Tables 5–7, the estimated coefficients for agricultural land and precipitation are statistically significant at the 1% level and positively correlated with the number of threatened species. This indicates that increased use of land for agricultural purposes correlates with greater biodiversity decline. Similarly, higher levels of precipitation are associated with an increased risk of species becoming threatened and endangered. Conversely, the coefficients for research and development in Table 5 are statistically significant at the 1% level and negatively associated with the frequency of threatened species. This pattern is consistent in Tables 6 and 7, where patent applications and high-technology exports, respectively, exhibit similar inverse relationships. These results suggest that the integration of artificial intelligence in agriculture may contribute to the reduction in the number of threatened species.

Table 5: Results of baseline model with research and development

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.000000694*** (15.79)	0.000000600*** (18.62)	0.000000726*** (10.61)	0.00000157*** (8.80)	0.000000858*** (11.34)
PR	0.000627*** (14.28)	0.000589*** (16.42)	0.000648*** (8.97)	0.00204*** (13.24)	0.00128*** (13.90)
RD	−0.257*** (−8.69)	−0.172*** (−7.27)	−0.312*** (−7.21)	−0.553*** (−6.59)	−0.287*** (−5.53)
C	2.032*** (30.81)	2.399*** (46.02)	1.551*** (14.73)	−0.279 (−1.21)	2.619*** (20.24)
ln α	−0.551*** (−9.31)	−1.044*** (−17.62)	0.370*** (5.91)	1.345*** (19.10)	0.576*** (11.40)
LR **p-value (χ^2)**	464.1 0.000	548.5 0.000	228.5 0.000	280.5 0.000	367.3 0.000
DF	3	3	3	3	3
Pseudo R^2	0.0856	0.0942	0.0499	0.0739	0.0530
N	687	687	687	687	687
LL	−2,480.2	−2,638.4	−2,174.5	−1,756.5	−3,279.2

Notes: *** denotes statistical significance at the 1% level. Magnitudes in parentheses () are t-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.
Source: Authors' own calculations

Table 6: Results of baseline model with patent applications

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.000000839*** (15.44)	0.000000709*** (17.98)	0.000000824*** (10.03)	0.00000190*** (11.71)	0.00000101*** (8.90)
PR	0.000677*** (18.48)	0.000580*** (19.92)	0.000773*** (13.36)	0.00213*** (18.02)	0.00132*** (18.57)
RD	−0.00000193*** (−6.25)	−0.00000142*** (−5.82)	−0.00000187*** (−3.97)	−0.00000462*** (−6.00)	−0.00000208*** (−3.56)
C	1.806*** (34.45)	2.253*** (54.91)	1.229*** (15.07)	−0.825*** (−5.00)	2.486*** (25.37)
ln α	−0.492*** (−9.79)	−0.984*** (−19.24)	0.350*** (6.67)	1.224*** (22.00)	0.659*** (15.26)
LR ***p*-value** **(χ^2)**	512.5 0.000	616.5 0.000	256.7 0.000	355.7 0.000	400.5 0.000
DF	3	3	3	3	3
Pseudo R^2	0.0699	0.0796	0.0408	0.0653	0.0419
N	908	908	908	908	908
LL	−3,411.7	−3,566.7	−3,017.2	−2,545.9	−4,574.0

Notes: *** denotes statistical significance at the 1% level. Magnitudes in parentheses () are *t*-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.

Source: Authors' own calculations

Table 7: Results of baseline model with high-technology exports

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.000000778*** (15.09)	0.000000680*** (17.81)	0.000000786*** (11.37)	0.00000226*** (11.63)	0.00000103*** (10.57)
PR	0.000587*** (16.02)	0.000489*** (16.31)	0.000694*** (13.33)	0.00196*** (17.49)	0.00135*** (19.28)
RD	−0.00701*** (−3.21)	−0.00544*** (−2.92)	−0.00969*** (−3.31)	−0.0288*** (−5.11)	−0.0217*** (−5.91)
C	1.926*** (36.42)	2.327*** (54.15)	1.308*** (17.79)	−0.640*** (−3.80)	2.540*** (26.71)
ln α	−0.387*** (−8.82)	−0.805*** (−17.99)	0.238*** (5.09)	1.313*** (26.35)	0.667*** (17.36)
LR ***p*****-value (**χ^2**)**	478.9 0.000	567.9 0.000	293.5 0.000	357.4 0.000	440.1 0.000
DF	3	3	3	3	3
Pseudo R^2	0.0537	0.0605	0.0383	0.0551	0.0377
N	1,124	1,124	1,124	1,124	1,124
LL	−4,215.9	−4,410.4	−3,680.8	−3,062.2	−5,620.6

Notes: *** denotes statistical significance at the 1% level. Magnitudes in parentheses () are *t*-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.

Source: Authors' own calculations

Tables 8–10 report the results interacting agricultural land with artificial intelligence measures using Equation (2). The likelihood ratio tests reject the null hypothesis of $\alpha = 0$ with all p-values < 0.01 in all the models, showing that the NB model is more appropriate than the Poisson model. The sign of the estimated coefficients is similar to those of Tables 3–5. The estimated coefficients of both variables (θ_3) show interesting interpretations. While artificial intelligence measures have consistently negative effects ($\theta_4 > 0$) and agricultural land has a positive effect on biodiversity loss ($\theta_2 > 0$), the interaction of agricultural land and research and development (*LAND* × *R&D*) is found to significantly reduce threatened mammals, birds, reptiles, amphibians and plants with all p-values < 0.01 in Table 8.

Similarly, the interaction terms ($LAND \times PA$ and $LAND \times HT$) also confirm a negative response of threatened species in Tables 9 and 10, respectively. In Table 9, the parameter estimates of the interaction of agricultural land and patent applications are negative and statistically significant for Model 2 (p-values < 0.01), Model 1 and Model 4 (p-values < 0.05) and Model 5 (p-values < 0.1). The estimated coefficients of the interaction of agricultural land and high-technology exports carry a negative and significant sign (p-values < 0.01) in all models of Table 10. This implies that a negative and significant parameter estimate of the interaction term implies that the introduction of artificial intelligence to agriculture may reduce biodiversity loss.

The key findings from the NB models highlight that both agricultural land and precipitation exert direct, positive effects on biodiversity loss, indicating that increases in these factors correlate with greater threats to species diversity. Conversely, measures of artificial intelligence are found to have a negative impact on biodiversity loss, suggesting that AI can mitigate some of the adverse effects. Furthermore, the analysis of interaction between agricultural land and artificial intelligence demonstrates that AI can soften the detrimental impact of agricultural expansion on biodiversity. Additionally, the consistency of results across both the interaction terms and the baseline specifications underscores the robustness of the findings, indicating that they hold even when alternative variables are included.

Table 8: Results of interaction term agricultural land and research and development

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.00000133*** (14.64)	0.00000102*** (14.79)	0.00000126*** (8.19)	0.00000285*** (10.35)	0.00000124*** (7.31)
PR	0.000633*** (14.97)	0.000593*** (16.96)	0.000669*** (9.40)	0.00223*** (14.84)	0.00131*** (14.15)
RD	−0.166*** (−5.35)	−0.107*** (−4.27)	−0.247*** (−5.35)	−0.335*** (−3.78)	−0.227*** (−3.93)
LAND* × *RD	−0.000000334*** (−8.66)	−0.000000217*** (−7.31)	−0.000000259*** (−4.13)	−0.000000655*** (−6.66)	−0.000000183*** (−2.65)
C	1.833*** (27.46)	2.266*** (42.26)	1.379*** (12.43)	−0.931*** (−4.01)	2.471*** (17.65)
ln α	−0.652*** (−10.79)	−1.120*** (−18.65)	0.345*** (5.49)	1.272*** (17.97)	0.568*** (11.23)
LR ***p*-value (χ^2)**	530.6 0.000	597.8 0.000	244.3 0.000	318.9 0.000	374.0 0.000
DF	4	4	4	4	4
Pseudo R^2	0.0978	0.103	0.0534	0.0841	0.0540
N	687	687	687	687	687
LL	−2,446.9	−2,613.7	−2,166.6	−1,737.3	−3,275.8

Notes: *** denotes statistical significance at the 1% level. Magnitudes in parentheses () are *t*-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.

Source: Authors' own calculations

Table 9: Results of interaction term agricultural land and patent applications

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.000000879*** (15.07)	0.000000747*** (17.84)	0.000000856*** (9.76)	0.00000209*** (10.99)	0.000000980*** (8.94)
PR	0.000671*** (18.41)	0.000571*** (19.86)	0.000768*** (13.33)	0.00213*** (18.34)	0.00133*** (18.54)
PA	0.000000249 (0.26)	0.00000125 (1.60)	−2.50E-08 (−0.02)	−0.000000623 (−0.29)	−0.00000512*** (−2.84)
LAND × PA	−4.72E-13** (−2.43)	−5.74E-13*** (−3.72)	−3.98E-13 (−1.37)	−9.71E-13** (−2.16)	6.15E-13* (1.72)
C	1.790*** (34.04)	2.237*** (54.74)	1.216*** (14.85)	−0.910*** (−5.43)	2.499*** (25.49)
ln α	−0.498*** (−9.92)	−1.002*** (−19.54)	0.347*** (6.62)	1.217*** (21.88)	0.657*** (15.20)
LR ***p*-value (χ^2)**	519.2 0.000	632.5 0.000	258.7 0.000	361.7 0.000	403.0 0.000
DF	3	3	3	3	3
Pseudo R^2	0.0708	0.0816	0.0411	0.0664	0.0422
N	908	908	908	908	908
LL	−3,408.3	−3,558.7	−3,016.2	−2,542.9	−4,572.8

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Magnitudes in parentheses () are *t*-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.

Source: Authors' own calculations

Table 10: Results of interaction term agricultural land and high-technology exports

	(1)	(2)	(3)	(4)	(5)
	MAMM	***BIRD***	***REPT***	***AMPH***	***PLANT***
LAND	0.00000151*** (14.28)	0.00000130*** (16.25)	0.00000155*** (9.99)	0.00000384*** (9.97)	0.00000209*** (9.40)
PR	0.000564*** (15.88)	0.000476*** (16.47)	0.000694*** (13.67)	0.00199*** (17.83)	0.00136*** (19.95)
PA	0.000884 (0.38)	0.00138 (0.70)	−0.00291 (−0.93)	−0.0118* (−1.79)	−0.0123*** (−3.07)
LAND* × *HT	−3.60E-08*** (−8.92)	−3.05E-08*** (−9.77)	−3.70E-08*** (−6.17)	−8.67E-08*** (−5.65)	−4.72E-08*** (−5.98)
C	1.789*** (33.18)	2.204*** (50.40)	1.154*** (15.01)	−0.967*** (−5.29)	2.298*** (22.32)
ln *α*	−0.452*** (−10.13)	−0.884*** (−19.43)	0.204*** (4.32)	1.288*** (25.77)	0.642*** (16.67)
LR ***p*-value (χ^2)**	549.5 0.000	652.3 0.000	326.9 0.000	380.6 0.000	473.4 0.000
DF	4	4	4	4	4
Pseudo R^2	0.0617	0.0695	0.0427	0.0587	0.0405
N	1124	1124	1124	1124	1124
LL	−4,180.6	−4,368.2	−3,664.1	−3,050.7	−5,603.9

Notes: ***, * denote statistical significance at the 1%, and 10% levels, respectively. Magnitudes in parentheses () are *t*-statistics. LR is the likelihood ratio test of $\alpha = 0$, DF is the degree of freedom, LL is the log likelihood.

Source: Authors' own calculations

5. Discussion

The analysis in Tables 5–7 elucidates two principal findings. Firstly, an increase in agricultural land is consistently associated with heightened biodiversity loss across the studied countries, corroborating earlier studies (Cordier *et al.*, 2021; Newbold *et al.*, 2016; Perrings and Halkos, 2015; Tan *et al.*, 2022). Broadly, human activities, particularly those involving land use changes such as deforestation and agriculture, pose significant threats to Earth's system functioning and biodiversity (Loboguerrero *et al.*, 2019; Tan *et al.*, 2023). These activities, including agriculture, cattle raising, urbanization, deforestation, silviculture and selective logging, variously affect the richness of amphibian and reptile species (Cordier *et al*., 2021). Perrings and Halkos (2015) also highlighted that while agricultural intensification significantly threatens species over long-time scales, its effects are less pronounced on shorter time scales in sub-Saharan Africa.

The second finding reveals that increasing application of artificial intelligence correlates with a slight reduction in the number of threatened species. This supports findings from previous research by Kerry *et al*. (2022) and Nti *et al*. (2022), which suggest that artificial intelligence enhances environmental governance, improves industrial environmental performance, reduces environmental risks and increases safety (Nti *et al*., 2022). Furthermore, transformative smart technologies, such as machine learning and AI, are improving the efficiency of existing techniques and enabling remote monitoring that supports biodiversity conservation (Kerry *et al*., 2022). Artificial intelligence also facilitates the achievement of Sustainable Development Goals, particularly SDG 14 (life below water) and SDG 15 (life on land) (Singh and Mayanglambam, 2022), and is becoming integrated into various aspects of life, enhancing efficiency and augmenting human capabilities (Anderson and Rainie, 2018). For instance, AI has the potential to mitigate the risk of infectious diseases by devising intelligent wildlife management strategies and preserving global biodiversity.

In summary, artificial intelligence enhances farming practices by reducing land exploitation and thereby mitigating biodiversity loss. This improvement is driven by the ability of AI to help farmers maximize crop yields and minimize the misuse of fertilizers and pesticides (Shivaprakash *et al*., 2022; Garske *et al*., 2021). For instance, farmers can use sensors, aerial drones and satellite imagery to determine the optimal times for planting seeds and to optimize production. Additionally, through research and development, farmers can identify the most effective fertilizers and pesticides to control weeds, pests and diseases. These advancements enable more efficient land use, contributing to both agricultural productivity and environmental sustainability.

6. Conclusion

This study provides valuable insights into the dual challenges of ensuring food security and conserving biodiversity in the face of growing global demand for agricultural products. By integrating advanced technologies such as AI into agricultural practices, it is possible to address these challenges more effectively. Our findings, spanning 132 countries from 2013 to 2021, demonstrate that AI can significantly mitigate biodiversity loss associated with agricultural expansion. The application of AI in agriculture has shown potential not only in enhancing productivity and efficiency but also in reducing the negative impacts of farming on biodiversity. Key results of our NB regression analysis suggest that while traditional agriculture intensifies biodiversity loss, AI applications in smart farming practices have a notable counteracting effect. This aligns with Sustainable Development Goals by promoting sustainable agriculture (SDG 2) and protecting terrestrial ecosystems (SDG 15).

For policymakers, our study underscores the importance of fostering technological innovation in the agricultural sector. To this end, policy measures such as subsidies for AI integration into agriculture, funding for R&D in sustainable agricultural technologies and stronger partnerships between academic institutions and the private sector are recommended. Such initiatives could accelerate the adoption of AI in agriculture, leading to more sustainable practices and better conservation of biodiversity. Furthermore, while this study provides a comprehensive macro-level analysis, there remains a substantial scope for micro-level research. Future studies could explore the specific mechanisms through which AI technologies affect biodiversity in different agricultural settings. Case studies focusing on the implementation of smart farming solutions and their direct effects on local biodiversity could provide deeper insights. Additionally, evaluating the long-term sustainability of AI-driven agricultural practices would further contribute to our understanding of their potential and limitations.

In conclusion, as the global population continues to rise and the demand for food increases, it is imperative to adopt innovative solutions such as AI that not only meet human needs but also safeguard our environmental heritage. This study provides a foundation for such advancements, suggesting a pathway towards a more sustainable and technologically integrated approach to agriculture that prioritizes both productivity and ecological well-being.

List of acronyms

AI	Artificial intelligence
AMPH	Amphibians
BIRD	Birds
GHG	Greenhouse gas
HT	High-technology exports
MAMM	Mammals
NB	Negative binomial
PA	Patent applications
PLANT	Plants
R&D	Research and development
RD	Development expenditures
REPT	Reptiles
SDGs	Sustainable Development Goals
SDG 2	Zero hunger
SDG 12	Responsible consumption and production
SDG 14	Life below water
SDG 15	Life on land

Acknowledgement

Conflicts of interest: The authors hereby declare that this article was neither submitted nor published elsewhere.

AI usage statement: The authors confirm that no artificial intelligence (AI) or AI-assisted tools were used in the creation of this manuscript.

Data availability: Data will be made available on request.

References

Amato, F., Havel, J., Gad, A., et al. (2015). Remotely sensed soil data analysis using Artificial Neural Networks: A case study of El-Fayoum depression. *ISPRS International Journal of Geo-Information*, 4(2), 677–696. https://doi.org/10.3390/ijgi4020677

Anderson, J., Rainie, L. (2018). *Improvements ahead: How humans and AI might evolve together in the next decade*. [Retrieved 2024-10-22] Available at: https://www.pewresearch.org/internet/2018/12/10/improvements-ahead-how-humans-and-ai-might-evolve-together-in-the-next-decade/

Andrew, A. A., Adebayo, T. S., Lasisi, T. T., et al. (2024). Moderating roles of technological innovation and economic complexity in financial development-environmental quality nexus of the BRICS economies. *Technology in Society*, 78, 102581. https://doi.org/10.1016/j.techsoc.2024.102581

Asafu-Adjaye, J. (2003). Biodiversity loss and economic growth: A cross-country analysis. *Contemporary Economic Policy*, 21(2), 173–185. https://doi.org/10.1093/cep/byg003

Atasel, O. Y., Guneysu, Y., Pata, U. K. (2022). Testing the agricultural induced EKC hypothesis: fresh empirical evidence from the top ten agricultural countries. *AGRIS on-line Papers in Economics and Informatics*, 14(1), 19–31. https://doi.org/10.7160/aol.2022.140102

Bacco, M., Barsocchi, P., Ferro, E., et al. (2019). The digitisation of agriculture: a survey of research activities on smart farming. *Array*, 3–4, 100009. https://doi.org/10.1016/j.array.2019.100009

Balafoutis, A., Beck, B., Fountas, S., et al. (2017). Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. *Sustainability*, 9(8), 1339. https://doi.org/10.3390/su9081339

Bannerjee, G., Sarkar, U., Das, S., Ghosh, I. (2018). Artificial intelligence in agriculture: A literature survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies*, 7(3), 1–6.

Barraclough, S. L., Ghimire, K. B. (2000). *Agricultural expansion and Tropical Deforestation: Poverty, International Trade and Land Use*. London: Earthscan. ISBN 9781315870533.

Benbrooke, C. M. (2016). Trends in glyphosate herbicide use in the United States and globally. *Environmental Sciences in Europe*, 28(3). https://doi.org/10.1186/s12302-016-0070-0

Bhat, S. A., Huang, N. F. (2021). Big data and ai revolution in precision agriculture: Survey and challenges. *IEEE Access*, 9, 110209–110222. https://doi.org/10.1109/ACCESS.2021.3102227

Butcher, K., Wick, A. F., DeSutter, T., et al. (2016). Soil salinity: A threat to global food security. *Agronomy Journal*, 108(6), 2189–2200. https://doi.org/10.2134/agronj2016.06.0368

Chagnon, M., Kreutzweiser, D., Mitchell, E. A. D., et al. (2015). Risks of large-scale use of systemic insecticides to ecosystem functioning and services. *Environmental Science and Pollution Research*, 22, 119–134. https://doi.org/10.1007/s11356-014-3277-x

Clausen, R., York, R. (2008). Global biodiversity decline of marine and freshwater fish: A cross-national analysis of economic, demographic, and ecological influences. *Social Science Research*, 37(4), 1310–1320. https://doi.org/10.1016/j.ssresearch.2007.10.002

Cordier, J. M., Aguilar, R., Lescano, J. N., et al. (2021). A global assessment of amphibian and reptile responses to land-use changes. *Biological Conservation*, 253, 108863. https://doi.org/10.1016/j.biocon.2020.108863

Dal Pont, S., Longo, L. (2007). Transformaciones productivas en la Provincia de Chaco: avance de la frontera agrícola e implicancias sobre la estructura agraria local. *IADE Revista Realidad Económica*, 228, 113–133.

Dammer, K. H., Wartenberg, G. (2007). Sensor-based weed detection and application of variable herbicide rates in real time. *Crop Protection*, 26(3), 270–277. https://doi.org/10.1016/j.cropro.2005.08.018

Dammer, K. H., Adamek, R. (2012). Sensor-based insecticide spraying to control cereal aphids and preserve lady beetles. *Agronomy Journal*, 104(6), 1694–1701. https://doi.org/10.2134/agronj2012.0021

Danielsen, F., Beukema, H., Burgess, N. D., et al. (2009). Biofuel plantations on forested lands: double jeopardy for biodiversity and climate. *Conservation Biology*, 23(2), 348–358. https://doi.org/10.1111/j.1523-1739.2008.01096.x

Donald, P. F., Sanderson, F. J., Burfield, I. J., et al. (2006). Further evidence of continent-wide impacts of agricultural intensification on European farmland birds, 1990–2000. *Agriculture, Ecosystems and the Environment*, 116, 189–196. https://doi.org/10.1016/j.agee.2006.02.007

Dudley, N., Alexander, S. (2017). Agriculture and biodiversity: a review. *Biodiversity*, 18(2–3), 45–49. https://doi.org/10.1080/14888386.2017.1351892

Dudley, N., Attwood, S. J., Goulson, D., et al. (2017). How should conservationists respond to pesticides as a driver of biodiversity loss in agroecosystems? *Biological Conservation*, 209, 449–453. https://doi.org/10.1016/j.biocon.2017.03.012

Eshel, G., Shepon, A., Makov, T., Milo, R. M. (2014). Land, irrigation water, greenhouse gas, and reactive nitrogen burdens of meat, eggs, and dairy production in the United States. *Proceedings of the National Academy of Sciences*, 111(33), 11996–12001. https://doi.org/10.1073/pnas.1402183111

FAO (2013). *Food Wastage Footprint: Impacts on Natural Resources – Summary Report*. Rome: Food and Agriculture Organization of the United Nations. ISBN 978-92-5-107752-8.

FAO (2019). *World fertilizer trends and outlook to* 2022. Rome: Food and Agriculture Organization of the United Nations. ISBN 978-92-5-131894-2.

FAO (2022a). *The State of the World's Land and Water Resources for Food and Agriculture – Systems at breaking point.* Rome: Food and Agriculture Organization of the United Nations.

FAO (2022b). *FAOSTAT*. [Retrieved 2024-10-22] Available at: https://www.fao.org/faostat/en/#data/QCL

Finger, R., Swinton, S. M., Benni, N. E., et al. (2019). Precision farming at the Nexus of agricultural production and the environment. *Annual Review of Resource Economics*, 11, 313–335. https://doi.org/10.1146/annurev-resource-100518-093929

Fisher, M. C., Henk, D. A., Briggs, C. J., et al. (2012). Emerging fungal threats to animal, plant and ecosystem health. *Nature*, 484, 186–194. https://doi.org/10.1038/nature10947

Foley, J. A., Ramankutty, N., Brauman, K. A., et al. (2011). Solutions for a cultivated planet. *Nature*, 478(7369), 337–342. https://doi.org/10.1038/nature10452

Garske, B., Bau, A., Ekardt, F. (2021). Digitalization and AI in European Agriculture: A Strategy for Achieving Climate and Biodiversity Targets? *Sustainability*, 13(9), 4652. https://doi.org/10.3390/su13094652

Gao, Y., Camtepe, S., Sultan, N. H., et al. (2024). security threats to agricultural artificial intelligence: Position and perspective. *Computers and Electronics in Agriculture*, 227, 109557. https://doi.org/10.1016/j.compag.2024.109557

Geiger, F., Bengtsson, J., Berendse, F., et al. (2010). Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland. *Basic and Applied Ecology*, 11(2), 97–105. https://doi.org/10.1016/j.baae.2009.12.001

Gerber, P. J., Steinfeld, H., Henderson, B., et al. (2013). *Tackling Climate Change through Livestock – A Global Assessment of Emissions and Mitigation Opportunities*. Rome: Food and Agriculture Organization of the United Nations (FAO). ISBN 978-92-5-107921-8.

Ghazali, A., Asmah, S., Syafiq, M., et al. (2016). Effects of monoculture and polyculture farming in oil palm small holdings on terrestrial arthropod diversity. *Journal of Asia-Pacific Entomology,* 19(2), 415–421. https://doi.org/10.1016/j.aspen.2016.04.016

Giam, X. (2017). Global biodiversity loss from tropical deforestation. *Proceedings of the National Academy of Sciences*, 114(23), 5775–5777. https://doi.org/10.1073/pnas.1706264114

Gibbs, H. K., Ruesch, A. S., Achard, F., et al. (2010). Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proceedings of the National Academy of Sciences*, 107, 16732–16737. https://doi.org/10.1073/pnas.0910275107

Holzinger, A., Keiblinger, K., Holub, P., et al. (2023). AI for life: Trends in artificial intelligence for biotechnology. *New Biotechnology*, 74, 16–24. https://doi.org/10.1016/j.nbt.2023.02.001

Huang, A., Dai, L., Ali, S., et al. (2024). From funds to footprints: Unravelling the asymmetric association between nuclear energy technology and environmental quality. *Energy*, 309, 133006. https://doi.org/10.1016/j.energy.2024.133006

IOM (2011). *Fungal Diseases: An Emerging Threat to Human, Animal, and Plant Health*. Washington, D.C.: The National Academies Press. PMID: 22259817.

IUCN (2022). *IUCN Red List of Threatened Species*. [Retrieved 2024-10-22] Available at: https://www.iucnredlist.org/

Javaid, M., Haleem, A., Khan. I. H., et al. (2023). Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*, 2(1), 15–30. https://doi.org/10.1016/j.aac.2022.10.001

Jha, K., Doshi, A., Patel, P., et al. (2020). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004

Kang, M. S., Banga, S. S. (2013). Global agriculture and climate change. *Journal of Crop Improvement*, 27(6), 667–692. https://doi.org/10.1080/15427528.2013.845051

Kaur, L., Yadav, S., Suby, S. B., et al. (2025). Spatio-temporal variability in insect dynamics under conservation agriculture-based cropping systems. *Journal of Plant Diseases and Protection*, 132(1), 1–19. https://doi.org/10.1007/s41348-024-01009-6

Kempenaar, C., Been, T., Booij, J., et al. (2018). Advances in variable rate technology application in potato in the Netherlands. *Potato Research*, 60, 295–305. https://doi.org/10.1007/s11540-018-9357-4

Kerry, R. G., Montalbo, F. J. P., Das, R., et al. (2022). An overview of remote monitoring methods in biodiversity conservation. *Environmental Science and Pollution Research*, 29(53), 80179–80221. https://doi.org/10.1007/s11356-022-23242-y

Kubo, H., Darmawan, A., Hendarto, Madar, A. D. (2021). The effect of agriculture certification schemes on biodiversity loss in the tropics. *Biological Conservation,* 261, 109243. https://doi.org/10.1016/j.biocon.2021.109243

Lioutas, E. D., Charatsari, C., De Rosa, M. (2021). Digitalization of agriculture: A way to solve the food problem or a trolley dilemma? *Technology in Society*, 67, 101744. https://doi.org/10.1016/j.techsoc.2021.101744

Loboguerrero, A., Campbell, B. M., Cooper, P., et al. (2019). Food and earth systems: Priorities for climate change adaptation and mitigation for agriculture and food systems. *Sustainability*, 11(5), 1372. https://doi.org/10.3390/su11051372

Luzardo, O. P., Ruiz-Suárez, N., Valerón, P. F., et al. (2014). Methodology for the identification of 117 pesticides commonly involved in the poisoning of wildlife using GCMS-MS and LC-MS-MS. *Journal of Analytical Toxicology*, 38(3), 155–163. https://doi.org/10.1093/jat/bku009

Martín-López, B., García-Llorente, M., Palomo, I., et al. (2011). The conservation against development paradigm in protected areas: valuation of ecosystem services in the Doñana social-ecological system (southwestern Spain). *Ecological Economics*, 70(8), 1481–1491. https://doi.org/10.1016/j.ecolecon.2011.03.009

McLaughlin, A., Mineau, P. (1995). The impact of agricultural practices on biodiversity. *Agriculture, Ecosystems and the Environment*, 55(3), 201–212. https://doi.org/10.1016/0167-8809(95)00609-V

McPherson, M. A., Nieswiadomy, M. L. (2005). Environmental Kuznets curve: Threatened species and spatial effects. *Ecological Economics*, 55(3), 395–407. https://doi.org/10.1016/j.ecolecon.2004.12.004

Meo, M. S., Adebayo, T. S. (2024). Role of financial regulations and climate policy uncertainty in reducing CO_2 emissions – an application of bootstrap subsample rolling-window Granger causality. *Clean Technologies and Environmental Policy*, 27, 2377–2393. https://doi.org/10.1007/s10098-024-02991-z

Mohamed, E. S., Belal, A., Abd-Elmabod, S. K., et al. (2021). Smart farming for improving agricultural management. *The Egyptian Journal of Remote Sensing and Space Sciences*, 24(3), 971–981. https://doi.org/10.1016/j.ejrs.2021.08.007

Musil, C. F., Milton, S. J., Davis, G. W. (2005). The threat of alien invasive grasses to lowland cape floral diversity: An empirical appraisal of the effectiveness of practical control strategies. *South African Journal of Science*, 101(7), 337–344.

Naidoo, R., Adamowicz, W. L. (2001). Effects of economic prosperity on numbers of threatened species. *Conservation Biology*, 15(4), 1021–1029. https://doi.org/10.1046/j.1523-1739.2001.0150041021.x

Newbold, T., Hudson, L. N., Arnell, A. P., et al. (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. *Science*, 353(6296), 288–291. https://doi.org/10.1126/science.aaf2201

Newbold, T., Hudson, L. N., Hill, S. L. L., et al. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, 520, 45–50. https://doi.org/10.1038/nature14324

Nguyen, Q. P., Vo, D. H. (2022). Artificial intelligence and unemployment: An international evidence. *Structural Change and Economic Dynamics*, 63, 40–55. https://doi.org/10.1016/j.strueco.2022.09.003

Nti, E. K., Cobbina, S. J., Attafuah, E. E., et al. (2022). Environmental sustainability technologies in biodiversity, energy, transportation and water management using artificial intelligence: A systematic review. *Sustainable Futures*, 4, 100068. https://doi.org/10.1016/j.sftr.2022.100068

Obersteiner, M., Kraxner, F., Mosnier, A., et al. (2014). Addressing the drivers of deforestation: exploring synergies between REDD (plus) and forest policy. Proceedings, XXIV IUFRO World Congress, Salt Lake City, USA, October 5–11. *The International Forestry Review*, 16, 545.

Opitz, I., Berges, R., Piorr, A., et al. (2016). Contributing to food security in urban areas: differences between urban agriculture and peri-urban agriculture in the Global North. *Agriculture and Human Values*, 33, 341–358. https://doi.org/10.1007/s10460-015-9610-2

Özkan, O., Adebayo, T. S. (2024). Unraveling the time-varying asymmetric impact of fossil fuel price volatility on high cleantech investments. *Environment, Development and Sustainability*, 28, 11525–11548. https://doi.org/10.1007/s10668-024-05432-5

Pacheco, P. (2012). *Soybean and oil palm expansion in South America: A review of main trends and implications*. Working Paper 90. https://doi.org/10.17528/cifor/003776

Pata, U. K. (2021). Linking renewable energy, globalization, agriculture, CO_2 emissions and ecological footprint in BRIC countries: A sustainability perspective. *Renewable Energy*, 173, 197–208. https://doi.org/10.1016/j.renene.2021.03.125

Perrings, C., Halkos, G. (2015). Agriculture and the threat to biodiversity in sub-Saharan Africa. *Environmental Research Letters*, 10(9), 95015. https://doi.org/10.1088/1748-9326/10/9/095015

Pitman, M. G., Läuchli, A. (2002). Global impact of salinity and agricultural ecosystems. In: Läuchli, A., Lüttge, U. *Salinity: Environment – Plants – Molecules*, pp. 3–20. Dordrecht: Kluwer Academic. ISBN 978-0-306-48155-0.

Pretty, J., Ball, A. S., Lang, T., et al. (2005). Farm costs and food miles: An assessment of the full cost of the UK weekly food basket. *Food Policy*, 30(1), 1–19. https://doi.org/10.1016/j.foodpol.2005.02.001

Raven, P. A., Wagner, D. L. (2020). Agricultural intensification and climate change are rapidly decreasing insect biodiversity. *PNAS*, 118, e2002548117. https://doi.org/10.1073/pnas.2002548117

Rehman, M. A., Fareed, Z., Salem, S., et al. (2021). Do diversified export, agriculture, and cleaner energy consumption induce atmospheric pollution in Asia? application of method of moments quantile regression. *Frontiers in Environmental Science*, 9, 781097. https://doi.org/10.3389/fenvs.2021.781097

Rojas-Downing, M. M., Nejadhashemi, A. P., Harrigan, T., et al. (2017). Climate change and livestock: Impacts, adaptation, and mitigation. *Climate Risk Management,* 16, 145–163. https://doi.org/10.1016/j.crm.2017.02.001

Shivaprakash, K. N., Swami, N., Mysorekar, S., et al. (2022). Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India. *Sustainability*, 14(12), 7154. https://doi.org/10.3390/su14127154

Shen, Z., Wang, S., Boussemart, J.-P., et al. (2022) Digital transition and green growth in Chinese agriculture. *Technological Forecasting and Social Change*, 181, 121742. https://doi.org/10.1016/j.techfore.2022.121742

Singh, S., Mayanglambam, P. (2022). *The role of artificial intelligence in wildlife conservation: A step for achieving SDGs*. [Retrieved 2024-10-22] Available at: https://timesofindia.indiatimes.com/readersblog/policyresearcher/the-role-of-artificial-intelligence-in-wildlife-conservation-a-step-for-achieving-sdgs-43767/

Sparrow, R., Howard, M., Degeling, C. (2021). Managing the risks of artificial intelligence in agriculture. *Impact in Agricultural and Life Sciences*, 93(1), 172–196. https://doi.org/10.1080/27685241.2021.2008777

Tace, Y., Tabaa, M., Elfilali, S., et al. (2022). Smart irrigation system based on IoT and machine learning. *Energy Reports*, 8(9), 1025–1036. https://doi.org/10.1016/j.egyr.2022.07.088

Talaviya, T., Shah, D., Patel, N., et al. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, 4, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Tan, Y.-L., Chen, J.-E., Yiew, T.-H., et al. (2022). Habitat change and biodiversity loss in South and Southeast Asian countries. *Environmental Science and Pollution Research*, 29, 63260–63276. https://doi.org/10.1007/s11356-022-20054-y

Tan, Y.-L., Yiew, T.-H., Habibullah, M. S., et al. (2023). Research trends in biodiversity loss: A bibliometric analysis. *Environmental Science and Pollution Research*, 30(2), 2754–2770. https://doi.org/10.1007/s11356-022-22211-9

Tanentzap, A. J., Lamb, A., Walker, S., et al. (2015). Resolving conflicts between agriculture and the natural environment. *PLoS Biology*, 13, e1002242. https://doi.org/10.1371/journal.pbio.1002242

Tavares, P. D., Uzêda, M. C., Pires, A. D. S. (2019). Biodiversity Conservation in Agricultural Landscapes: The Importance of the Matrix. *Floresta e Ambiente*, 26(4), e20170664. https://doi.org/10.1590/2179-8087.066417

Taylor, R., Dudley, N., Stolton, S., et al. (2015). Deforestation fronts: 11 places where most forest loss is projected between 2010 and 2030. *Paper presented at the XIV World Forestry Congress*, Durban, South Africa, September 7–11.

Thomine, E., Mumford, J., Rusch, A., et al. (2022). Using crop diversity to lower pesticide use: Socio-ecological approaches. *Science of the Total Environment*, 804, 150156. https://doi.org/10.1016/j.scitotenv.2021.150156

UN (2019). *Growing at a slower pace, world population is expected to reach 9.7 billion in 2050 and could peak at nearly 11 billion around 2100*. [Retrieved 2024-10-22] Available at: https://www.un.org/development/desa/en/news/population/world-population-prospects-2019.html

Vijayakumar, S., Kumar, R. M., Choudhary, A. K., et al. (2022). Artificial intelligence (AI) and its application in agriculture. *Chronicle of Bioresource Management*, 6(1), 25–31.

Wezel, A., Herren, B. G., Kerr, R. B., et al. (2020). Agroecological principles and elements and their implications for transitioning to sustainable food systems. A review. *Agronomy for Sustainable Development*, 40, 40. https://doi.org/10.1007/s13593-020-00646-z

Whig, P. (2023). Leveraging AI for sustainable agriculture: opportunities and challenges. *Transactions on Latest Trends in Artificial Intelligence*, 4(4).

WB (2022a). *Climate Change Knowledge Portal (CCKP)*. [Retrieved 2024-10-22] Available at: https://climateknowledgeportal.worldbank.org/download-data

WB (2022b). *World Development Indicators (WDI)*. [Retrieved 2024-10-22] Available at: https://databank.worldbank.org/source/world-development-indicators#

UN, DESA, Population Division (2017). *World Population Prospects: The 2017 Revision, Key Findings and Advance Tables.* Working Paper No. ESA/P/WP/248.

WWF (2014). *The Growth of Soy: Impacts and Solutions.* WWF International, Gland, Switzerland. [Retrieved 2025-04-19] Available at: https://wwfeu.awsassets.panda.org/downloads/wwf_soy_report_final_jan_10.pdf

Zambrano-Monserrate M. A., Subramaniam, Y., Adnan, N., et al. (2024). Dynamic factors driving PM2.5 concentrations: Fresh evidence at the global level. *Environmental Pollution*, 362, 124940. https://doi.org/10.1016/j.envpol.2024.124940

Zha, J. (2020). Artificial intelligence in agriculture. *Journal of Physics: Conference Series*, 1693(1), 012058. https://doi.org/10.1088/1742-6596/1693/1/012058