Review Article

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Environment, Artificial Intelligence and Sustainability: An Overview

Jehan Baban[1*] and Mohammed Al Abadie[2]

[1]*Fellow of The Institute of Environmental Sciences, United Kingdom*

[2]*University of Wolverhampton, North Cumbria Integrated Care NHS Foundation Trust, United Kingdom*

[*]Corresponding Author
Jehan Baban, Fellow of The Institute of Environmental Sciences, United Kingdom.
Mohammed Al Abadie, University of Wolverhampton, North Cumbria Integrated Care NHS Foundation Trust, United Kingdom

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Abstract

Artificial Intelligence (AI) is a redefining tool in addressing global environmental challenges and promising higher-quality decision-making, predictions and modelling. Its early application in weather forecasting, AI has advanced from Machine Learning to deep learning and Neural Networks supporting climate change modelling, hydrology, renewable energy, pollution control, biodiversity, waste management and smart agriculture. However, ethical and Ecological concerns are raised, such as transparency, bias, energy demand, water consumption and electronic waste from large-scale infrastructure. This overview highlights the dual role of AI to advance sustainability whilst generating new environmental challenges.

Keywords: Artificial Intelligence, Environment, Climate Change, Hydrology, Pollution, Renewable Energy

1. Introduction

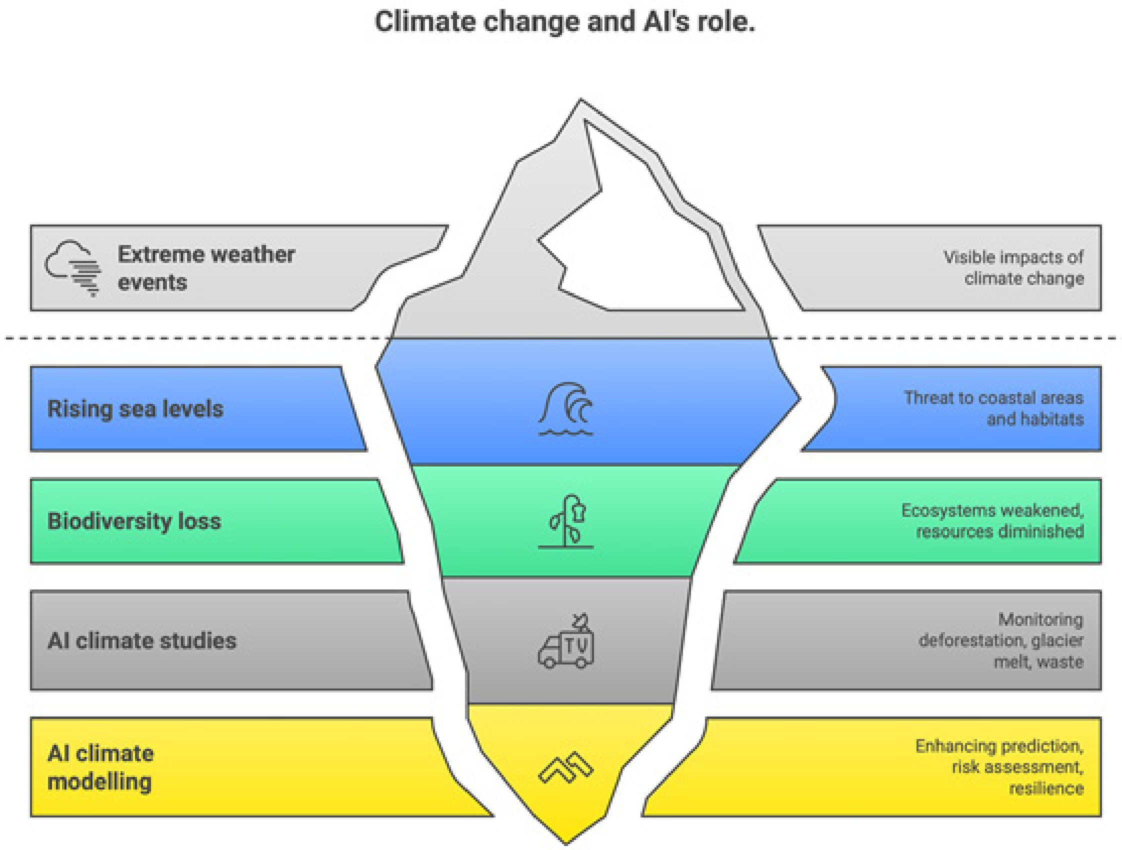
The term "Artificial Intelligence" was coined by John McCarthy in 1956. However, the year 1984 marks the inception of the Artificial Intelligence Research in the Environmental Sciences (AIRES) workshops, which pioneered Artificial Intelligence (AI) applications in environmental studies, with a primary focus on extreme weather forecasting, such as cyclones, hail, and tornadoes [1].

Subsequently, the fundamental transformation occurred with the advent of new AI technologies, namely machine learning and deep learning (ML/DL), which supported the transition from analytic processing to visual pattern recognition, aided by the rise of supercomputers capable of storing and analysing large amounts of data for forecasting extreme weather events. Hydrology was another area that benefited from the development of AI applications (water supply, hydropower generation, drought/flood, landslide risks, precipitation impact on surface water). AI technology has helped develop climate applications to support decision-making, predict future climate patterns, and enhance forecasting [1].

The learning ability of AI systems has paved the way for this technology to adapt and improve over time, as evidenced by innovative new applications that support professionals in addressing environmental challenges and mitigating risks. However, the role of AI in ecological sciences is a work in progress to harness its full potential [2]. Moreover, Machine Learning (ML), Deep Learning (DL), Neural Network (NN), rapidly emerged as powerful tools in many fields, including image, speech recognition, natural language processing, medicine and indeed environment, represent two distinct branches of Artificial Intelligence (AI) is well-positioned to process vast amounts of data efficiently, making it a popular tool deployed in many fields of environmental studies to enhance decision-making and predictions to a level previously unavailable to scientists and policymakers. The progression into supercomputer hardware facilitates this, as noted by Koosha S et al. (2023).

Not surprisingly, Artificial intelligence applications are becoming increasingly popular and taking the lead as essential tools among environmental scientists and engineers, ushering in new horizons for research, innovation, and a better understanding of complex environmental challenges through the efficient use of vast and complex data sets in varied formats and from different sources. These datasets can be Numeric (air quality index measurements or water quality values), categorical (types of land use or disease categories), or Text-based (social media posts or scientific abstracts), or Image-based (such as satellite photos or medical scans). AI experts are developing deep learning algorithms that can comprehend information, leading to significant progress in environmental research, such as modelling, simulation predictions, and reaching more effective solutions for mitigating and adapting to climate change, among other applications [1]. Some researchers argue that AI algorithms have begun to surpass humans in an increasing number of tasks, with a new culture of collaboration between environmental scientists, AI engineers, and experts evolving rapidly. At the same time, this has introduced associated issues, such as ethical aspects and ecological consequences of AI. The following is an attempt to highlight some AI applications in the field of environmental science studies.

1.1 Climate Change



This domain represents a major global environmental challenge that attracted worldwide attention because of the vast impact on the plant due to Extreme weather events like floods, droughts, and heatwaves becoming more frequent and intense, threatening homes, food supplies, and lives, Rising sea levels pose a significant threat to coastal cities and island nations, displacing millions of people over time and endangering the habitats of wildlife. These habitats are shrinking or shifting, causing a loss of Biodiversity and weakening ecosystems that provide us with clean air, water, and food [3]. AI technology is steadily taking the lead in climate change studies, analysing satellite imagery as a dataset for monitoring and identifying illegal Deforestation, tracking glacier melt, and plastic waste in oceans. Recognises patterns that humans require years to find manually.

Furthermore, AI algorithms are revolutionising climate modelling by enhancing predictive accuracy and improving climate risk assessment, resource optimisation, and infrastructure resilience through the processing of diverse datasets from satellites, ground-based sensors, and atmospheric monitoring systems. These AI-driven enhancements contribute to what is known as "AI-driven climate resilience," where AI-enhanced climate models inform data-driven policy decisions, shaping sustainable development [4]. Thus, researchers employed AI applications in research related to greenhouse gas (GHG) emissions and carbon footprint.

Furthermore, experts predicted that AI would drive the process of transforming scientific understanding of climate change management with a rise in the speed of problem-solving using AI applications that offer more efficient approaches to understand the causes of climate change, respond to its impacts, and formulate solutions, including measures to mitigate and adapt to its effects. For example, using AI tools could improve the accuracy of climate system modelling, estimate emissions inventories, refine climate scenario projections, and climate impact assessments, as well as develop applications for low-carbon technology use in the power industry, transportation, and construction.

Already, AI simulations and machine learning are being integrated into weather and climate modelling, enabling the forecasting of weather patterns and climate processes with greater consistency, data efficiency, and improved generalisation [5]. Indeed, AI is currently deployed in many climate change-related applications, such as flood risk modelling frameworks to increase the performance and accuracy of prediction methods or by using neural networks for weather and climate modelling to improve agriculture and crop production predictions under a range of climate scenarios, or in monitoring soil quality, or pest outbreaks.

Lobo S, et al. [6]. This study combines AI, deep learning, and statistical techniques to examine the impact of deforestation and population growth on carbon footprints in Indian cities. Additionally, AI is a powerful tool for assessing and developing carbon markets, as well as generating more accurate carbon price models, including dynamic carbon pricing mechanisms and more robust comparison models for carbon price forecasting. Such methods have been applied by scientists in studying emissions trading schemes in many countries, including the UK [7, 8].

Within this context, the application of AI tools has raised social and ethical issues, including transparency regarding the trade-off between the GHG emissions generated by AI research and the energy and resource efficiency gains that AI can offer in understanding and combating climate change, while reducing its environmental impact [9-11].

1.2 Hydrology

Received ample AI attention, reflecting the importance of water as a crucial resource, as evidenced by the wide range of published studies utilising ML. For example, forecasting precipitation requires the processing of large amounts of data, which is well-suited for machine learning to facilitate effective planning, crisis management, and the reduction of losses to life and property [12]. In an earlier study conducted in 1994, Karunanithi, N. W., focused on the use of neural networks as a tool to develop an adaptive model synthesiser and predictor of the Huron River at the Dexter sampling station, near Ann Arbour [13]. Within the hydrology subdomain, rainfall is one of the most challenging fields to predict accurately. It requires thorough knowledge of the atmospheric moisture and vertical motion fields to forecast the location and amount of rainfall, which are challenging quantities to predict accurately.

Krasnopolsky, V. M et al., Took a novel approach based on learning from data using the neural network (NN) technique for improving 24-hour precipitation forecasts over the continental US [14]. Using AINN tools was superior to Numerical Weather Prediction (NWP), which relies on mathematical modelling of the atmosphere and oceans to forecast precipitation, due to the limitations in representing cloud dynamics and the microphysical processes involved in rainfall generation. Chun Zhou et al., published a comprehensive review outlining recent advancements in the application of artificial intelligence to satellite precipitation data fusion, including the integration of information from multiple sources for improved data accuracy and reliability, as well as downscaling techniques and flood forecasting[15]. They concluded that AI deep learning techniques have surpassed the limitations of traditional forecasting methods.

Drought prediction is increasingly significant in the field of hydrology. Scientists in drought assessment, monitoring, management and forecasting use Artificial Intelligence techniques [16]. Maier, H. R., and Dandy, G. C. noted that AI is increasingly used to predict water resource variables [17]. The study outlined steps for developing water resource prediction models using Neural Networks technology, which outperform traditional statistical approaches.

1.3 Meteorology and Weather

Researchers have utilised AI tools in a wide range of meteorology applications, including cloud classification, tornado prediction and detection, wind damage assessment, hail size determination, precipitation classification, and storm tracking, as well as in rainfall-runoff modelling and flood forecasting [18]. Researchers repeatedly observe the limitations of numerical weather prediction (NWP) models [19]. Kumler-Bonfanti, C. J. echoed these limitations in detecting significant differences between human and AI/ML techniques, which are effective in identifying complex and ambiguous phenomena, and can be trained to perform object recognition tasks at superhuman levels [20]. Particularly effective for image analysis, as it can recognise essential features within the image.

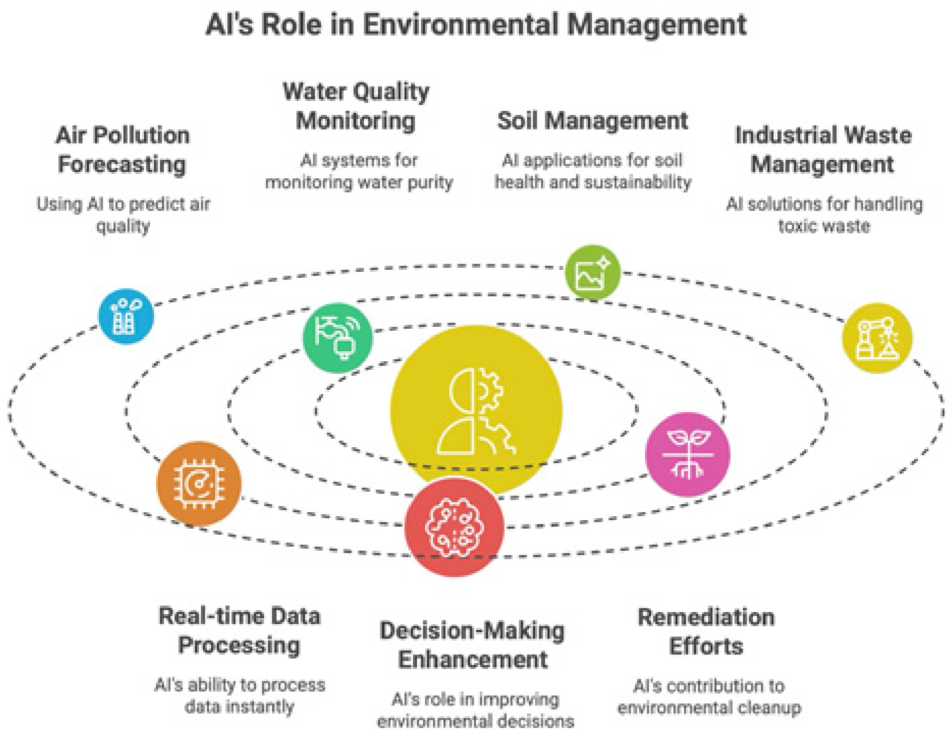
A major extreme weather event in the USA is hail, which causes billions of dollars in property and crop destruction and is a significant liability for insurance companies. Gagne, D. J., et al. and the 2019 studies applied deep learning models to predict the likelihood of severe hailstorms by investigating upper-air dynamic and thermodynamic fields [21, 22].

1.4 Renewable Energy

AI has also been applied to renewable energy as part of the global shift from fossil fuels to green sources, such as solar and wind, to meet the carbon reduction targets set by the Paris Climate Accord (2015). However, constructing a renewable electricity site must account for many variables that impact the energy output. Moreover, since the power production infrastructure is expected to last decades, it is imperative to consider future changes in the power prediction potential and other variables related to climate change. As a case study, Haupt, S. E., et al. discussed topics related to the Kuwait Renewable Energy Prediction System (KREPS), which the United States developed [22]. The system aims to achieve a combined wind and solar generation capacity of approximately 4 GW. The park contains wind turbines, photovoltaic panels, and concentrated solar renewable energy technologies with storage capabilities. For short-term prediction, AI methods utilise historical observations to train algorithms that predict future states. The system also includes extreme event alerting capabilities for high wind speeds and high temperatures that could cause wind turbine derating or cut-out. Al-Othman reported that AI techniques are being utilised in the deployment of data-integrated renewable energy networks, in estimating and forecasting solar radiation and wind energy resources, and in micro-grid management [23].

A significant challenge for installing solar energy systems is Clouds as they move over the solar power site, which represents one of the most essential variables in forecasting shortrange solar-energy power generation, as they cause near-instantaneous changes in power generation, by using an artificial neural network (RD-ANN) system trained to classify cloud regimes with a specific algorithm based on a combination of surface weather observations, irradiance observations, and satellite data to predict the irradiance variability more accurately compared to less efficient techniques [24]. Furthermore, Di Sabatino, M et al, approached renewable energy provision from another angle by exploring the adoption of AI ML in the manufacturing of silicon-based solar cells, driven by the heightened demand for solar panels [25]. AI technology has advanced cell designs that improve the quality of the silicon solar cell in producing electricity.

Pollution Control and Management



Environmental scientists recognise air, water, and soil pollution as global concerns. Numerous countries are implementing sustainable economic strategies, including the adoption of a green circular economy, to preserve a safer environment for future generations.

AI is effective for future pollution control and environmental management (Hoang, 2022). Artificial intelligence is increasingly used to monitor and manage air, water, and soil, including industrial toxic waste, to enhance sustainability [26]. Ye Z, discussed several AI approaches, which start with the reliable mapping of nonlinear behaviour between inputs and outputs in chemical and biological processes in terms of prediction models [27].

Air pollution is one of the leading contributors to the global environmental burden of disease and poor health (WHO, 2017), which has attracted environmental scientists to apply an AI/ML approach [28]. A comparative review found that deep neural networks outperform other AI methods in air pollution forecasting [29]. Within this context, accurate air quality forecasting is crucial for effective pollution control, as well as for maintaining public health and wellness.

Moreover, AI has emerged as a vital tool for improving efficiency, accuracy, and sustainability in managing polluted air, water, and soil. AI techniques, particularly machine learning and deep learning, have been successfully employed to forecast pollution trends, enhance management and control approaches, and assess the ecological effects of contaminants. AI's real-time data processing enables quick responses to environmental hazards, improves decision-making, and advances remediation efforts for a cleaner, safer, and more sustainable environment [27, 30]. Machine learning plays a crucial role in managing air pollution and greenhouse gas emissions, thereby supporting progress toward a low-carbon society.

1.5 Biodiversity and Conservation

Nature conservation projects can benefit from Machine Learning AI/ML technology to map habitats, model species distributions, and monitor vegetation and tree growth. They could aid decisions on establishing protected zones and preserving local Biodiversity [31]. AI technology is leading the way in Automated Species Identification in real-time, using AI-powered camera traps and drones that can identify animals through computer vision pattern recognition, enabling the tracking of individual animals. AI/ML could also assist by using data from audio recordings to detect species by their calls and distress signals or changes in vocal behaviour linked to environmental stress. In the Amazon, Satellite imagery combined with AI can monitor Habitat and Deforestation to detect illegal logging, land-use changes, and habitat fragmentation.

Furthermore, AI/ML can assist in Predictive Modelling that forecasts migration patterns, breeding cycles, or ecosystem disruptions by analysing historical and real-time data. AI technology has also democratised data collection by integrating AI tools into mobile apps, allowing the public to contribute observations. These innovations have enhanced species protection and introduced additional measures to protect endangered species. [32, 33].

1.6 Waste Management and Recycling

The use of AI tools in solid wate management is a has been evolving as shown by systemic literature review that identified 85 research studies, published between 2004 and 2019, Abdallah, M, that showed AI/ML can assist with forecasting solid waste characteristics, waste bin level detection, process parameters prediction, vehicle routing, and planning [34]. Furthermore, ML technologies can detect and identify illegal landfills from unmanned aerial vehicle (UAV) images and videos, which is a more efficient and cost-effective approach [35]. AI innovations have transformed recycling by utilising sensors and cameras to identify waste types in bins, categorising them into paper, cardboard, glass, metal, plastic, and other categories, supported by AI robotics [34].

1.7 Smart Agriculture

The role of AI/ML extends beyond efficiency to encompass resilience, sustainability, and adaptation to a changing climate, thereby ensuring food security. Smart agriculture, also known as precision farming, is reshaping agriculture industry by integrating advanced technologies like AI, IoT (The Internet of Things is a network of physical objects "things", equipped with sensors, software, and communication tech that collect and exchange data with other devices like environmental sensors over the internet), robotics, and big data into every stage of the agricultural cycle [36, 37]. The outcome is Precision Crop Management, utilising sensors in the soil and drones to monitor moisture, nutrient levels, and plant health in real-time. AI analyses this data to guide irrigation, fertilisation, and pest control, minimising waste and maximising crop yield. This method enables the use of autonomous machinery—such as self-driving tractors, robotic harvesters, and drone sprayers—that operate around the clock and adjust to field conditions, thereby decreasing reliance on manual labour. Another benefit is that Climate-Smart Forecasting technology can predict weather patterns, disease outbreaks, and crop performance under various climate scenarios, enabling farmers to make informed decisions and reduce losses from extreme events. AI tools can support Livestock Monitoring by tracking animal health, behaviour, and productivity. AI helps detect early illness or stress, boosting welfare and reducing antibiotic use. Vertical and controlled environment farming, especially in climate-stressed urban areas, uses AI to manage light, temperature, and nutrients in indoor farms. This enables continuous production throughout the year while requiring relatively low amounts of water and land [38, 39].

In another study, Hoang, T.D., et al., proposed an interactive AI-based crop and pest management system integrated into a mobile application, designed to enhance sustainable agricultural productivity by adopting advanced deep learning techniques, which can classify insects and pests efficiently and monitor macronutrient levels, Nitrogen, Phosphorus, Potassium, soil pH, and climatic parameters (Temperature, Humidity, Rainfall) [26]. The Pest Detection module uses real-time field data to support pest identification and treatment decisions.

1.9 Sustainability and SDGs

On September 25, 2015, the United Nations adopted the 2030 Sustainable Development Agenda, which lists 17 Sustainable Development Goals SDGs and 169 targets to support planetary, human, and economic well-being [40]. According to Vinuesa, experts report that AI technologies can contribute to achieving at least 134 of the 169 targets (about 79%) related to the SDGs by 2030. Furthermore, the SDGs for the environment group are related to climate action, life below water and life on land (SDGs 13, 14, and 15) [41].

Environmental policy and decision-making are increasingly data-driven, using the Environmental Performance Index (EPI) as a measure to assess sustainability. Effective governance is crucial for balancing the various aspects of sustainability. EPI is also used as a guide to the level of progress on sustainability management and pollution control [42]. Baig, M. A. A., et al. discussed AI as a significant technology that could accelerate progress in meeting the environmental, social, and economic aspects of the SDGs, provided it is deployed with an ethical approach [43]. AI algorithms have the indisputable potential to accelerate innovation that maximises sustainability [44].

2. Ethics, Trade-Offs, and Laws

Despite overwhelming views that AI can help improve and expand current understanding and management of environmental challenges, two sets of problems have been recognised. Firstly, the social and ethical impacts of AI, and secondly, the contribution to climate change of the greenhouse gases emitted by training data and computation-intensive AI systems [45]. These emerging issues are referred to as AI, a double-edged tool. In AI-driven climate modelling, scientists must address ethical issues related to bias in training data, lack of transparency, and potential inequities in climate adaptation strategies to ensure fair and responsible AI implementation. Indeed, fairness and transparency are crucial in AI-driven climate modelling. Biased datasets skew projections, harming vulnerable regions by underestimating risks and misallocating resources. Fairness depends on diverse datasets and frequent bias audits to achieve equity. Bartmann, M., thus supporting the view that AI systems are only as good as the data they learn from [46]. David De Cremer & Garry Kasparov argued for continuing the push towards AI innovation, with use supported by a sense of moral awareness and responsibility and promoting training efforts to establish more responsible leadership [47].

Another pertinent issue is related to the impact of AI technology on the environment. For example, the carbon footprint of AI research is very significant. It highlights the need for more evidence concerning the trade-off between the GHG emissions generated by AI research and the energy and resource efficiency gains that AI can offer.

On the other hand, training and running large AI models demand massive Energy consumption, due to their complexity, which requires substantial computational power, particularly during the training phase. AI models, for instance, are more energy-intensive than simpler classification models. Indeed, the significant energy required for powering AI systems will lead to considerable GHG emissions, primarily if the energy source is from non-renewable power plants.

Another environmental impact is linked to the high water consumption required by large data centres. These centres require cooling systems that consume vast amounts of water to prevent overheating and sustain performance. This usage can exacerbate water scarcity in regions already vulnerable to such stress. Moreover, the hardware underlying AI, including servers and other specialised equipment, also has an environmental impact (e-waste), as rapid turnover of hardware contributes to the growing problem of electronic waste, much of which is not recycled correctly [48-50].

2. Conclusion

AI, ML, DL and NN technologies are shaping every aspect of the human experience, including environmental management and control. It is an evolving and rapidly developing experience that may usher in the dawn of a new, brave world dominated by an AI-driven environment that is green, safe, and healthy, with attention paid to the environmental consequences of even greater AI infrastructure and more challenging ethical and social issues.

References

1. Haupt S.E., Gagne D.J., William W.H, Krasnopolsky V, McGovern A, Marzban A, Valliappa W.M., Lakshmanan P.T., and Williams J.K., (2022). The History and Practice of AI in the Environmental Sciences, Bulletin of the American Meteorological Society, Volume 103: Issue 5, 2022.
2. Konya P.A., Nematzadeh P., (2024). Recent applications of AI to environmental disciplines: A review, Science of the Total Environment, Volume 906, 1 January 2024, 167705
3. Intergovernmental Panel on Climate Change, Climate Change: The Physical Science Basis Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2021.
4. Alizadeh, O. (2022). Advances and challenges in climate modelling. Climatic Change 170, 18 (2022).
5. Lewis, J.I., Toney, A. & Shi, X. Climate change and artificial intelligence: assessing the global research landscape. Discov Artif Intell 4, 64 (2024).
6. Lobo, S., Amin, I., Agarwal, M., Gurnani, R., Priya, R.L. (2021). Analyzing the Impact of Deforestation and Population on Carbon Footprint in Indian Cities Using Statistical and DeepLearning Techniques. In: Reddy, V.S., Prasad, V.K., Wang, J., Reddy, K.T.V. (eds) Soft Computing and Signal Processing. Advances in Intelligent Systems and Computing, vol 1325. Springer, Singapore.
7. Ojo, M. (2019). The Future of UK Carbon Pricing: Artificial Intelligence and the Emissions Trading System. MPRA paper. University Library of Munich, Germany. 2019.
8. Hu, B., Asim, S., Sibt-e-Ali, M. et al. (2023)Exploring the relationships between attitudes toward emission trading schemes, artificial intelligence, climate entrepreneurship, and sustainable performance. Environ Sci Pollut Res 30, 95720–95737.
9. Arya, A., Bachheti, A., Bachheti, R.K., Singh, M., Chandel, A.K. (2024). Role of Artificial Intelligence in Minimising Carbon Footprint: A Systematic Review of Recent Insights. In: Chandel, A.K. (eds) Biorefinery and Industry 4.0: Empowering Sustainability. Green Energy and Technology. Springer, Cham.
10. Cowls, J., Tsamados, A., Taddeo, M. et al. (2023). The AI Gambit: Leveraging Artificial Intelligence to Combat Climate Change—Opportunities, Challenges, and Recommendations. AI & Soc 38, 283–307.
11. Lewis, J.I., Toney, A. & Shi, X. (2024). Climate change and artificial intelligence: assessing the global research landscape. Discov Artif Intell 4, 64 (2024).
12. Agrawal, S., L. Barrington, C. Bromberg, J. Burge, C. Gazen, & J. Hickey. (2019). Machine Learning for Precipitation Nowcasting from Radar Images. arXiv, 6 pp.,
13. Karunanithi, N., W. J. Grenney, D. Whitley, and K. Bovee (1994). Neural networks for river flow prediction. J. Comput. Civ. Eng., 8, 201–220.
14. Krasnopolsky, V. M., and Y. Lin, (2012). A neural network nonlinear multimodel ensemble to improve precipitation forecasts over the continental US. Adv. Meteor., 2012, 649450.
15. Chun Zhou, Lingling Wu, Zhongshun Gu, Yinan Guo and Li Zhou, AI in Hydrometeorology: Deep Learning for Satellite Precipitation Fusion and Flood Forecasting, 2025, Advances in the Theory and Prediction of Rainfall.
16. Kikon, A., Deka, P.C. (2022). Artificial intelligence application in drought assessment, monitoring and forecasting: a review. Stoch Environ Res Risk Assess 36, 1197–1214.
17. Maier, H. R., and G. C. Dandy (2000). Neural networks for the prediction and forecasting of water resources variables: A review of modelling issues and applications. Environ. Modell. Software, 15, 101–124,
18. Crespo, J. L., and E. Mora. (1993) Drought estimation with neural networks. Adv. Eng. Software, 18, 167–170,

19. Dawson, C. W., and R. L. Wilby. (2001) Hydrological modelling using artificial neural networks. Prog. Phys. Geogr., 25, 80–108.
20. Kumler-Bonfanti, C., J. Stewart, D. Hall, and M. Govett. (2020) Tropical and extratropical cyclone detection using deep learning. J. Appl. Meteor. Climatol., 59, 1971– 1985.
21. Gagne, D. J., S. E. Haupt, D. W. Nychka, and G. Thompson. (2019). Interpretable deep learning for spatial analysis of severe hailstorms. Mon. Wea. Rev.., 147, 2827– 2845.
22. Gagne, D. J., II, A. McGovern, S. E. Haupt, R. A. Sobash, J. K. Williams, and M. Xue. (2017). Storm-based probabilistic hail forecasting with machine learning applied to convection-allowing ensembles. Wea. Forecasting, 32, 1819– 1840.
23. Gagne, D. J., S. E. Haupt, D. W. Nychka, and G. Thompson. (2019). Interpretable deep learning for spatial analysis of severe hailstorms. Mon. Wea. Rev.., 147, 2827– 2845.
24. Haupt, S. E., Sue Ellen Haupt, Tyler C. McCandless, Susan Dettling, Stefano Alessandrini, Jared A. Lee, Seth Linden, William Petzke, Thomas Brummet, Nhi Nguyen, Branko Kosović, Gerry Wiener, Tahani Hussain and Majed Al-Rasheedi (2020),: Combining artificial intelligence with physics-based methods for probabilistic renewable energy forecasting. Energies Published: 16 April 2020.
25. Al-Othman, A., Tawalbeh, M., Martis, R., Dhou, S., Orhan, M., Qasim, M., Olabi, A.G. (2022). Artificial intelligence and numerical models in hybrid renewable energy systems with fuel cells: advances and prospects. Energy Convers Manage. 2022;253(February): 115154.
26. Candless, T. C., G. S. Young, S. E. Haupt, and L. M. Hinkelman. (2016). Regime-dependent short-range solar irradiance forecasting. J. Appl. Meteor. Climatol., 55,1599–1613.
27. Di Sabatino, M.; Hendawi, R., Garcia, A.S. (2024). Silicon Solar Cells: Trends, Manufacturing Challenges, and AI Perspectives, Crystals 2024, 14, 167.
28. Hoang, TD., Ky, N.M., Thuong, N.T.N., Nhan, H.Q., Ngan, N.V.C. (2022). Artificial Intelligence in Pollution Control and Management: Status and Future Prospects. In: Ong, H.L., Doong, R., Naguib, R., Lim, C.P., Nagar, A.K. (eds) Artificial Intelligence and Environmental Sustainability. Algorithms for Intelligent Systems. Springer, Singapore.
29. Ye, Z., Yang, J, Zhong, N, Tu, X., Jia, J, Wang, J., (2020). Tackling environmental challenges in pollution controls using artificial intelligence: a review. Sci Total Environ 699:134279.
30. WHO 2017, World health statistics 2017: monitoring health for the SDGs, sustainable development goals.
31. Masood, A., & Ahmad, K. (2021). A review on emerging artificial intelligence (AI) techniques for air pollution forecasting: Fundamentals, application and performance. Journal of Cleaner Production, 322, 129072.
32. Balakumar, S., Mahesh, N., Kamaraj, M. et al. (2025). Harnessing artificial intelligence for sustainable environmental remediation: A review. Int. J. Environ. Sci. Technol. (2025).
33. Da Silveira-Junior, W.J., de Souza, C.R., Mariano, R.F. et al. (2021). Conservation conflicts and their drivers in different protected area management groups: a case study in Brazil. Biodivers Conserv 30, 4297–4315.
34. Reynolds, S.A., Beery, S., Burgess, N., Burgman, M., Butchart, S.H.M., Cooke, S.J.,Coomes, D., Danielsen, F., Di Minin, E., Durán, A.P., Gassert, F., Hinsley, A., Jaffer, S., Jones, J.P.G., Li, B.V., Mac Aodha, O., Madhavapeddy, A., O'Donnell, S.A.L., Oxbury, W.M., Peck, L., Pettorelli, N., Rodríguez, J.P., Shuckburgh, E., Strassburg, B., Yamashita, H., Miao, Z., & Sutherland, W.J. (2025). The Potential for AI to Revolutionise Conservation: A Horizon Scan. Trends in Ecology & Evolution, 40(2), 206.
35. Ullah, F., Saqib, S. & Xiong, YC. (2025). Integrating Artificial Intelligence in Biodiversity Conservation: Bridging Classical and Modern Approaches. Biodivers Conserv 34, 45–65 (2025).
36. Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial intelligence applications in solid waste management: A systematic research review. Waste Management, 109, 231246.
37. Torres, R.N., Fraternali, P. (2023). AerialWaste dataset for landfill discovery in aerial and satellite images. Sci Data 10, 63 (2023).
38. Goel, R. K., Yadav, C. S., Vishnoi, S., & Rastogi, R. (2021). Smart agriculture – Urgent need of the day in developing countries. Sustainable Computing: Informatics and Systems, 30, 100512.
39. Adli, H. K., Remli, M. A., Syazwan, K. N., Ismail, N. A., Corchado, J. M., & Mohamad, M. S. (2023). Recent Advancements and Challenges of AIoT Applications in Smart Agriculture: A Review. Sensors, 23(7), 3752.
40. Shaikh F. K., M. A. Memon, N. A. Mahoto, S. Zeadally and J. Nebhen. (2022). Artificial Intelligence Best Practices in Smart Agriculture," in IEEE Micro, 42,1724.
41. Assimakopoulos, F., Vassilakis, C., Margaris, D., Kotis, K., & Spiliotopoulos, D. (2025). AI and Related Technologies in the Fields of Smart Agriculture: A Review. Information, 16(2), 100.
42. Rashed, A.H., Shah, A. (2021). The role of the private sector in the implementation of the Sustainable Development Goals. Environ Dev Sustain 23, 2931–2948.
43. Vinuesa, R., Azizpour, H., Leite, I. et al. (2020). The Role of Artificial Intelligence in Achieving the Sustainable Development Goals. Nat Commun 11, 233.
44. How, M., Cheah, S., Chan, Y., Khor, A. C., & Say, E. M. (2020). Artificial Intelligence-Enhanced Decision Support for Informing Global Sustainable Development: A HumanCentric AI-Thinking Approach. Information, 11(1), 39.
45. Baig., Mirza Abdul Aleem., Jingchen Huang., Jingzehua Xu. (2024). AI for United Nations sustainable development goals: AI for UNSDGs. (2024).
46. Clark, T., Zolnikov, T.R., Furio, F., Salinas, N.D., Dick, S. (2025). The Role of Artificial Intelligence in Achieving Sustainable Development Goals (SDGs). In: Brears, R.C. (eds) The Palgrave Handbook of Ecosystems and Wellbeing. Palgrave Studies in Sustainable Futures.Palgrave Macmilla

Cham.
47. Cowls, J., Tsamados, A., Taddeo, M. et al. (2023). The AI Gambit: Leveraging Artificial Intelligence to Combat Climate Change—Opportunities, Challenges, and Recommendations. AI & Soc 38, 283–307 (2023).
48. Bartmann, M. (2022). The Ethics of AI-Powered Climate Nudging—How Much AI Should We Use to Save the Planet? Sustainability, 14(9), 5153.
49. David De Cremer & Garry Kasparov. (2022). Opinion paper: The ethics of technology innovation: a double-edged sword? AI and Ethics (2022) 2:533–537.
50. Agrawal, S., L. Barrington, C. Bromberg, J. Burge, C. Gazen, and J. Hickey (2019). Machine Learning for Precipitation Nowcasting from Radar Images. arXiv, 6 pp.,