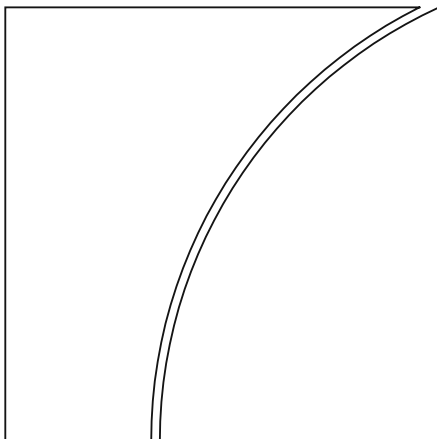




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Artificial intelligence and climate change: balancing innovation and sustainability

Leonardo Gambacorta and Salvatore Polizzi*

Abstract

Artificial intelligence (AI) is becoming an increasingly important factor in the climate transition. AI can improve energy efficiency, optimise resource use, accelerate climate innovation and strengthen climate forecasting, adaptation and risk management. At the same time, the development and deployment of AI require substantial computational resources, increasing electricity demand and, depending on the carbon intensity and timing of electricity use, associated emissions. We examine AI's direct environmental footprint, its contribution to climate mitigation and adaptation, and rebound effects arising from lower costs, higher productivity and wider adoption. The overall impact of AI on climate change also depends on how AI capabilities evolve. We consider two stylised scenarios. Under an AI copilot scenario, benefits and environmental costs are likely to build up more gradually, but the net climate effect remains uncertain, depending on whether efficiency gains outpace growth in AI use, on the carbon intensity of additional electricity needed to power AI, and on how productivity gains translate into economic activity and resource use. Under a more transformative scenario involving artificial general intelligence (AGI), with cognitive capabilities comparable to those of humans across a broad range of tasks, both the potential benefits and environmental risks could become larger and more uncertain. The paper also reviews emerging policy responses and highlights the relevance of the AI–climate nexus for central banks. By affecting productivity, energy systems and climate-related risks, the AI–climate nexus can influence potential output and inflation dynamics, while the scale and financing of investment in AI and energy infrastructure may also have implications for financial stability.

JEL classification: O33, Q51, Q55.

Keywords: artificial intelligence, artificial general intelligence, climate change, energy consumption, carbon emissions, sustainability, rebound effects, geopolitical risks.

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1. Introduction

Artificial intelligence (AI) is a double-edged sword in the fight against climate change. On the one hand, AI offers powerful innovative tools to reduce greenhouse gas emissions and help societies adapt to climate impacts (Verdecchia et al (2023); Tabbakh et al (2024)). For instance, AI-powered solutions can optimise transportation systems to reduce carbon dioxide (CO₂) emissions, accelerate climate-friendly innovations, forecast extreme weather events caused by climate change and support the development of strategies to achieve climate goals. These are just a few examples of the broad “greentech” concept regarding the use of technology in general and AI in particular in the fight against climate change (Cœuré (2021)). On the other hand, training and deploying AI systems can consume vast energy resources, potentially adding to the problem of climate change (Metaculus (2026)). AI is not only part of a potential solution to climate change but the resulting increase in electricity demand makes it also a possible source of additional environmental pressures. This concern has become more salient in an environment of heightened geopolitical fragmentation and energy market uncertainty, which may affect both energy costs and the availability of critical inputs for AI development. The interaction between AI and climate change operates through several channels, including AI’s direct environmental footprint, its contribution to climate mitigation and adaptation, and rebound effects stemming from higher productivity and wider AI adoption.

The climate implications of AI also depend critically on how the technology evolves. One possible scenario is the use of an *AI copilot*, in which large language model (LLM)¹ applications complement human decision-making and task execution. In this scenario, AI could support climate mitigation and adaptation through efficiency gains and improved resource allocation, while its benefits and environmental costs are likely to build up relatively gradually. A second scenario is the emergence of *artificial general intelligence* (AGI), characterised by cognitive capabilities comparable to those of humans (Naudé and Dimitri (2020)). Such a development could not only substantially amplify AI’s contribution to climate solutions but also increase energy consumption and resource demands, with uncertain implications for climate outcomes. These two scenarios should not be viewed as discrete outcomes but rather as points along a continuum, in which increasingly capable copilots evolve into more autonomous AI agents² and, potentially, towards AGI, which may replace many human functions. Despite unprecedented investments in AI infrastructure, the economic viability of current investment patterns and the ultimate returns from AI remain unclear (Aldasoro, Doerr and Rees (2026)). If AI development results mainly in incremental copilot applications, current valuations may prove difficult to justify. By contrast, the emergence of AGI could generate productivity gains large enough to support current investment levels.

The AI–climate nexus also has important implications for central banks. AI may raise potential output through productivity gains and by accelerating innovation in climate-related technologies, while AI-enabled mitigation and adaptation could limit

¹ An LLM copilot is defined as a tool designed to assist humans in performing tasks such as developing software, summarising documents, drafting emails and generating images. It operates in response to natural language prompts provided by humans.

² Among the various definitions of AI agents, we define an agent as an LLM capable of utilising a computer. For a discussion, see Bell et al (2025).

climate-related losses to productive capacity. At the same time, energy-intensive AI deployment can increase electricity demand and expose economies to grid bottlenecks and higher energy costs, with consequences for inflation dynamics and the assessment of economic slack. The interaction between AI, climate risks and the energy transition may also have implications for financial stability. Large-scale investment in data centres and energy infrastructure can create significant financial exposures, particularly if expected returns from AI-related investment fail to materialise. At the same time, investment in carbon-intensive energy infrastructure needed to power AI may increase transition risks if climate policies tighten. The AI–climate nexus therefore matters not only for environmental policy but also for macroeconomic and financial stability assessment.

This paper examines the interaction between AI and climate change. It reviews the potential contribution of AI to climate mitigation and adaptation, assesses the environmental costs and unintended consequences associated with AI deployment and analyses how these opportunities and challenges may evolve under different trajectories of technological progress along the AI copilot–AGI continuum. The paper also discusses emerging policy and governance responses aimed at aligning AI innovation with sustainability objectives.

The remainder of the paper is organised as follows. Section 2 examines the opportunities for climate action that AI offers, focusing on its potential to support climate mitigation and adaptation, enhance productivity and foster innovation. Section 3 discusses the challenges associated with AI deployment, including its environmental footprint, energy consumption, rebound effects and broader geopolitical and distributional implications. Section 4 considers how these opportunities and challenges may evolve under two alternative technological development scenarios: AI copilot and AGI. Section 5 discusses the implications of the AI–climate nexus for central banks, including potential output, monetary policy and financial stability, and reviews emerging policy and governance responses aimed at improving transparency, promoting sustainable AI innovation and strengthening international cooperation. Section 6 concludes.

2. Opportunities: AI as a tool for climate action

AI is emerging as an enabler of climate solutions in multiple domains. From optimising energy systems and industrial processes to improving climate risk forecasting and agricultural resilience, AI-driven applications can boost efficiency, innovation and informed decision-making in the climate context. Crucially, these technologies offer not only environmental benefits but also economic gains through productivity improvements and new markets for green technologies. The left column of Table 1 summarises the main opportunities associated with the use of AI in the climate transition, ranging from climate mitigation and adaptation to broader economic and innovation benefits.

Beyond its direct applications described in the subsequent paragraphs, AI may also accelerate climate innovation by reducing the cost and increasing the speed of developing low-carbon technologies. In economic terms, AI has the potential to lower the marginal cost of emissions abatement by accelerating directed technological change towards cleaner technologies and making mitigation options that were previously too costly increasingly economically viable (Acemoglu et al (2012)).

Opportunities	Challenges
Mitigation (section 2.1) Sector-specific - Energy: forecasting and grid optimisation; temporal and spatial shifting of flexible computing workloads - Transportation: smart traffic management - Manufacturing: identification of energy-saving opportunities Cross-sectoral - AI-assisted carbon capture - Emissions monitoring	Energy consumption and carbon emissions of AI (section 3.1) - Energy-intensive training of large AI models - Growing electricity demand from AI inference and deployment - Rising electricity consumption of data centres - Peak demand, grid congestion and reliability risks from inflexible or correlated workloads at data centres
Adaptation (section 2.2) Sector-specific - Agriculture: improved weather forecasting and extreme-event prediction - Insurance: AI-enhanced assessment of physical climate risks and risk pricing Cross-sectoral - AI-powered climate risk modelling - Disaster response - Resource management	Jevons paradox, rebound effects and unintended consequences (section 3.2) - More efficiency → more AI use → smaller energy savings - More productivity → more output and consumption → more resource use - Environmental spillovers (critical minerals extraction and water use)
Innovation and economic benefits (section 2.3) Sector-specific - Agriculture: autonomous robots and smart sensors - Energy: predictive maintenance, fault detection and grid automation Cross-sectoral - Increase in total factor productivity - Innovation in batteries, photovoltaic cells and climate-related technologies - Lower emissions intensity of economic activity - More efficient resource allocation	Geopolitical and distributional implications (section 3.3) Who benefits - Tech firms controlling key segments of the AI supply chain - Countries hosting data centres and advanced semiconductor production - Countries and firms capturing rents from critical-mineral supply chains Who bears the costs - Least developed and less technologically advanced countries - Small island developing states and climate-vulnerable economies

Source: Authors' elaboration.

2.1 Mitigation: energy efficiency and emissions reduction

AI can contribute to climate change mitigation in several ways, particularly through improvements in energy efficiency and resource allocation.

In the *energy sector*, AI algorithms facilitate the integration of renewable power into the grid and improve load balancing. For example, AI forecasting by DeepMind increased the economic value of wind energy by about 20% through better predictions of supply and demand (Stern and Romani (2025)). Power utilities use AI to predict equipment maintenance needs and optimise generation dispatch, reducing wasted energy (Cho (2023)). Similarly, AI-enabled “smart grids” analyse consumption patterns in real time to balance supply with demand, minimise energy waste and enable a higher penetration of solar and wind power (Zhao et al (2024)). AI can also strengthen the reliability of the electricity system by improving demand and renewable-generation forecasting, detecting equipment failures and grid anomalies earlier and supporting faster restoration following disruptions. An additional opportunity comes from the potential flexibility of data centres’ electricity demand. The scope for such flexibility depends on the type of computational workload. Delay-tolerant workloads, such as some training and fine-tuning tasks, can be shifted in time and, in some cases, across locations, whereas latency-sensitive applications, including real-time inference, offer less scope for postponement. Flexible workloads can therefore be moved away from periods of peak electricity demand or towards times and locations with abundant low-carbon electricity, reducing system costs, easing pressure on the grid and facilitating renewable integration. However, flexibility does not necessarily reduce emissions: if workloads are shifted primarily in response to electricity prices rather than carbon intensity, they may move towards off-peak periods in which marginal electricity generation remains carbon-intensive (Senga et al (2026)).

In *buildings*, AI-driven control systems can significantly reduce energy use. Advanced machine learning models have been shown to optimise HVAC (heating, ventilation and air conditioning) operations and reduce energy consumption by up to 73% without sacrificing comfort (Lee and Lee (2023)).

Manufacturing processes are also being refined by AI to lower fuel use and material waste by identifying opportunities for energy savings, thus curbing industrial emissions (Ekwaro-Osire et al (2024)). AI is also being used in emissions monitoring and carbon capture efforts, from computer vision systems that detect methane leaks in pipelines to machine-learning optimisation of carbon capture processes for power plants (Cho (2023)).

In *transportation*, AI contributes to route optimisation and smart traffic management. For instance, Google’s AI-based eco-routing in Maps suggests fuel-saving routes (eg flatter roads and less congestion) and has prevented over 1 million tonnes of CO₂ emissions per year – equivalent to removing 200,000 cars from the road (Stern and Romani (2025)). Emerging AI systems for autonomous and connected vehicles may deliver further efficiency gains in logistics and transit, though their ultimate impact on emissions will depend on the broader adoption of clean energy in transport.

2.2 Adaptation: climate risk prediction and resilience

Beyond mitigation, AI can support climate adaptation by enhancing the ability to predict, detect and respond to climate-related hazards. Machine learning models are

improving the *accuracy of weather forecasting and extreme-event prediction*, helping communities prepare for disasters such as floods, droughts, wildfires and storms (Camps-Valls et al (2025)). For example, specialised AI systems such as the British Antarctic Survey's IceNet and Google's FloodHub³ ingest vast data sets in real time to provide early warnings of sea ice changes or flood risks, respectively. These tools enable authorities to take proactive measures, thereby reducing potential damage and disruption.

In *agriculture*, AI-driven analytics help farmers adapt to changing climate conditions. AI-powered remote sensing can now detect multiple climate hazards (drought, heat stress and floods) affecting crops, as demonstrated in recent studies across Europe (Hrast Essenfelder et al (2025)). By processing decades of agro-climatic data, the models in these studies identify emerging threats to farms and provide uncertainty estimates, improving early warning systems and decision-making support for farmers. The result is more climate-resilient agriculture, with improvements in water management, planting decisions and crop protection under extreme weather conditions.

AI is also transforming the *insurance* sector by improving risk assessment (Eling et al (2022)), including the assessment of physical climate risks. By combining satellite imagery, remote sensing and machine learning, AI systems can generate detailed property-level assessments of exposure to floods, wildfires and storms. More accurate risk pricing can strengthen incentives for households and firms to invest in adaptation measures, such as flood barriers, vegetation management or more resilient buildings, by having insurance premiums better reflect these investments.

AI is also increasingly used in *ecological monitoring and environmental management*. Neural networks sift through satellite imagery to monitor deforestation and coral reef health, while drones and sensors track environmental changes on the ground (Cho (2023)). In disaster preparedness and adaptation planning, AI-driven risk maps and forecasting models help governments identify communities most vulnerable to climate impacts (such as those facing concurrent heatwaves and droughts), allowing adaptation resources (eg cooling centres or irrigation support) to be targeted more effectively (Hrast Essenfelder et al (2025)).

2.3 Economic benefits and innovation opportunities

Deploying AI in climate-related contexts can yield significant economic benefits. Early micro-evidence suggests that generative AI can deliver substantial productivity gains, particularly by automating components of non-routine cognitive tasks. Existing studies typically report productivity improvements ranging from 10% to 65%, with especially strong effects in coding, consulting tasks and professional writing (Graph 1.A). Evidence also indicates that AI tends to compress differences in workplace performance, as less experienced workers often benefit more than their senior peers (Graph 1.A, filled versus empty dots). The extent to which these micro-level gains will translate into higher aggregate total factor productivity (TFP) remains an open question and depends heavily on the underlying assumptions and scenarios

³ IceNet is a forecasting system developed by the British Antarctic Survey that uses satellite observations and climate data to predict Arctic sea ice conditions. See <https://www.bas.ac.uk/project/icenet/>. FloodHub is an early-warning platform developed by Google Research that uses machine learning and hydrological data to provide flood forecasts in vulnerable regions. See <https://sites.research.google/floods/>.

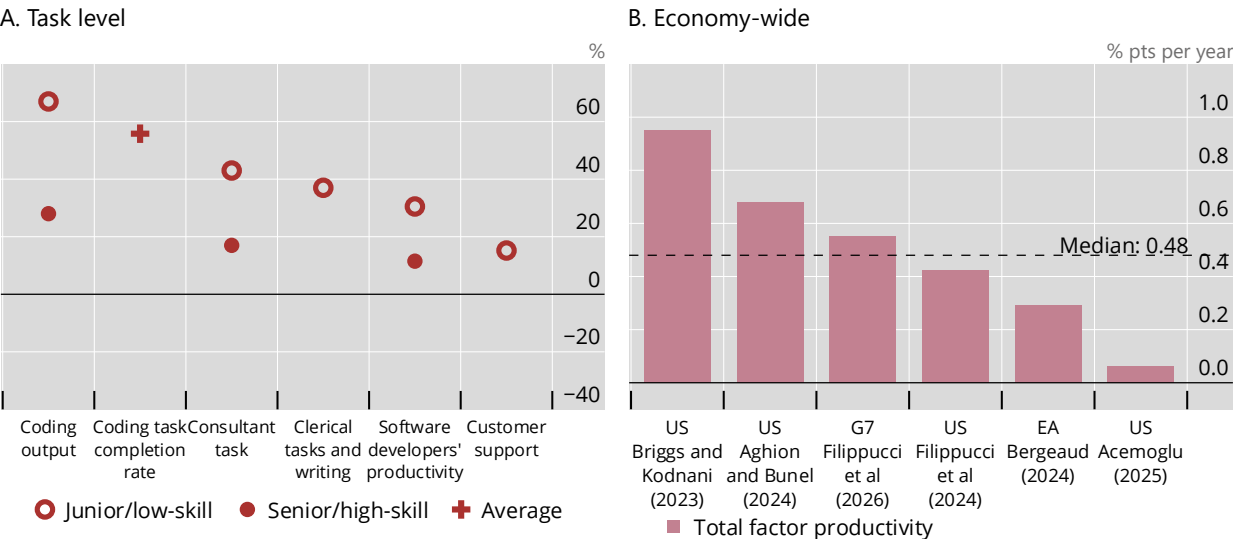
considered.⁴ However, median estimates across studies point to an increase in annual TFP growth of around 0.5 percentage points over a 10-year horizon (Graph 1.B). These productivity gains could also raise potential output. Their net effect on productive capacity, however, will also depend on whether AI helps to reduce climate-related damages and energy inefficiencies or instead intensifies energy and resource constraints.

Some studies suggest that AI could support both economic growth and emissions reductions by improving efficiency and accelerating innovation. For example, a study by PwC and Microsoft estimates that the application of AI to environmental solutions in key sectors, including energy, transport, agriculture and water, could increase global GDP by 3.1–4.4% by 2030 while reducing global emissions by around 4% (Herweijer et al (2019)). The underlying mechanisms include more efficient resource allocation, lower energy losses and improved production processes. In agriculture, precision farming technologies based on AI, such as autonomous robots and smart sensors, could increase productivity while reducing fuel consumption and fertiliser use. In the energy sector, AI-enabled efficiencies, including predictive maintenance and grid automation, are estimated to deliver a 1.6–2.2% rise in GDP and an even larger reduction in emissions by 2030, as smarter systems cut energy losses.

AI may also contribute to scientific discovery and innovation in climate-related technologies. Advanced AI techniques, such as deep learning models, are being used to discover new materials for batteries, design more efficient photovoltaic cells and

Estimates of productivity gains from AI vary¹

Graph 1



¹ Data sources for task-level productivity gains: coding output from Gambacorta, Qui et al (2026); coding task completion rate from Peng et al (2024); consultant tasks from Dell’Acqua et al (2023); clerical tasks and writing from Noy and Zhang (2023); software developers’ productivity from Cui et al (2025); and customer support from Brynjolfsson, Li and Raymond (2025).

Sources: Brynjolfsson, Li and Raymond (2025); Cui et al (2025); Dell’Acqua et al (2023); Gambacorta, Qui et al (2026); Noy and Zhang (2023); Peng et al (2024).

⁴ Productivity gains may also materialise gradually because firms often need time to adapt business processes and undertake complementary investments following the introduction of new technologies, consistent with the “productivity J-curve” discussed by Brynjolfsson et al (2021).

develop climate-friendly alternatives to carbon-intensive products (Stern and Romani (2025)).⁵

Beyond its effects on GDP growth, the way AI is adopted across tasks may also have implications for the climate transition. AI can complement human input or substitute for tasks that can be partially or fully automated (Trammell and Korinek (2023); Bell et al (2025)).⁶ These different forms of adoption can influence productivity, the scale of AI deployment and, consequently, computational and energy demand. However, the climate implications do not follow mechanically from whether AI complements or substitutes human labour. Rather, they depend on how productivity gains affect resource use. If AI allows a given level of output to be produced with fewer inputs, then emissions and resource use may decline. Conversely, if higher productivity leads to greater output and wider AI deployment, the associated increase in energy demand and economic activity may partly offset these gains through rebound effects. In the near term, many firms remain in an experimentation phase, suggesting that the full implications of these adjustments are likely to emerge only gradually.⁷

A related question is how the interaction between AI and the climate transition may affect employment. Some studies suggest that the combination of digital transformation and decarbonisation could create new employment opportunities in AI-driven clean-tech industries. For example, modelling exercises estimate that net job creation associated with environmental AI could range from 18.4 million to 38.2 million positions globally by 2030, reflecting growing demand for workers involved in deploying and maintaining these technologies (Herweijer et al (2019)). However, such estimates are highly uncertain and depend on a range of assumptions regarding technological progress, the pace of AI adoption, labour market adjustment and future climate policies.

3. Challenges: environmental costs, rebound effects and broader risks

While AI offers significant opportunities for the climate transition, it also presents important challenges. The opportunities discussed in the previous section implicitly assume that AI accelerates innovation in low-carbon technologies, reducing the cost of emissions abatement and expanding the set of economically viable mitigation options. However, AI is a general purpose technology and its innovative capacity is not intrinsically directed towards climate objectives. The same capabilities that reduce the cost of clean technologies can also improve the efficiency and profitability of carbon-intensive activities, including fossil fuel extraction and logistics. Consequently,

⁵ A notable example is DeepMind's AlphaFold, an AI system that has predicted the structure of more than 200 million proteins. These advances are supporting research in areas ranging from alternative proteins to improved enzymes for carbon capture. See <https://deepmind.google/science/alphafold/>.

⁶ Some evidence of labour displacement has emerged in AI-exposed occupations. Employment among young US workers in highly AI-exposed occupations has fallen by around 13% since 2022 (Brynjolfsson, Chandar and Chen (2025)). Similar effects have been found among freelancers performing tasks such as graphic design, customer support and transcription (Hui et al (2023)) and in call centres and business process outsourcing in India and the Philippines (Cucio and Hennig (2025); Singh (2025)).

⁷ Firms typically wait for clearer productivity gains before reorganising work (Crafts (2021)), and in the early stages new technologies often complement existing jobs or create additional roles (eg in supervision, maintenance or quality control (Bosone et al (2026))).

AI may simultaneously accelerate both green and carbon-intensive innovation, making its overall climate impact dependent on the incentives shaping technological development. As for the direct effect of AI on the climate, AI systems – especially large-scale models – can have a substantial environmental footprint through their energy consumption and associated carbon emissions. Moreover, efficiency gains enabled by AI may induce rebound effects, whereby lower costs and higher productivity stimulate demand for AI services and other economic activities, partly offsetting the associated environmental benefits. These mechanisms are closely related to the Jevons paradox: improvements in efficiency can lead to higher overall resource consumption. The infrastructure underpinning AI also raises geopolitical and distributional concerns. This section examines these challenges, focusing on energy use and emissions, rebound effects and broader geopolitical and distributional implications. The main challenges associated with AI and climate change are summarised in the right column of Table 1.

3.1 Energy consumption and carbon emissions of AI

Modern AI systems, particularly deep learning and LLMs, are highly computationally intensive. Training cutting-edge models requires processing vast data sets over extended periods using thousands of GPUs (graphics processing units) in data centres (Cho (2023)), resulting in substantial electricity consumption and associated carbon emissions. A landmark study found that training a single large natural language processing model emitted roughly 284 tonnes of CO₂, equivalent to the lifetime emissions of five average cars (Strubell et al (2019)). Since then, the scale of models has increased dramatically. For example, GPT-3, with 175 billion parameters, is estimated to have consumed 1,287 megawatt-hours of electricity during training, generating about 502 tonnes of CO₂ emissions based on an assumed average electricity generation mix (Cho (2023)). More recent models are likely to require even greater computational resources.

Energy use does not stop once a model has been trained. AI inference – the use of trained models in real-world applications such as chatbots and image recognition systems – can account for a large share of total energy consumption. Google estimates that around 60% of the energy used by its AI workloads is associated with inference, compared with 40% for training (Patterson (2022)). Although the energy required for an individual query may be small, widespread adoption by millions of users can substantially increase aggregate electricity demand. For example, Elsworth et al (2025) estimate that a Gemini Apps text query consumes a median of 0.24 watt-hours, roughly equivalent to nine seconds of television viewing. However, at scale, such usage can significantly increase the overall environmental footprint of AI.

The environmental impact of AI extends beyond model training and inference. Server manufacturing, transportation and end-of-life processes account for more than 10% of total greenhouse gas emissions across the AI life cycle, from model development to establishment of end user equipment (Mistral AI (2025)). Overall, the widespread deployment of AI systems implies that a growing share of their environmental footprint may arise from ongoing use rather than initial model training.

For popular AI services integrated into search engines or cloud platforms, the cumulative electricity demand associated with inference can be substantial. One estimate suggests that adding AI to internet searches could require up to five times more computing power per query, potentially increasing energy demand significantly

as AI becomes more widespread (Getahun (2023)). This growing computational burden is concentrated in data centres, which are becoming an increasingly important source of electricity demand. By 2021, data centres consumed roughly 0.9–1.3% of global electricity (Cho (2023)). In major technology hubs, the rapid expansion of data centres is already placing pressure on local power systems. In the United States, some states attribute more than 10% of their electricity consumption to data centres, while in Ireland such facilities account for over 20% of national electricity demand (Spencer and Singh (2024)). Looking ahead, the International Energy Agency projects global electricity consumption by data centres will roughly double by 2030, with AI-related workloads a leading driver (International Energy Agency (2025)).

Beyond its effects on electricity consumption and emissions, the expansion of AI infrastructure may also affect the reliability of power systems.⁸ Large data centres can increase peak demand, transmission congestion and the need for additional generation and grid capacity, particularly where computational workloads are latency-sensitive or otherwise difficult to shift away from periods of system stress. Even where some workloads are flexible, rapidly growing electricity demand from data centres may place pressure on local grids if generation and transmission capacity cannot adjust sufficiently quickly. The net effect of AI on electricity reliability is therefore ambiguous: AI can improve forecasting, fault detection and demand flexibility, while the infrastructure supporting AI can itself increase the demands placed on electricity networks.

The quantification of AI's impact on energy consumption remains highly uncertain. Bonfiglioli et al (2025) find a positive and statistically significant effect of AI penetration on CO₂ emissions across US commuting zones over the 2002–22 period. Although the empirical strategy supports a causal interpretation, the findings should be treated with some caution. The measure of AI penetration is based on the prevalence of data-intensive occupations and therefore serves as an indirect proxy for the diffusion of AI-related technologies rather than a direct measure of the deployment and use of AI systems. Moreover, data centres support a broad range of digital activities beyond AI, including cloud computing, web hosting and streaming services.

More comprehensive estimates are available for the broader information and communication technology (ICT) sector. De Roucy-Rochegonde and Buffard (2025) estimate that the ICT sector accounts for around 9% of global electricity consumption, while data centres account for roughly 1–1.3%. AI-related workloads, in turn, account for around 10% of data centre electricity consumption, corresponding to less than 0.2% of global electricity consumption. These estimates suggest that AI represents a small share of global electricity consumption, although this share could rise substantially as AI adoption expands and AI-related workloads account for a growing share of data centre activity.

The climate impact of AI depends not only on the scale of computational demand but also on the carbon intensity of the electricity used to power data centres. While average grid emissions provide a useful benchmark, the emissions associated with incremental AI workloads depend on the marginal source of electricity, which may remain relatively carbon-intensive even in grids with a large share of renewable energy. Encouragingly, improvements in hardware and cooling technologies have

⁸ The economic consequences of such reliability risks can be substantial. For example, Gonzales et al (2026) find that economic activity declined by around 35% on the day of Chile's nationwide blackout in February 2025.

helped contain energy consumption despite rapid growth in data traffic. For example, global electricity use by data centres has remained broadly stable at around 1% of total electricity consumption, reflecting substantial gains in chip performance and energy efficiency (OECD (2022)). However, whether such efficiency improvements can continue to offset rapidly growing AI workloads remains uncertain, particularly in an environment of heightened energy market volatility amid geopolitical fragmentation (Singh (2026)).

The balance between growing computational demand and continued improvements in energy efficiency will ultimately determine the future environmental footprint of AI. If AI workloads expand faster than efficiency gains, the energy and carbon costs of AI could rise substantially, increasing pressure on electricity systems and complicating the transition to a low-carbon economy (OECD (2022)).

3.2 Jevons paradox, rebound effects and unintended consequences

The environmental benefits of AI may be partly offset by rebound effects, a phenomenon closely related to the Jevons paradox. First articulated by Jevons (1865), the paradox states that improvements in efficiency can increase, rather than decrease, total resource consumption if they reduce costs and stimulate demand (Lekve Bjelle et al (2018)). In the context of AI, efficiency gains may lower the cost of producing goods and services, increase productivity and encourage greater use of AI-enabled applications. As a result, some of the environmental benefits associated with improved efficiency may be partially offset by higher levels of economic activity and energy consumption.

Several channels may generate such rebound effects. A direct rebound effect arises when AI makes a service cheaper or more convenient, leading to greater use of that service. For example, AI systems that optimise logistics and transportation can reduce fuel consumption per shipment, but lower transport costs may also encourage higher freight volumes, offsetting part of the initial energy savings. Similarly, as AI reduces the cost of generating text, images and other digital content, demand for these services may increase substantially, resulting in higher computing workloads. Some analysts predict that AI-related computing demand could increase far more rapidly than improvements in hardware efficiency over the coming years.⁹

Rebound effects may also operate at the economy-wide level. By raising productivity, AI can increase output, profits and incomes, which in turn may stimulate additional consumption and resource use across the economy (Aldasoro et al (2024); Kaack et al (2022)). In this case, efficiency gains achieved in one sector may be partly offset by higher energy demand elsewhere.

Beyond energy consumption, AI may generate broader environmental pressures. Growing demand for servers, chips and data centre infrastructure could increase the extraction of critical minerals and associated environmental impacts. In addition, the large quantities of water required to cool some data centres may place pressure on local water resources, particularly in water-scarce regions (Diab (2025)).

⁹ An example of this mechanism is the rapid growth in AI-generated content. As AI reduces the cost of producing text, images and other digital outputs, demand for these services may increase substantially. Analysts have projected a 50-fold increase in AI-related computing workloads by 2028, far outpacing expected improvements in hardware performance (McGregor (2023)). As a result, aggregate energy consumption may rise sharply even if the energy required for individual AI operations continues to decline.

Overall, rebound effects and other unintended consequences imply that improvements in efficiency do not automatically translate into proportional environmental gains. The ultimate impact of AI on climate outcomes therefore depends not only on technological efficiency but also on how these technologies are adopted and used throughout the economy (Ahmann et al (2022)).

3.3 Geopolitical and distributional implications for the climate transition

The geopolitical implications of AI are also relevant for climate outcomes because the development and deployment of AI-enabled climate solutions depend on access to energy, semiconductors, computing infrastructure and critical minerals. The increasing concentration of these strategic inputs and capabilities may therefore influence both the pace and the distribution of the climate transition across countries.

The AI supply chain is highly concentrated, both geographically and among firms (Gambacorta and Shreeti (2025)). This concentration means that the environmental costs associated with AI infrastructure are also unevenly distributed across countries and regions. A small number of countries host a large share of advanced semiconductor production, large-scale data centres and frontier AI development. This concentration has important implications for the environmental footprint of AI. The carbon intensity of AI systems depends not only on the amount of computation performed but also on where models are trained and deployed. AI workloads located in regions with carbon-intensive electricity systems generate higher emissions than those powered by low-carbon energy sources. At the same time, regions that host large concentrations of data centres may face growing pressure on electricity infrastructure. For example, concerns about electricity supply constraints have led Ireland to restrict new data centre construction in the Dublin area until 2028 (Spencer and Singh (2024)). Lawmakers in several US states, including New York, Virginia and Pennsylvania, have considered moratoria or other restrictions on development of new data centres.¹⁰

The capacity to use AI for climate mitigation and adaptation is also unevenly distributed. Advanced economies and large technology firms are currently best positioned to capture the productivity gains associated with AI and to develop and deploy AI-enabled climate solutions, while many developing countries face constraints in terms of digital infrastructure, access to computing resources and technical capabilities (Gambacorta, Kharroubi et al (2026)). As a result, AI could widen existing technological and economic divides if access to AI-enabled climate mitigation and adaptation tools remains uneven (Gibbons (2021)). These concerns are particularly relevant for less developed countries and small island developing states, which are among the most vulnerable to climate change but often have limited access to advanced digital technologies (Kreft and Fournier-Tombs (2024)).

AI development also has broader geopolitical implications through its growing demand for energy, semiconductors and critical minerals. The expansion of data centres and computing infrastructure increases demand for inputs such as advanced chips, rare earth elements and other strategic materials, strengthening the links between AI development, international trade and global supply chains (de Soyres et

¹⁰ See National Conference of State Legislatures, "Which states are banning data centers?", 15 September 2026, <https://www.ncsl.org/fiscal/which-states-are-banning-data-centers>. See also Dandapani (2026).

al (2026)). Consequently, the development and deployment of AI may increasingly depend on geopolitical developments, trade restrictions and disruptions to the supply of critical inputs (Schmidt (2023)). Such disruptions could affect not only the pace of AI development but also the availability and cost of AI-enabled climate technologies. At the same time, rising demand for critical minerals may increase the strategic importance of countries and firms able to capture rents from these supply chains, while intensifying the environmental pressures associated with mineral extraction.

Overall, geopolitical fragmentation may shape both the environmental footprint of AI and countries' ability to access and deploy AI-enabled climate mitigation and adaptation solutions, potentially widening existing inequalities in the climate transition.

4. Effects of AI on climate change under two AI development scenarios

The ultimate impact of AI on climate change depends not only on how AI is used but also on how the technology itself evolves. The previous sections highlighted both the opportunities and the challenges associated with AI. This section brings these elements together by considering two stylised scenarios of technological development. The first is an **AI copilot** scenario, in which increasingly capable but narrow AI systems complement human decision-making and task execution. The second is an **AGI** scenario, in which AI systems acquire cognitive capabilities comparable to those of humans across a wide range of tasks. These should be viewed as illustrative endpoints of a continuum of possible technological outcomes rather than as discrete outcomes.

4.1 AI as a copilot

Under an AI copilot scenario, AI is primarily used to augment human capabilities rather than replace them. In this environment, the opportunities discussed in section 2 are likely to materialise gradually through the wider deployment of specialised AI applications. For example, AI systems could improve the integration of renewable energy sources into electricity grids, optimise industrial energy consumption and enhance transportation efficiency through route optimisation and traffic management. Existing evidence already points in this direction. DeepMind's forecasting tools have increased the economic value of wind energy by improving predictions of electricity supply and demand (Stern and Romani (2025)), while AI-enabled smart grids and building management systems have demonstrated significant energy savings (Lee and Lee (2023); Zhao et al (2024)). Similarly, advances in weather forecasting, flood prediction and climate risk modelling could strengthen adaptation efforts by improving disaster preparedness and resource allocation (Camps-Valls et al (2025)).

The environmental costs associated with AI would also increase but are likely to build up more gradually than under a more transformative AI scenario. This outcome would depend in part on continued advances in hardware, software and model efficiency, which could allow AI capabilities to expand without a proportional increase in computational requirements. Recent developments suggest that substantial efficiency gains remain possible. For example, improvements in model architecture and computing efficiency have reduced the computational resources required to

achieve a given level of performance (Wu et al (2024)). As AI adoption expands, electricity demand from inference would nevertheless continue to rise, although further efficiency gains could moderate the overall increase.

Rebound effects would nevertheless remain relevant. Lower costs and higher productivity may encourage greater use of AI-enabled services, partially offsetting some of the environmental benefits discussed in section 2. Whether these effects remain contained depends on the balance between improvements in computational efficiency and the expansion in demand for AI services. Lower energy requirements per AI task reduce energy consumption, while greater use of AI increases the number of tasks performed. The net effect therefore depends on which of these forces dominates and in particular on how responsive demand for AI services is to lower costs. More broadly, the climate impact will also depend on the carbon intensity of the electricity used to power additional AI workloads and on whether AI-induced productivity gains translate mainly into digital activity or into greater production and consumption of material- and energy-intensive goods and services. These effects would unfold more slowly under the AI copilot scenario, reflecting the gradual development of AI capabilities, although their overall magnitude remains uncertain. Similarly, existing geopolitical and distributional asymmetries would persist. Advanced economies, large technology firms and countries hosting critical digital infrastructure would remain the primary beneficiaries of AI adoption, while countries with limited digital capabilities could face difficulties in capturing similar gains (Gambacorta and Shreeti (2025)).

Overall, this scenario suggests that AI could support climate mitigation and adaptation. The balance between benefits and costs would nevertheless remain uncertain and depend on whether improvements in computational efficiency outpace the growth in AI use, on the carbon intensity of the electricity used to power additional AI workloads, and on how AI-induced productivity gains translate into economic activity and resource use.

4.2 Artificial general intelligence (AGI)

A second scenario is the emergence of AGI, defined as AI systems capable of performing a broad range of cognitive tasks at a level comparable to, or exceeding, that of humans (Naudé and Dimitri (2020)). Such a scenario remains highly uncertain, both in terms of timing and technological feasibility. According to the expert survey launched by Müller and Bostrom (2016), “general” or “strong” AI could be developed between 2040 and 2060.

The climate implications of AGI are correspondingly uncertain. On the one hand, AGI could accelerate scientific discovery, improve climate modelling and enable breakthroughs in energy systems, materials science and emissions reduction technologies. The potential gains in productivity and innovation could be substantially larger than under the AI copilot scenario.

On the other hand, these benefits could be accompanied by a substantial increase in computational demand and resource consumption. More capable AI systems are likely to require greater computing resources for both training and deployment, while stronger rebound effects could amplify economy-wide demand for goods, services and digital technologies. The magnitude of these effects remains highly uncertain. According to forecasts collected by Metaculus (2026), global energy consumption five years after the emergence of AGI could reach around 423,000 terawatt-hours, an increase of approximately 160% relative to 2024 levels. Although such estimates should be interpreted with caution, they illustrate the possibility that

rapid advances in AI capabilities could generate energy demand on a scale that substantially exceeds current levels. The concentration of advanced AI capabilities in a small number of firms and countries could also intensify existing geopolitical and distributional tensions (Lazanyuk et al (2025)). Compared with the AI copilot scenario, both the potential benefits and environmental costs of AGI could be larger, making its net climate impact considerably more uncertain.

5. Implications for central banks and policy responses

The AI–climate nexus raises important issues for both macroeconomic and financial stability and for the design of policy and governance frameworks. For central banks, it may affect potential output, inflation dynamics and financial risks through changes in productivity, energy demand, climate-related risks and infrastructure investment. At the same time, governments, international organisations and other stakeholders are developing policy and governance responses aimed at improving transparency, promoting more sustainable AI innovation and strengthening international cooperation. This section first discusses the implications of the AI–climate nexus for central banks and then reviews these broader policy and governance responses.

5.1 Implications for central banks

The interaction between AI and climate change matters for central banks insofar as it affects the productive capacity of the economy, inflation dynamics and the resilience of the financial system. Central banks are not responsible for directing technological development or climate policy, but the economic consequences of these structural transformations fall directly within their macroeconomic and financial stability assessments.

One important dimension concerns **potential output**. As discussed in section 2.3, AI could raise productivity by improving the efficiency of existing production processes and accelerating innovation (Herweijer et al (2019)). AI-enabled mitigation and adaptation could reinforce these effects by reducing energy losses, improving the resilience of infrastructure and limiting the economic damage associated with climate-related shocks. However, the interaction can also work in the opposite direction. Where electricity demand from data centres cannot be sufficiently shifted away from periods of system stress, its rapid growth may increase energy costs and exacerbate grid and generation bottlenecks. Moreover, efficiency gains that lower the cost of AI use may encourage wider adoption and greater economic activity, thereby increasing demand for energy and other resources through rebound effects. The net effect of AI on potential output therefore depends not only on its direct productivity gains but also on how AI deployment interacts with energy systems and climate risks.

A second dimension concerns **monetary policy**. In general, AI can affect aggregate demand and supply simultaneously and with different timing, blurring cyclical signals and complicating the assessment of underlying economic conditions and the calibration of monetary policy (Aldasoro et al (2026)). The AI–climate nexus adds a further dimension to this challenge. Productivity gains from AI could expand supply capacity and reduce production costs, while higher electricity demand, grid constraints and climate-related disruptions may generate upward pressure on energy prices and increase inflation volatility. Moreover, these effects may materialise at different speeds, with pressures from AI-related investment and energy demand potentially emerging before it becomes clear whether, when and to what extent AI-

related productivity gains will materialise. This can make it more difficult for central banks to distinguish cyclical demand pressures from structural changes in productive capacity and therefore to assess potential output and the output gap. These challenges may be particularly pronounced where electricity infrastructure adjusts only slowly to rapidly rising data centre demand.

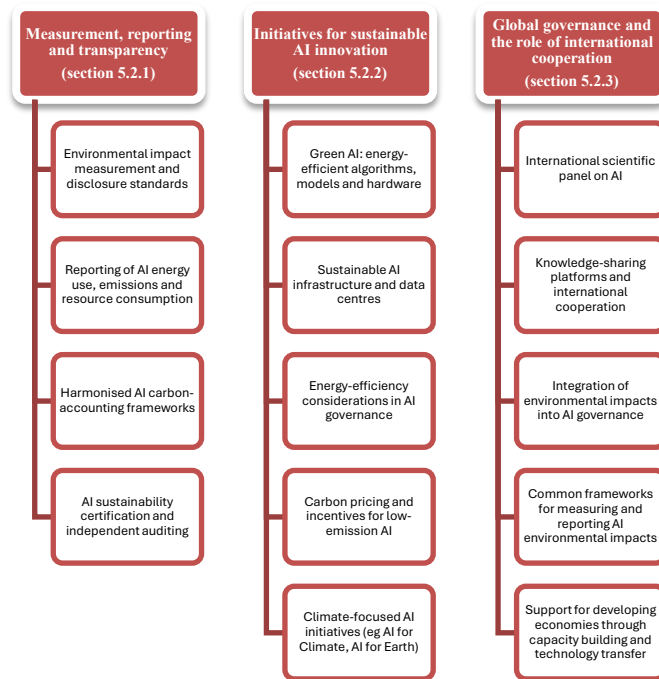
A third dimension concerns **financial stability**. In general, the AI boom is generating large investment and financing flows, with spending on data centres and related infrastructure increasingly relying on private credit and bond markets (Aldasoro et al (2026)). If expectations about the returns from AI prove overly optimistic, this could lead to overinvestment, resource misallocation, weaker credit quality and asset-price corrections. These financial stability risks are further shaped by the interaction between AI and climate change, particularly through the financing of the energy infrastructure needed to support AI-related electricity demand. Meeting rapidly growing AI-related electricity demand might require substantial investment in electricity generation and grid infrastructure, while the type and resilience of this infrastructure can shape future climate-related exposures. Investments in carbon-intensive generation could cause carbon lock-in and increase transition risks if climate policies subsequently tighten, while grid disruptions and extreme weather could generate operational losses and impair borrowers' cash flows. Conversely, AI-enabled improvements in climate forecasting, insurance pricing and risk measurement can help financial institutions and authorities identify and manage physical and transition risks more effectively.

AI can also strengthen central banks' capacity to monitor these developments. Projects undertaken by the BIS Innovation Hub, in collaboration with partner central banks, illustrate how AI and related technologies can help fill important gaps in climate data. Project Danu uses digital-twin simulations to assess the economic impact of extreme weather events by integrating climate, geospatial and socioeconomic data, enabling forward-looking analysis of physical risks. Project Gaia applies artificial intelligence and natural language processing to extract climate-relevant indicators from corporate disclosures, improving the consistency and comparability of transition-risk data. Project Symbiosis leverages big data and AI to map scope 3 supply chain emissions, strengthening transparency around indirect transition exposures. Such applications can support macroeconomic analysis, financial stability monitoring and early-warning systems as the interaction between technological change and climate-related risks becomes increasingly complex.¹¹

5.2 Policy and governance responses

The rapid expansion of AI and its implications for climate change have attracted increasing attention from policymakers, international organisations and other stakeholders. Emerging policy discussions focus on a range of issues, including the measurement and reporting of AI-related energy use and emissions, the promotion of more energy-efficient AI systems, and the governance challenges arising from the growing interaction between AI and climate objectives. While policy approaches differ across jurisdictions, a number of common themes are beginning to emerge. This section reviews selected policy frameworks, governance initiatives and international discussions related to the AI–climate nexus. Graph 2 summarises the main areas of policy attention.

¹¹ See the BIS Innovation Hub website for a more comprehensive overview of completed and ongoing climate-related projects and collaborative initiatives: <https://www.bis.org/about/bisih/about.htm>.



Source: Authors' elaboration.

5.2.1 Measurement, reporting and transparency

A growing area of discussion concerns the measurement and disclosure of the environmental footprint of AI systems. Despite increasing attention to the energy use and emissions associated with AI, there is currently no universally accepted framework for measuring or reporting the carbon footprint of AI training and inference activities (Debus et al (2023)). This lack of standardisation complicates comparisons across models, firms and jurisdictions and makes it difficult to assess the overall environmental impact of AI.

Several international organisations have highlighted the importance of improving transparency in this area. The OECD (2022), for example, distinguishes between the direct environmental impacts associated with the development, deployment and disposal of AI systems and their broader indirect effects, emphasising the need for improved measurement and data collection. At the same time, some technology companies have begun to disclose information on the energy efficiency of their AI infrastructure. Google, for instance, has published data on the performance of its data centres and reported improvements associated with the use of renewable energy sources, more efficient cooling systems and custom AI chips designed to reduce energy consumption per training task (Cho (2023)). Such initiatives provide examples of how firms are beginning to measure and communicate the environmental implications of AI development.

These discussions increasingly intersect with broader debates on sustainability reporting and corporate disclosure. Existing accounting frameworks for greenhouse gas emissions may provide a basis for incorporating information related to AI and high-performance computing activities. In parallel, the concept of "green AI" has

gained prominence within the research community, encouraging the reporting of computational costs and the development of more energy-efficient AI techniques (Verdecchia et al (2023)). Some academic conferences and journals have also started to consider the disclosure of computational requirements and energy use as part of the research process.

Taken together, these developments point to a growing emphasis on transparency and measurement as part of the broader discussion on AI and sustainability. However, reporting practices remain heterogeneous, and no common international standard for measuring and disclosing AI-related environmental impacts has yet emerged. Improved measurement and harmonised disclosure would enable firms and investors to assess the carbon footprint of AI-related activities and their consistency with climate objectives, while providing policymakers with better information to design and monitor transition plans.

5.2.2 Initiatives for sustainable AI innovation

As concerns about the environmental footprint of AI have grown, governments, research institutions and industry participants have launched a range of initiatives aimed at promoting more sustainable AI innovation. The growing strand of green AI research emphasises reducing the computational resources required to train and deploy AI models while maintaining performance (Tabbakh et al (2024)). This objective can be pursued through advances in algorithms, model architectures, semiconductors and cooling technologies, all of which contribute to lowering the energy intensity of AI applications.¹²

Several initiatives have emerged to encourage innovation in this direction. For example, the Green Computing Foundation has organised the GreenMind Hackathon,¹³ while Stanford University has hosted green AI hackathons¹⁴ aimed at promoting solutions that improve the environmental sustainability of AI systems. These initiatives reflect a broader effort within the research community to incorporate energy efficiency and sustainability considerations into the evaluation of AI progress, alongside traditional performance metrics such as accuracy and speed.

However, beyond improving the energy efficiency of AI models, policy interventions can also support the development of a more sustainable energy infrastructure while at the same time fostering AI development. The rapid expansion of AI-related electricity demand creates a unique opportunity to accelerate investments in additional renewable energy generation and storage capacity. Evidence from Chile, for example, shows that investments in grid integration can stimulate substantial additional renewable generation and reduce carbon emissions (Gonzales et al (2023)). If public incentives encourage AI companies to increasingly rely on new renewable energy generation, energy storage and related innovation, AI deployment could stimulate a broader decarbonisation of electricity systems rather than simply redirecting existing low-carbon electricity towards data centres. Such policies may also generate positive knowledge spillovers, accelerating technological

¹² Sustainability can also be improved by adapting when and where computational workloads are executed. For example, Google has developed a carbon-aware computing platform that shifts non-urgent compute tasks towards periods when low-carbon electricity is more abundant, with the possibility of extending this approach to shifting flexible workloads across data centre locations (Radovanovic (2020)).

¹³ <https://hackathon.greencomputingfoundation.org/>.

¹⁴ <https://www.greenaihackathon.com/>.

advancements and reducing the cost of sustainable energy over time. In contrast, continued investment in energy generation based on fossil fuels to power data centres could lock economies into carbon-intensive infrastructure for decades, slowing the transition towards a low-carbon energy system. This perspective is consistent with the literature on directed technical change, which argues that carbon pricing should be complemented by research subsidies and innovation policies that redirect technological progress towards cleaner technologies (Acemoglu et al (2012)).

Policy discussions have also increasingly focused on the environmental implications of AI infrastructure and computing demand. In the European Union, sustainability considerations have been incorporated into broader initiatives concerning data centres and digital infrastructure, while the EU Artificial Intelligence Act includes transparency provisions that may facilitate the monitoring of AI-related resource use. In China, draft regulations released in 2023 highlighted the importance of energy efficiency in the training of large AI models and signalled growing attention to the resource requirements of AI development.¹⁵ More generally, the rapid expansion of AI-related electricity demand has led policymakers and regulators in several jurisdictions to examine the interaction between AI deployment, energy systems and climate objectives.¹⁶

At the same time, public and private programmes increasingly support AI applications that contribute directly to climate mitigation and adaptation. Examples include the “AI for Climate”¹⁷ and “AI for Earth”¹⁸ initiatives, as well as similar initiatives supporting projects in climate modelling, biodiversity monitoring, disaster prediction, energy management and sustainable agriculture. Such programmes fund a wide range of applications, including AI-enhanced weather and flood forecasting systems, optimisation of renewable energy integration into electricity grids, monitoring of deforestation and ecosystem degradation through satellite imagery, and precision agriculture technologies aimed at improving resource efficiency. More broadly, these initiatives reflect growing interest in harnessing AI to address specific climate challenges while fostering innovation in environmentally sustainable technologies. They also contribute to the development of expertise, data infrastructure and research networks at the intersection of AI and climate science, supporting the diffusion of AI-based solutions across both advanced and developing economies.

¹⁵ China’s Interim Measures for the Management of Generative Artificial Intelligence Services, released in 2023, signalled increasing regulatory attention to the resource implications of AI development. Related policy discussions have emphasised energy efficiency considerations for large AI models and the monitoring of computing-resource use.

¹⁶ Recent policy discussions have also considered market-based approaches. For example, Hebous and Vernon-Lin (2024) propose an environmental tax on AI-related energy consumption, arguing that pricing the environmental costs associated with large AI workloads could encourage more efficient use of computational resources.

¹⁷ The AI for Climate and Environment initiative, jointly led by the Data Science Institute and the Institute for Climate and Sustainable Growth at the University of Chicago, promotes the use of AI for climate modelling, environmental monitoring and sustainable energy solutions. See <https://datascience.uchicago.edu/research/aice-ai-for-climate/>.

¹⁸ AI for Earth is a Microsoft initiative that supports the use of AI and data science to address environmental challenges, including climate change, biodiversity conservation and sustainable resource management. See G Spencer, “AI for Earth: helping save the planet with data science”, *Microsoft Features*, 4 September 2018, <https://news.microsoft.com/apac/features/ai-for-earth-helping-save-the-planet-with-data-science/>.

5.2.3 Global governance and the role of international cooperation

Because both AI and climate change are global in nature, international organisations have increasingly examined the interaction between the two. Recent discussions have focused on improving understanding of the environmental implications of AI, promoting the use of AI for climate mitigation and adaptation, and ensuring that the benefits of AI are accessible across countries and regions.

Within the United Nations system, attention to the AI–climate nexus has increased in recent years.¹⁹ The United Nations High-level Advisory Body on Artificial Intelligence highlighted the potential of AI to support sustainable development objectives while also recognising the challenges associated with its environmental footprint and governance.²⁰ Similarly, discussions under the United Nations Framework Convention on Climate Change have increasingly considered the role of AI in climate action, including applications related to climate modelling, emissions monitoring, disaster preparedness and adaptation. Since COP28, dedicated workstreams have explored both the opportunities and risks associated with AI for climate policy and implementation.

Other international organisations have incorporated environmental considerations into broader AI governance discussions. The OECD (2022), for example, distinguishes between the direct and indirect environmental impacts of AI systems and has emphasised the importance of improved measurement, transparency and data collection. The Global Partnership on AI (GPAI)²¹ has also established activities focusing on the environmental implications of AI and the promotion of sustainable AI practices. More broadly, these initiatives reflect growing recognition that the governance of AI and the governance of climate change are becoming increasingly interconnected.

6. Conclusions

Artificial intelligence has the potential to become an important force in the climate transition. AI can support climate mitigation through more efficient use of energy and resources; it can strengthen adaptation through improved forecasting and risk management; and it can accelerate innovation in climate-related technologies. These benefits are already emerging across sectors, from energy and transportation to agriculture and climate-risk analysis.

At the same time, AI introduces new environmental and economic challenges. The development and deployment of increasingly powerful AI systems require substantial computational resources, contributing to rising electricity demand, carbon emissions and pressure on electricity infrastructure. Moreover, some of the efficiency gains enabled by AI may be offset by rebound effects, whereby lower costs and higher productivity stimulate additional demand for AI services and other resource-intensive activities. The concentration of AI capabilities and infrastructure also raises broader

¹⁹ The UN Secretary-General has repeatedly identified both climate change and AI governance among the most significant global challenges facing the international community.

²⁰ Commentators have proposed the creation of an international scientific panel on AI, analogous to the Intergovernmental Panel on Climate Change, to assess the societal and environmental implications of AI development (Kreft and Fournier-Tombs (2024)).

²¹ The GPAI is a multi-stakeholder initiative launched in 2020 that brings together governments, academia, industry and civil society to support responsible development and use of AI.

geopolitical and distributional concerns. The climate implications of AI therefore extend well beyond the technology itself, affecting energy systems, global supply chains and patterns of economic development.

A key message of the paper is that AI influences both sides of the climate equation. It can reduce emissions through efficiency gains, innovation and improved decision-making, while simultaneously increasing energy consumption and resource use. The overall impact of AI on climate change will depend on the balance between these opposing forces and on how AI capabilities evolve. The paper considers two stylised scenarios. Under an AI-as-a-copilot scenario, benefits and environmental costs are likely to build up more gradually, but the net climate effect remains uncertain. It will depend on whether improvements in computational efficiency outpace growth in AI use, on the carbon intensity of additional electricity demand and on how productivity gains translate into economic activity and resource use. Under a more transformative scenario involving AGI, an increasingly autonomous AI system, both the opportunities and the risks could become larger and more uncertain.

The AI–climate nexus also has important implications for central banks. By affecting productivity, climate resilience and energy constraints, it can influence potential output and complicate the assessment of economic slack and inflationary pressures. At the same time, large-scale investment in AI and energy infrastructure, together with evolving physical and transition risks, may create new financial stability vulnerabilities. Understanding these interactions is therefore becoming increasingly relevant for assessing how structural transformations affect the macroeconomy and the financial system.

These considerations underscore the importance of policy and governance. As AI becomes more deeply integrated into economic activity, policy frameworks can influence how its benefits and environmental costs evolve. Emerging initiatives aimed at improving transparency, developing carbon accounting standards, promoting energy-efficient AI systems and more sustainable energy infrastructure, and strengthening international cooperation represent important steps in this direction. Policies that foster AI-enabled climate innovation may also help to expand the range of technologies available for mitigation and adaptation. For central banks, AI may provide additional tools for climate-risk analysis, while governments and international organisations can support the development of appropriate measurement and governance frameworks.

Ultimately, AI is neither inherently a climate solution nor inherently a climate problem. Its contribution to the climate transition will depend on how the technology evolves, how widely it is adopted and the energy systems and economic activities that support and result from its use. The coming decade will therefore be critical in determining whether AI becomes a force that accelerates the transition to a more sustainable economy or one that intensifies existing environmental pressures. The balance will ultimately depend on whether technological progress, energy system development and policy and governance frameworks allow the benefits of AI to expand without a commensurate increase in its environmental footprint.

References

- Acemoglu, D (2025): "The simple macroeconomics of AI", *Economic Policy*, vol 40, no 121.
- Acemoglu, D, P Aghion, L Bursztyn and D Hemous (2012): "The environment and directed technical change", *American Economic Review*, vol 102, no 1.
- Aghion, P and S Bunel (2024): "AI and growth: where do we stand?", *Federal Reserve Bank of San Francisco*.
- Ahmann, L, M Banning and C Lutz (2022): "Modeling rebound effects and counteracting policies for German industries", *Ecological Economics*, vol 197, 107432.
- Aldasoro, I, S Doerr, L Gambacorta and D Rees (2024): "The impact of artificial intelligence on output and inflation", *BIS Working Papers*, no 1179.
- Aldasoro, I, S Doerr and D Rees (2026): "Financing the AI boom: from cash flows to debt", *BIS Bulletin*, no 120.
- Aldasoro, I, L Gambacorta, E Kharroubi and M Rottner (2026): "AI and the global economy: implications for central banks", *BIS Bulletin*, no 130.
- Bell, S, B Gadanez, L Gambacorta, F Perez-Cruz and V Shreeti (2025): "Artificial intelligence and human capital: challenges for central banks", *BIS Bulletin*, no 100.
- Bergeaud, A (2024): "The past, present and future of European productivity", paper presented at the ECB Forum on Central Banking, Sintra, July.
- Bonfiglioli, A, R Crinò, M Filomena and G Gancia (2025): "Data, power and emissions: the environmental cost of AI", *CEPR Discussion Papers*, no 20686.
- Bosone, C, L Gambacorta, P Giudici, E Kharroubi and U Lewrick (2026): "Robots, ICT and employment: evidence from advanced and emerging EU countries", *BIS Working Papers*, no 1334.
- Briggs, D and D Kodnani (2023): "Generative AI: hype, or truly transformative?", *Goldman Sachs Global Macro Research Report*, no 120.
- Brynjolfsson, E, B Chandar and R Chen (2025): "Canaries in the coal mine? Early warning signs of labour market impacts from generative AI", *Stanford Digital Economy Lab Working Paper*.
- Brynjolfsson, E, D Li and L Raymond (2025): "Generative AI at work", *Quarterly Journal of Economics*, vol 140, no 2.
- Brynjolfsson, E, D Rock and C Syverson (2021): "The productivity J-curve: how intangibles complement general purpose technologies", *American Economic Journal: Macroeconomics*, vol 13, no 1.
- Camps-Valls, G et al (2025): "Artificial intelligence for modeling and understanding extreme weather and climate events", *Nature Communications*, vol 16, 1919.
- Cho, R (2023): "AI's growing carbon footprint", *State of the Planet*, Columbia Climate School.
- Cœuré, B (2021): "Digital rails for green transformation", speech at the Salzburg Global Finance Forum, 22 June.
- Crafts, N (2021): "Artificial intelligence as a general-purpose technology: an historical perspective", *Oxford Review of Economic Policy*, vol 37, no 3.

Cucio, M and T Hennig (2025): "Artificial Intelligence and the Philippine labour market", *IMF Working Papers*, no 2025/043.

Cui, Z, M Demirer, S Jaffe, L Musolff, S Peng and T Salz (2025): "The effects of generative AI on high-skilled work: evidence from three field experiments with software developers", *Management Science*, forthcoming.

Dandapani, K (2026): "Impact of artificial intelligence on ESG", presentation at the 33rd Annual Global Finance Conference.

de Roucy-Rochegonde, L and A Buffard (2025): "AI, data centers and energy demand: reassessing and exploring the trends", *French Institute of International Relations (Ifri) Papers*.

de Soyres, F, A Haag, M Liu and E Van Leemput (2026): "The global trade effects of the AI infrastructure boom", *FEDS Notes*, 13 February.

Debus, C, M Piraud, A Streit, F Theis and M Götz (2023): "Reporting electricity consumption is essential for sustainable AI", *Nature Machine Intelligence*, vol 5, no 11.

Dell'Acqua, F, E McFowland III, E Mollick, H Lifshitz-Assaf, K Kellogg, S Rajendran, L Kraye, F Candelon and K Lakhani (2023): "Navigating the jagged technological frontier: field experimental evidence of the effects of AI on knowledge worker productivity and quality", *Harvard Business School Working Paper*, no 24-013.

Diab, R (2025): "Jevons paradox makes regulating AI sustainability imperative", *TechPolicy Press*.

Ekwaro-Osire, H, D Bode, J-H Ohlendorf and K-D Thoben (2024): "Manufacturing process energy consumption modeling: a methodology to identify the most appropriate model", *Journal of Intelligent Manufacturing*, vol 36.

Eling, M, D Nuessle and J Staubli (2022): "The impact of artificial intelligence along the insurance value chain and on the insurability of risks", *The Geneva Papers on Risk and Insurance – Issues and Practice*, vol 47.

Elsworth, C et al (2025): "Measuring the environmental impact of delivering AI at Google scale", *arXiv:2508.15734*.

Filippucci, F, P Gal, C Jona-Lasinio, A Leandro and G Nicoletti (2024): "The impact of artificial intelligence on productivity, distribution and growth", *OECD Artificial Intelligence Papers*, no 15.

Filippucci, F, P Gal, K Laengle, M Schief and M Yildirim (2026): "AI meets trade: global linkages and the cross-country distribution of the gains from AI", *OECD Artificial Intelligence Working Papers*, no 57.

Gambacorta, L, E Kharroubi, A Mehrotra and L Pancotto (2026): "Economic impact of AI in emerging market economies", *BIS Bulletin*, no 121.

Gambacorta, L, H Qiu, D Rees and S Shan (2026): "Generative AI and labour productivity: a field experiment on coding", *Journal of Financial Stability*, vol 84, 101543.

Gambacorta, L and V Shreeti (2025): "The AI supply chain", *BIS Papers*, no 154.

Getahun, H (2023): "The internet contributes 1.6 billion annual tons in greenhouse gas emissions. Google and Microsoft's AI search war will make it worse", *Business Insider*, 13 February.

Gibbons, E (2021): "Toward a more equal world: the human rights approach to extending the benefits of artificial intelligence", *IEEE Technology and Society Magazine*, vol 40, no 1.

Gonzales, L, K Ito and M Reguant (2023): "The investment effects of market integration: evidence from renewable energy expansion in Chile", *Econometrica*, vol 91, no 5.

——— (2026): "Zero energy day: how nationwide blackouts affect the economy", *NBER Working Papers*, no 35066.

Hebous, S and N Vernon-Lin (2024): "Carbon emissions from AI and crypto are surging and tax policy can help", *IMF Blog*, 15 August.

Herweijer, C, B Combes and J Gillham (2019): *How AI can enable a sustainable future*, PwC UK.

Hrast Essenfelder, A, A Toreti and L Seguni (2025): "Expert-driven explainable artificial intelligence models can detect multiple climate hazards relevant for agriculture", *Communications Earth and Environment*, vol 6, 207.

Hui, X, O Reshef and L Zhou (2023): "The short-term effects of generative artificial intelligence on employment: evidence from an online labor market", *CESifo Working Paper*, no 10601.

International Energy Agency (2025): *Energy and AI*.

Jevons, W S (1865): *The coal question: an inquiry concerning the progress of the nation, and the probable exhaustion of our coal mines*, Macmillan.

Kaack, L, P Donti, E Strubell, G Kamiya, F Creutzig and D Rolnick (2022): "Aligning artificial intelligence with climate change mitigation", *Nature Climate Change*, vol 12.

Kreft, S and E Fournier-Tombs (2024): "Aligning AI and climate governance", *UNU-EHS Commentary*, 18 September.

Lazanyuk, I, M Eyeberdiyeva and M H A Z Diaz (2025): "AI and the digital divide: challenges and opportunities", in E Popkova (ed), *Management of digital technologies in the innovative economy*, Springer.

Lee, D and S-T Lee (2023): "Artificial intelligence enabled energy-efficient heating, ventilation and air conditioning system: design, analysis and necessary hardware upgrades", *Applied Thermal Engineering*, vol 235, 121253.

Lekve Bjelle, E, K Steen-Olsen and R Wood (2018): "Climate change mitigation potential of Norwegian households and the rebound effect", *Journal of Cleaner Production*, vol 172.

McGregor, J (2023): "Generative AI breaks the data center: data center infrastructure and operating costs projected to increase to over \$76 billion by 2028", *Forbes*.

Metaculus (2026): "Five years after AGI, what will be humanity's energy consumption?", *Metaculus Forecasting Platform*.

Mistral AI (2025): "Our contribution to a global environmental standard for AI".

Müller, V and N Bostrom (2016): "Future progress in artificial intelligence: a survey of expert opinion", in V Müller (ed), *Fundamental issues of artificial intelligence*, Springer.

Naudé, W and N Dimitri (2020): "The race for an artificial general intelligence: implications for public policy", *AI and Society*, vol 35.

- Noy, S and W Zhang (2023): "Experimental evidence on the productivity effects of generative artificial intelligence", *Science*, vol 381, no 6654.
- Organisation for Economic Co-operation and Development (OECD) (2022): "Measuring the environmental impacts of artificial intelligence compute and applications: the AI footprint", *OECD Digital Economy Papers*, no 341.
- Patterson, D (2022): "Good news about the carbon footprint of machine learning training", *Google Research Blog*, 15 February.
- Peng, S, W Swiatek, A Gao, P Cullivan and H Chang (2024): "AI revolution on chat bot: evidence from a randomized controlled experiment", *arXiv Working Paper*, no 10956.
- Radovanovic, A (2020): "Our data centers now work harder when the sun shines and wind blows", *Google*, 22 April.
- Schmidt, E (2023): "Innovation power: why technology will define the future of geopolitics", *Foreign Affairs*, vol 102.
- Senga, J R, S Wang and C Knittel (2026): "Flexible data centers reduce power system costs but can increase emissions", *iScience*, vol 29, no 7, 116497.
- Singh, D (2026): "Conflict", in D Singh (ed), *Endogenous and exogenous crises and the complex adaptive polycrisis state: rethinking bank crisis management frameworks*, forthcoming.
- Singh, P K (2025): "AI and the future of employment in India's IT and BPO industry", *International Journal for Multidisciplinary Research*, vol 7, no 3.
- Spencer, T and S Singh (2024): "What the data centre and AI boom could mean for the energy sector", *International Energy Agency Commentary*, 18 October.
- Stern, N and M Romani (2025): "What is AI's role in the climate transition and how can it drive growth?", *World Economic Forum Opinion*, 16 January.
- Strubell, E, A Ganesh and A McCallum (2019): "Energy and policy considerations for deep learning in NLP", in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, Florence, Italy, July.
- Tabbakh, A et al (2024): "Towards sustainable AI: a comprehensive framework for Green AI", *Discover Sustainability*, vol 5, 408.
- Trammell, P and A Korinek (2023): "Economic growth under transformative AI", *NBER Working Papers*, no 31815.
- Verdecchia, R, J Sallou and L Cruz (2023): "A systematic review of Green AI", *WIREs Data Mining and Knowledge Discovery*, vol 13, no 4.
- Wu, C-J, B Acun, R Raghavendra and K Hazelwood (2024): "Beyond efficiency: scaling AI sustainably", *IEEE Micro*, vol 44, no 5.
- Zhao, Z, N Holland and J Nelson (2024): "Optimizing smart grid performance: a stochastic approach to renewable energy integration", *Sustainable Cities and Society*, vol 111, 105533.