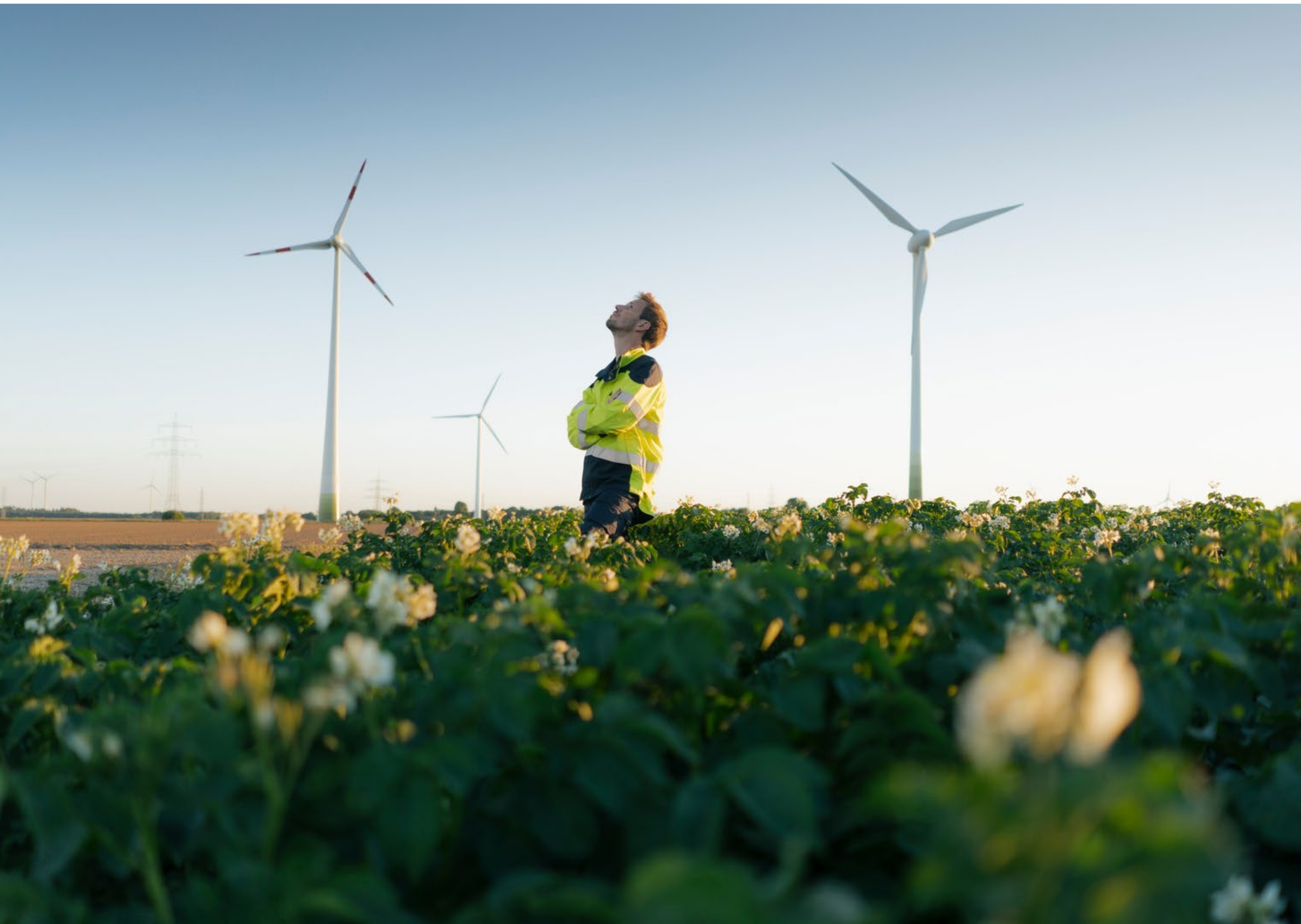
Australia's National Science Agency

AI for Climate R&D Roadmap

Consultation paper

May 2025



Citation

Naughtin C, Evans D, Mason C & Trinh K, 2025. AI for Climate R&D Roadmap: Consultation paper. CSIRO.

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Important disclaimer

Acknowledgement of Country

CSIRO acknowledges the Traditional Owners of the lands, seas and waters, of the area that we live and work on across Australia. We acknowledge all Aboriginal and Torres Strait Islander peoples and their continuing connection to their culture and pay our respects to Elders past and present. CSIRO is committed to reconciliation and recognises that Aboriginal and Torres Strait Islander peoples have made and will continue to make extraordinary contributions to all aspects of Australian life including culture, economy and science.

Acknowledgements

The authors would like to acknowledge the contributions of the various individuals who shared their expertise and experience as part of this roadmap development process. This includes government, industry, academia and the not-for-profit sector representatives who participated in expert interviews. These insights were instrumental in shaping the direction of this research, identifying candidate artificial intelligence (AI) use cases for climate mitigation and adaptation and brainstorming potential models for cross-sectoral collaboration. We also thank Mahesh Prakash, Moana Simpson, Leah Moss, Cara Stitzlein, Brent Henderson and Nandini Ramesh for their helpful guidance and feedback in developing this report and Shanae Burns for assisting in the report production.

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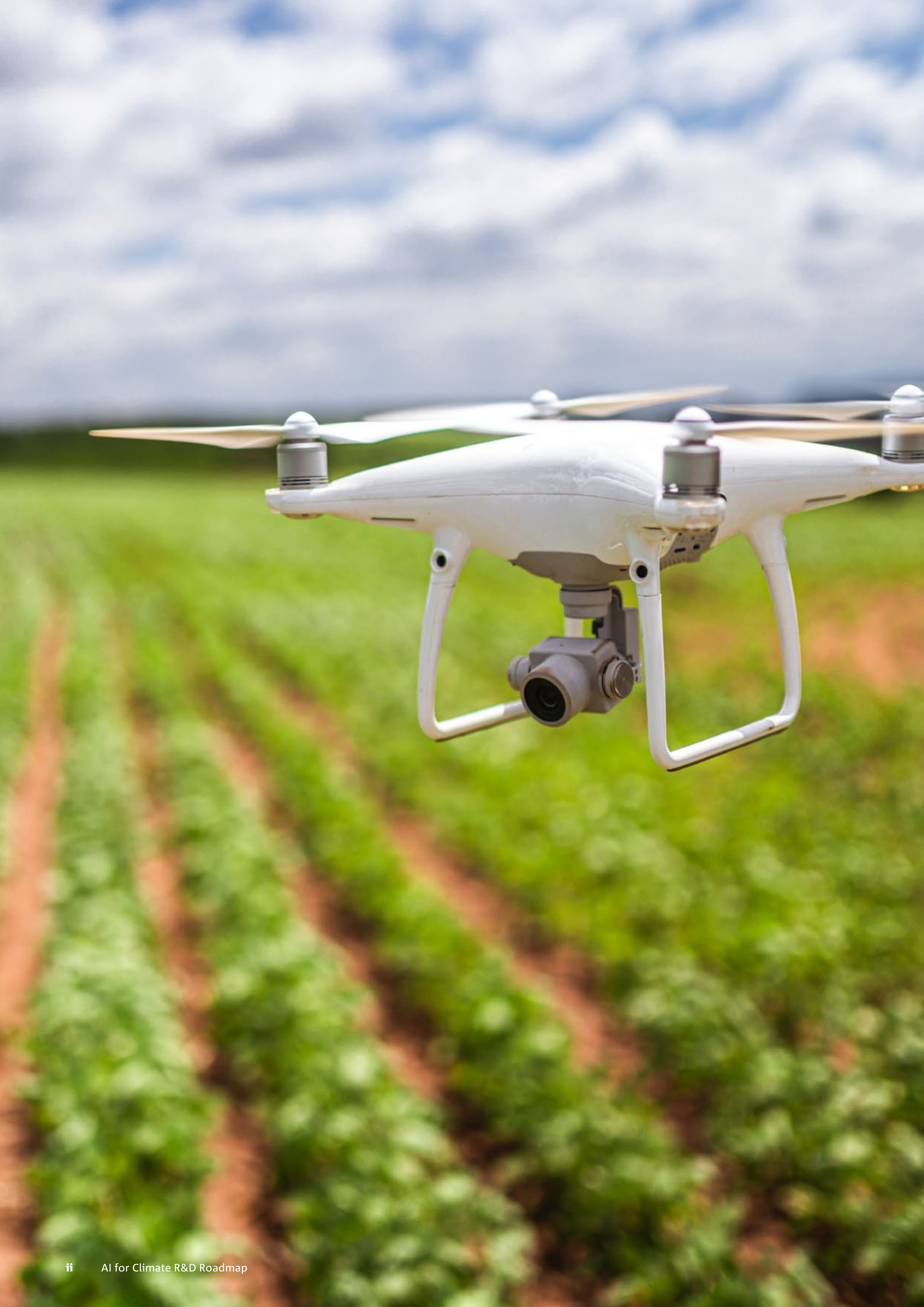
Currency conversions

All dollar value figures denote Australian dollars unless otherwise specified.

Contents

Abbreviations

ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ACCESS	Artificial Intelligence for Changing Climate and Environmental Sustainability
ACT	Australian Capital Territory
ADViCE	Artificial Intelligence for Decarbonisation's Virtual Centre of Excellence
AI	artificial intelligence
AI4ER	AI for the Study of Environmental Risks
CCTV	closed-circuit television
ICIP	Indigenous Cultural and Intellectual Property
IPCC AR6	Intergovernmental Panel on Climate Change Sixth Assessment Report
LLM	large language model
ML	machine learning
NASA	National Aeronautics and Space Administration
NRT	National Science Foundation Research Traineeship
NSF	National Science Foundation
NSW	New South Wales
R&D	research and development
SAMMI	Seqwater's Autonomous Motorised Monitoring Instrument
SustAI	UKRI AI Centre for Doctoral Training in AI for Sustainability
UK	United Kingdom
UKRI	UK Research and Innovation
UN	United Nations
US	United States



Introduction

Australia is among many countries actively responding to the global challenge of reducing greenhouse gas emissions and adapting to a changing climate. Despite progress towards net zero, recent forecasts suggest that the world is not on track to meet the Paris Agreement [12]. A continuation of current policies is projected to result in global warming of 3.1 °C by 2100 and the world would need to reduce greenhouse gas emissions by 30% to limit global warming to 2 °C [12]. These impacts are already being felt in Australia, with annual costs associated with extreme weather events expected to increase from $38 billion in 2020 to $73 billion by 2060 [13].

With its superior processing speed, capacity to handle large and diverse datasets and powerful predictive capabilities, there is growing interest in leveraging artificial intelligence (AI) to tackle the climate crisis. While AI applications have been developed to solve or support various climate mitigation and adaptation needs, many of these developments have been opportunistic and lack strong collaboration between researchers, industry, government and not-for-profit sectors.

Many leaders are also not clear on how AI can support their climate action. In 2022, Boston Consulting Group found that 87% of global business leaders working in climate or AI felt that AI would be a helpful tool in responding to climate change, but less than half (43%) had clarity on how to use AI in their climate change efforts [14]. Where AI is being applied as part of climate efforts, these applications are skewed towards mitigation, with less focus on how AI can support organisations and communities in adapting to a changing climate [15]. Leveraging the full potential of AI to accelerate climate action requires working across sectors to align future AI directions with current and emerging market needs.

> With AI and climate, we are dealing with a problem space that is very broad and a piece of technology that can mean many things.
>
> – Expert interviewee

Scope of this paper

This report serves as a discussion starter on where and how Australia can leverage AI to accelerate climate action. It draws on insights from industry, government and not-for-profit representatives and AI experts to provide a market-led view of future AI research and development (R&D) opportunities for climate mitigation and adaptation. While AI can support climate and weather forecasting, this paper focuses on downstream applications of AI concerning climate challenges facing critical infrastructure, emergency management, agriculture, energy, water and health care, noting that this is not an exhaustive list of areas where AI can be applied as part of climate responses.

Specifically, this report:

- provides an overview of existing domain-specific AI applications for climate mitigation and adaptation and untapped opportunities where AI could be applied in the future
- identifies cross-cutting AI applications that could support responses to common climate challenges impacting multiple sectors
- highlights the potential risks posed by the increasing use of AI in tackling the climate crisis and considerations for ensuring AI is used safely and responsibly
- seeks feedback on potential pathways for Australia to accelerate the role of AI in climate adaptation and mitigation responses, considering learning from other existing initiatives.

Feedback on this paper will help inform future AI-for-climate efforts across industry, government, academic and not-for-profit organisations, including CSIRO. These include mechanisms for engaging stakeholders across the Australian R&D ecosystem, building awareness and capabilities, coordinating R&D efforts and resources, and promoting the safe and responsible use of AI. This paper does not seek to cover all potential needs and issues relating to AI, but rather to build a shared understanding of the types of climate problems with which AI can assist and how industry, government, academia and not-for-profit sectors can work together towards these opportunities.

Defining artificial intelligence

While there is no universally accepted definition for AI, in this paper we define it as **a collection of computer science and interrelated statistical approaches and technologies that can be used to learn from data, solve problems and perform tasks autonomously to achieve defined objectives** [4].

The following table provides examples of some of the AI technologies referred to in this report and a high-level snapshot of how they can be deployed for a range of functions and the specific ways in which they can support climate-related challenges, which are expanded on in this paper.

EXAMPLE AI TECHNOLOGIES	GENERAL APPLICATIONS	CLIMATE-SPECIFIC APPLICATIONS
Machine learning (ML) Building computer systems that can learn from data to find relationships and patterns, and make predictions from training data without explicit instructions	**Diagnosing melanomas:** ML can help clinicians identify malignant skin lesions from images, enabling early clinical intervention	**Weather forecasting:** ML models can provide faster and more granular weather forecasts and test a range of climate scenarios
Computer vision Enabling computers to analyse and extract information from images	**Protecting a national icon:** Computer vision, combined with other AI technologies, has been applied to the Great Barrier Reef to detect crown-of-thorns starfish – a key contributor to coral bleaching	**Detecting infrastructure faults:** Computer vision can be used to detect maintenance issues early (e.g. pipeline leaks) so that they can be repaired, strengthening resilience to future extreme weather events
Robotics and autonomous systems An interdisciplinary field of AI that designs and develops systems that can interact with their environment	**Industrial robotics:** Autonomous haulage trucks managed by remote operators are used on mining sites, improving worker safety and productivity	**Disaster evacuation:** Driverless vehicles, combined with other AI technologies, can help evacuate affected individuals while protecting the safety of frontline responders
Human language technologies Advanced models that are trained on large volumes of human language to generate human-like outputs	**Virtual assistants:** Human language technologies underpin virtual assistants like Siri, Alexa and Google Assistant, enabling them to interact conversationally with users and streamline everyday administrative tasks	**Assessing damage:** Natural language processing models can be used to analyse social media data following a natural hazard event to direct resources to individuals or properties that require support

Current and emerging AI use cases for climate action

There is a wealth of examples of where AI has already been applied to improve foundational climate and weather modelling capabilities and address climate mitigation and adaptation challenges in specific domains. This section highlights examples of how AI can be applied in weather and climate forecasting and specific application domains at different scales, focusing on critical infrastructure, emergency management, agriculture, energy, water and health care. We also build on these existing applications to identify future opportunities to use AI to further mitigate or solve climate challenges emerging in one or more of these domains.

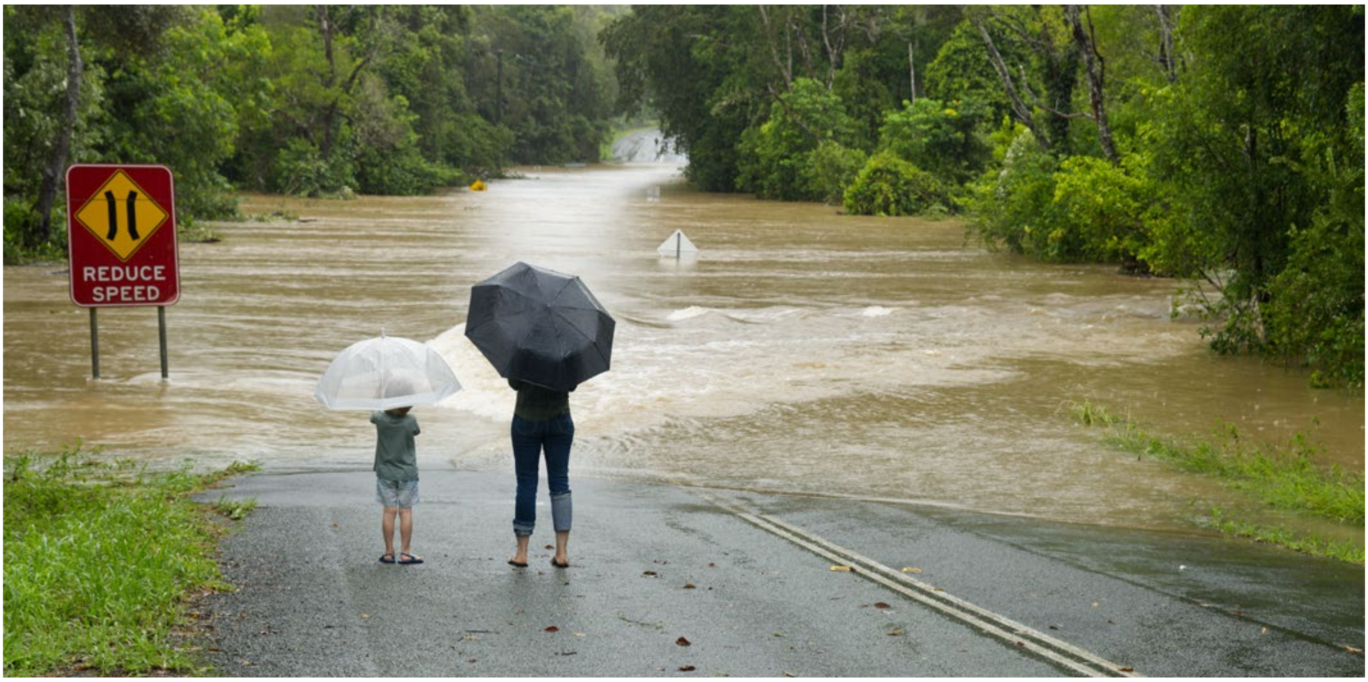
Foundational climate and weather modelling

How can AI improve climate and weather forecasting?

Given the capacity of AI to be applied to diverse datasets and provide inferences at finer scales and under multiple scenarios, it can help improve foundational climate and weather modelling capabilities. A host of AI-enabled tools have been developed to **improve the speed, accuracy, and spatial and temporal resolution of weather forecasts** [16–19]. For example, Microsoft's Aurora uses AI to forecast a range of weather variables 10 days in advance [16, 20] and Google's GenCast probabilistic weather model can generate 15-day weather forecasts at a 0.25° latitude–longitude resolution [19].

AI models can also **expand the capabilities of traditional climate models**, which are based on the fundamental laws of physics to simulate the Earth's climate system. While physics-based climate models can accommodate poorer data environments and extrapolate events that go beyond historical data, they are underpinned by complex equations and can be computationally intensive. AI can be applied to additional datasets to model climate processes that are currently not well predicted by physics-based model s, thereby revealing how to improve the parameters within these traditional models (e.g. [21–23]).

This capability has proven useful in a range of climate-related applications that draw on climate variables (e.g. temperature, weather patterns, ocean currents) and human activities (e.g. emissions, land use and population patterns) of varying spatiotemporal scales [15]. Examples include Microsoft's ClimaX, a novel foundational model that uses diverse datasets collected at different spatiotemporal scales to produce climate and weather projections [24]. Because AI-based approaches are limited to the data on which they are trained, they are unable to extrapolate to unknown future climate conditions [25]. **Hybrid models that combine the accuracy, precision and efficiency of AI with physics-based simulation approaches may therefore offer an optimal approach** [25, 26].



Future opportunities to expand foundational AI capabilities for climate action

Emerging AI developments in **multimodal foundational models are opening new avenues for climate and weather forecasting and associated downstream applications**. Foundational AI models provide key efficiency benefits in that they can be trained on unlabelled data and then fine-tuned using a smaller amount of labelled data for specific applications [27–29]. Technology company IBM and the National Aeronautical and Space Administration (NASA) have joined forces to develop a multimodal AI foundational model for climate and weather prediction, which aims to overcome the limitations of current AI climate models [29]. Specifically, the model will have the capacity to predict extreme events that differ from average conditions and to continuously update as climate conditions and data evolve.

Experts also acknowledged the opportunity to **develop a geospatial AI foundational model for Earth observation** that could be used for a range of industry and community applications. In addition, NASA and IBM Research have developed the first open-source geospatial AI foundational model trained on satellite data collected by NASA [27, 28]. These capabilities can make it easier to deploy industry-specific AI tools for monitoring natural hazards, predicting crop yields and more [27, 28]. Importantly, the realisation of these foundational AI model opportunities will rest on access to high-performance computing infrastructure, which has typically been a challenge for Australian companies and researchers [30].

The foundational AI model developments could **support climate resilience and capacity building in developing nations in the Pacific**. Small Pacific Island nations are among the most vulnerable to the impacts of climate change [31] and the Australian Government has committed to supporting the Pacific Island region in strengthening its climate and disaster resilience [32]. Foundational models could be leveraged to reduce the computational cost and complexity of downscaling climate models [26], making this information more accessible, timely and cost-effective for decision-makers in the Pacific.

AI could also be used to **support the management of data sources that underpin climate modelling**. There are currently large volumes of data that are poorly structured or documented, limiting the capacity to use these data in climate-related AI applications. AI could act as a 'data custodian', assisting in extracting metadata and documenting information on climate datasets and querying these datasets. This capability could enhance and simplify the process of data discovery and facilitate greater opportunities for integration between research projects.

Critical infrastructure

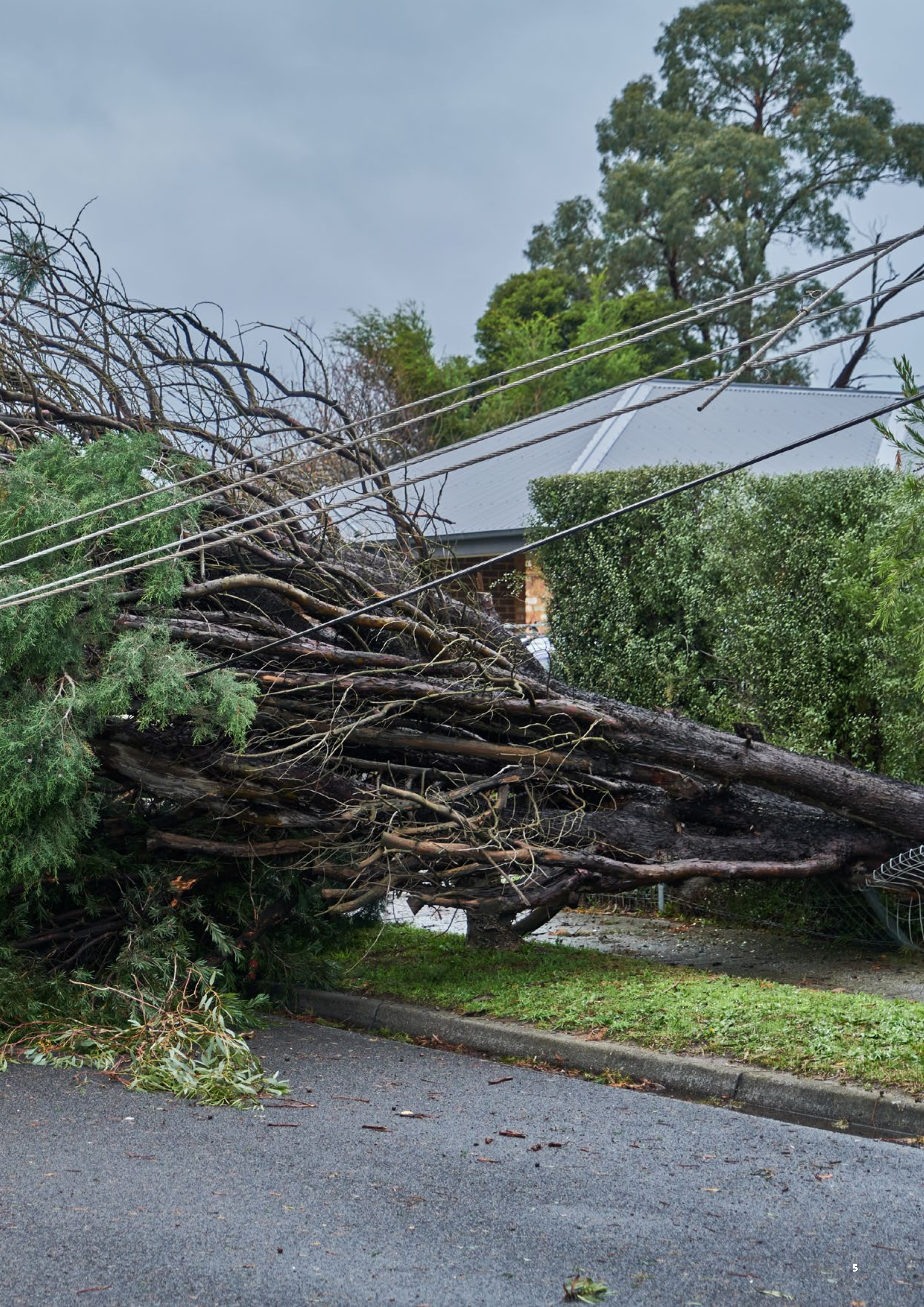
How can AI help adapt critical infrastructure to a changing climate?

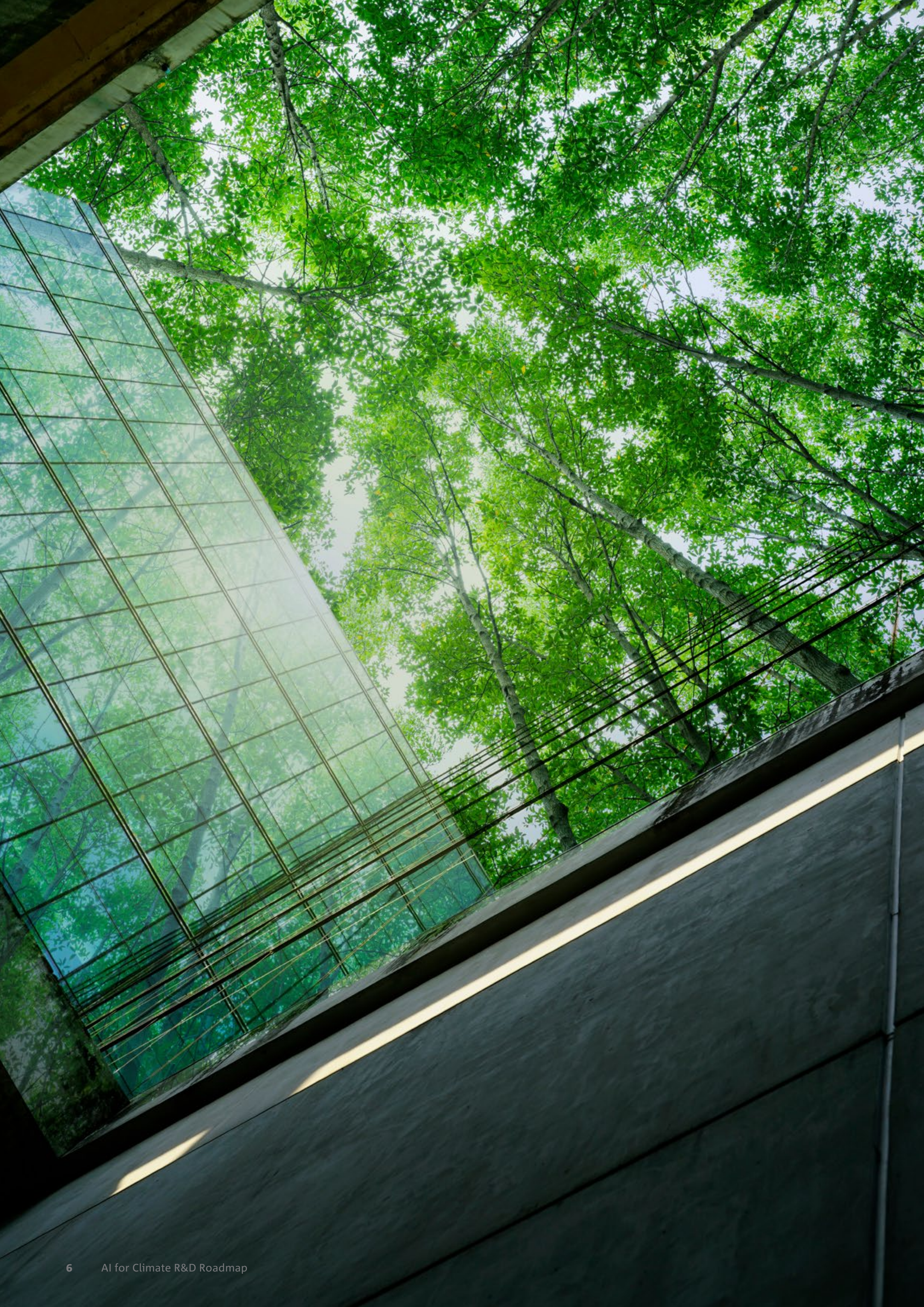
Critical infrastructure includes a broad range of systems, assets and supply chains that are central to the social and economic wellbeing, sovereignty and security of Australia (e.g. transportation, energy, telecommunication) [33]. Protecting Australia's critical infrastructure from natural disasters – along with cyberattacks and global supply chain disruptions – is a key priority for government and industry in continuing to deliver essential services [33].

AI can **pre-emptively detect and predict infrastructure vulnerability** to maintenance issues, helping to reduce the costs of or need for repair after a natural hazard event. Unmanned aerial vehicles or sensors can collect data on infrastructure performance remotely, which are analysed by computer vision algorithms to detect damage to structural components (e.g. cracks in concrete, leaks in pipelines) [34, 35]. For example, Sydney-based company VAPAR analyses closed-circuit television (CCTV) footage using AI and machine learning (ML) to assess the condition of wastewater pipes, reducing the cost of infrastructure management [36].

Other applications use AI to **rapidly assess damage to critical infrastructure during or after a disaster event**, improving on previous time-intensive processes [37, 38]. Using deep neural network and ML approaches, images collected via satellites or social media users can be compared pre- and post-disaster to diagnose the level of damage [37, 39]. Researchers have also used AI with social media or satellite data to detect areas affected by power and communications outages in real time [40, 41]. These insights can help decision-makers direct resources, including emergency management.

Bayesian neural network and neural network-based causal approaches have been used to **assess the resilience of critical infrastructure to a range of interconnected factors** and the potential cascading impacts of a natural hazard event across multiple assets [42, 43]. National Hazards Research Australia plans to explore these approaches in the Australian context [44]. Understanding the impacts of natural hazards on interconnected infrastructure networks could better pre-empt the effects of natural hazards across multiple systems and coordinate investment for climate mitigation and adaptation.





How can AI help decarbonise critical infrastructure?

AI can **measure and monitor the carbon footprint associated with critical infrastructure** to identify opportunities to reduce emissions. Google's Environmental Insights Explorer can help city planners in the United States (US) assess the emissions generated by buildings and transport through aerial measures of tree canopy coverage and available rooftop solar installations [45]. This approach could be extended by using AI to assess the emissions profile of individual assets or to identify planning areas that would benefit from decarbonisation interventions (e.g. planning more green cover).

There are emerging use cases for AI to **track and audit direct and indirect emissions (scope 1 and 2 emissions, respectively) across industrial supply chains (scope 3 emissions)**. Existing commercial applications use AI to combine multiple data streams, match emissions to specific products and business activities, and predict the impact of different interventions [46–48]. AI applications, such as ClimateBERT, have also been developed to analyse climate risk disclosures from company reports to assess compliance between climate-related reporting and demonstrable climate actions [49, 50]. This capability is increasingly relevant to many Australian companies that will be required to monitor and report scope 1, 2 and 3 emissions under new mandatory climate-related financial disclosure reporting requirements [51].

AI has been deployed to **help decarbonise heavy-emitting industries like transportation**. In aviation, Google Research, in collaboration with American Airlines and Breakthrough Energy, has used AI to predict contrails during flight – a leading source of aviation emissions [52]. By optimising aircraft routes using AI, they were able to reduce contrails by 54% over 70 flights [53]. AI has also been used to identify more fuel- and carbon-efficient road transport routes. Examples include Google Maps' Project Green Light, which uses AI to identify routes that get users to their destination using fewer emissions [54] and the United Parcel Service, which has introduced similar capabilities to support more fuel-efficient logistics [55].

Future climate-related use cases for AI in critical infrastructure

While there are emerging use cases using AI to assess the co-dependence between critical infrastructure [42, 43], industry and government experts consulted in this research noted further opportunities to use AI to **understand the second- and third-order impacts of natural hazards across critical infrastructure**. With this information, decision-makers could make strategic investments that limit the flow-on impacts of natural hazards across systems. These use cases will need to consider regulations related to data sharing, concerns about commercially sensitive information and differing stakeholder interests.

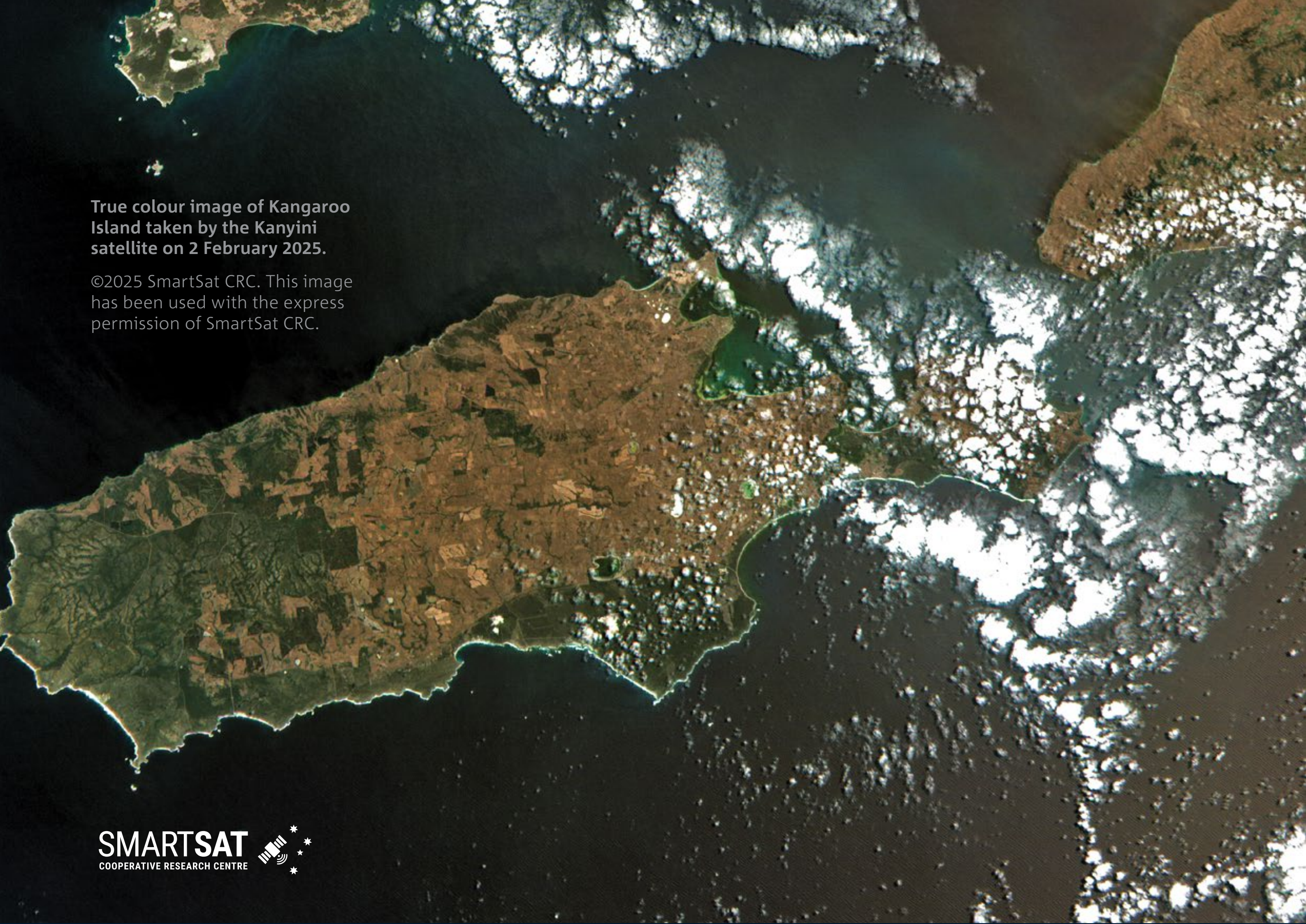
The transition to renewables and investments to improve the resilience of critical infrastructure can be costly. AI could be used to mine existing datasets (e.g. government approvals, company announcements) to **identify opportunities to coordinate infrastructure investments and minimise duplication**. For example, if the regional energy provider is building resilience into their network, other infrastructure owners in the region may not need to invest in backup power generators.

New mandatory climate-related financial disclosure reporting requirements for Australian companies [51] will likely bring greater scrutiny to the estimates associated with emissions. While commercial offerings are available, industry representatives noted difficulties in evaluating the quality of these commercial 'black box' solutions. They also seek independent guidance regarding standards and best practices for modelling emissions across industrial supply chains. There are opportunities to use AI to **improve the monitoring and reporting of emissions and other climate-related risks and assess the impact of such disclosures**.

Emergency management

How can AI help emergency management adapt to a changing climate?

Early prediction of natural hazards can help emergency management agencies better direct resources. AI can **detect and predict natural hazards better than traditional methods** by learning from patterns in historical meteorological and satellite data [56–59]. Google Research has used AI as part of Flood Hub, which provides a 5-day prediction for extreme riverine events [60, 61] and FireSat, which can detect bushfires that are 5 square metres in area [62]. Emerging applications are also using satellites with onboard AI to detect bushfire smoke (see *Case study: Detecting bushfires from space*) and AI with unmanned aerial vehicle imagery to detect hazards at a finer spatial and temporal resolution than satellite data [63–70].



True colour image of Kangaroo Island taken by the Kanyini satellite on 2 February 2025.

CASE STUDY

Detecting bushfires from space

Australian scientists are working to provide faster and more reliable bushfire detection as part of the Kanyini mission [3]. This mission is led by the University of South Australia and supported by the Cooperative Research Centre for Smart Satellite Technologies and Analytics.

Researchers are using a satellite equipped with a hyperspectral imager that captures reflected light from Earth across various wavelengths to create detailed surface maps for monitoring bushfires, water quality and land management [9]. A computationally efficient (lightweight) AI model processes these satellite data onboard and differentiates smoke from cloud.

This approach allows for the early detection of fire smoke before the fire generates significant heat, resulting in quicker alerts to ground crews and response times. The performance of the Kanyini system marks a substantial improvement over conventional approaches, detecting smoke 500 times faster than traditional ground-based methods [3]. The system is scheduled for full implementation in 2025.

Social media is also increasingly used in AI applications to **streamline rescue and evacuation operations**. Here, natural language processing models are used to analyse social media posts during a disaster event to assist rescue teams in detecting and prioritising requests for help [71]. CSIRO has worked with emergency services agencies in Queensland to use social media data and other datasets to forecast call centre requests during an emergency event. AI has also been used with social media data to provide a fine-grained temporal and geospatial representation of affected individuals and areas during and after the event [72].

AI can **support more sustainable workloads for emergency management personnel working in call centres**. These personnel are often required to process, interpret and respond to information from many sources during an emergency. The RapidSOS system used in emergency call centres in the US uses AI to generate insights and alerts based on data collected from a range of devices, informing operators' decisions about crisis response [73]. AI-based recommendation systems can reduce staff information overload and decrease perceived workloads and heart rates, indicating potential decreases in stress levels [74, 75]. However, the evidence is mixed on how these systems impact operators' situational awareness [74, 75].

Future climate-related use cases for AI in emergency management

AI could be used to combine various data sources (e.g. social media, prior interactions with emergency or government assistance, mobile phone usage) to **provide tailored emergency information to individuals and households based on their risk profile** [76]. This information could be delivered via AI-enabled chatbots to help citizens prepare during high-risk periods or take the appropriate safety measures during a natural hazard [76]. To ensure AI applications are safe and responsible, developers need to consider the ethical, data security and privacy issues associated with using AI in these emergency management contexts [76].

With the prevalence of cybercrime reports on the rise in Australia [77], there is a growing need to ensure that emergency alert systems are secure and resilient to cybersecurity risks. For instance, there is the risk that cyber actors could gain access to these systems and issue fake alerts to the public. AI could help to **detect false or malicious emergency alerts**. Increasing reliance on AI-generated predictions and alerts in emergency management creates a need for systems, such as an immutable record, that allow users to establish the provenance and quality of forecasts and information.

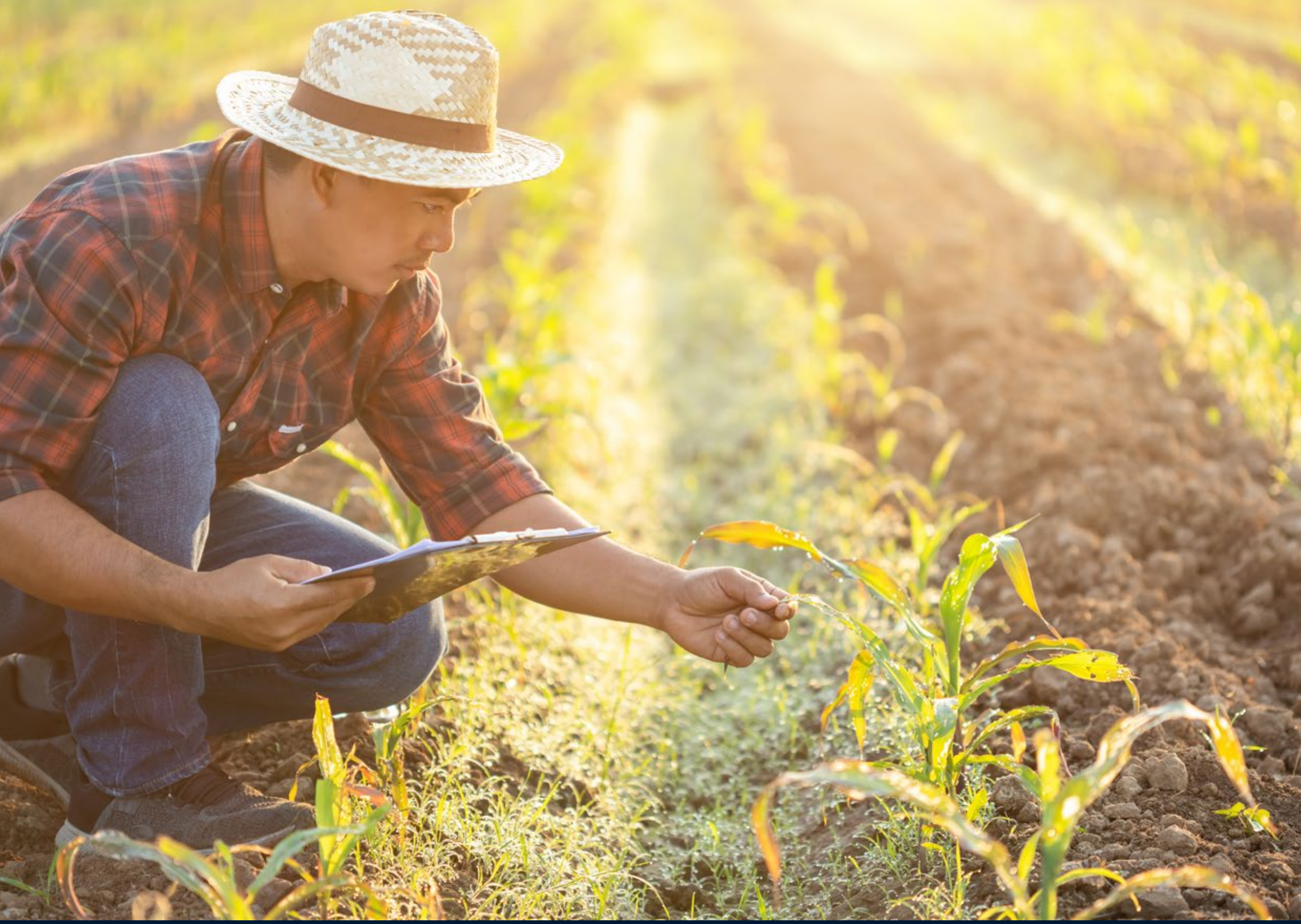
Agriculture

How can AI help the agricultural sector adapt to a changing climate?

AI tools can provide climate insights to farmers to help them **optimise farm operations and strengthen climate resilience in the face of more severe and frequent extreme weather events**. In collaboration with the Bureau of Meteorology, CSIRO has developed My Climate View – a digital tool that provides Australian farmers with insights into current climate trends relevant to their specific region and commodity [78]. The Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) has also developed 'farmpredict' which is a microsimulation model that uses ML to make climate-informed predictions on a range of business inputs and outputs (see *Case study: ABARES farmpredict model*).

Precision agriculture technologies can help farmers tailor their operations to crop and environmental conditions. AI can **optimise and automate precision agriculture systems based on current climate conditions** [79], helping farmers adapt to changing and variable climate conditions while adopting more sustainable farming practices. Existing applications use AI to draw on data about climate, soil, crop and weather conditions to automate irrigation decisions [80] and reduce herbicide use through targeted weed and pest spraying [81, 82]. Future developments in wireless sensors and AI algorithms could enable sensors to process information and make on-farm decisions autonomously without relying on external servers [83].

AI can **accelerate the identification of plant varieties that are more responsive or resilient to emerging climate conditions** [84]. By analysing large and complex datasets generated by genomics, phenomics and other 'omics' technologies, AI can simulate plant responses to environmental stressors and identify genetic markers associated with desirable traits [84]. While existing AI applications have focused on single-omics data, emerging AI methods have the potential to integrate data from multiple sources [84].



CASE STUDY

ABARES farmpredict model

ABARES farmpredict is a microsimulation model designed to analyse Australian broadacre farming businesses [2]. The model simulates physical and financial outcomes for Australian farming businesses under prevailing climate conditions and commodity prices.

It does so by drawing on a range of climate variables, including rainfall and temperature, to assess their impact on crop yields, livestock management and overall productivity. This approach enables a detailed understanding of how environmental conditions influence farming decisions and outcomes.

The simulation component of farmpredict builds on these statistical insights to generate scenario-based forecasts that simulate farm performance under different conditions [10]. The model forecasts production for crops, livestock and inventory holdings, and combines these with input and output prices to estimate financial results. The simulation provides insights into revenue, costs and stock changes, helping farmers make informed decisions and adapt to environmental and economic changes.

How can AI help decarbonise the agricultural sector?

AI approaches are being increasingly used to **measure and predict the carbon sequestration potential of land and oceans**. ML approaches have been used to integrate satellite data and other data sources to measure soil carbon stocks [85] or to continuously monitor forest cover and its carbon impact, as illustrated by the Pachama platform [86]. In addition, CSIRO is working with the Australian Government and Google Australia to use ML to map seagrass ecosystems in the Indo-Pacific and Australia. Seagrass is a critical long-term carbon sink that can store 35 times more carbon than tropical rainforests [87, 88].

Alternative proteins, such as plant-based proteins, are increasingly in demand and can significantly reduce the reliance on more carbon-intensive animal proteins [89]. AI can **utilise vast amounts of scientific data to accelerate innovations in alternative proteins**, including optimising the formulations needed for growing cells or identifying candidate bioactive ingredients [90–92]. Examples of companies using these applications include: Vivici, which has partnered with Ginkgo Bioworks in using AI to select promising strains for dairy protein production [93]; and Shiru, which has leveraged AlphaFold [94] to predict protein structure and to identify and produce proteins that can replace traditional food ingredients [95].

Future climate-related use cases for AI in agriculture

Autonomous field management enabled by AI reflects the next evolution of precision agriculture, with emerging AI developments providing the building blocks towards fully autonomous farming systems [96, 97]. Here, AI can bring together large and more diverse datasets for predictive analysis [98], enhance pest and disease detection [99] and enable higher levels of autonomy in tasks such as spraying, planting and harvesting [100]. While fully autonomous farming systems are yet to be realised due to technical and non-technical reasons (e.g. legislative, economic) [101], they could provide avenues for farmers to streamline decisions and processes that reduce environmental impacts and maximise economic returns.

AI could be used to **improve the granularity of emissions monitoring to the individual-property level**, helping to identify and potentially incentivise farmers who are engaging in low-emissions farming practices. Farmers undertaking carbon sequestration activities are required to use very complex sensors and software and often need to rely on external consultants for support. Satellites equipped with spectrometers can measure changes in methane and nitrogen levels in the atmosphere, which could be integrated and analysed using AI to monitor emissions associated with farming practices.

Methane emissions produced from enteric fermentation in livestock (i.e. the natural process through which microbes break down food as part of the digestive process in ruminant animals, producing methane as a by-product) account for 70% of greenhouse gas emissions in Australian agriculture [102]. AI can **help the agricultural sector reduce the amount of methane produced through enteric fermentation**. This could include using AI in the discovery of new livestock feeds and feed supplements that inhibit methane production [102] or to identify low-methane breeding traits [103].

Energy

How can AI help the energy sector adapt to a changing climate?

Like other types of critical infrastructure, AI can **support the maintenance and optimisation of energy infrastructure**. Rather than relying on fixed schedules or reactive responses, deep learning models can bring together historical performance data, weather data and sensor data to predict potential failures based on weather conditions [104–106]. Researchers from the Argonne National Laboratory in the US have developed AI models for predicting maintenance issues in energy infrastructure and found these tools helped to reduce maintenance costs by up to 56% and unnecessary crew visits by up to 66% [107].

How can AI help decarbonise the energy sector?

One of the most common use cases for AI in the energy sector is to **optimise energy distribution** [108]. AI is already used to manage fluctuations across the energy grid, including controlling grid networks and forecasting supply and demand [109]. AI can support the consolidation of information across complex and diverse energy networks, which often include a range of energy sources and organisations. This information is being used to identify ways to optimise energy use and energy-related emissions as part of Alphabet's Tapestry project (see *Case study: Alphabet's Tapestry project*).

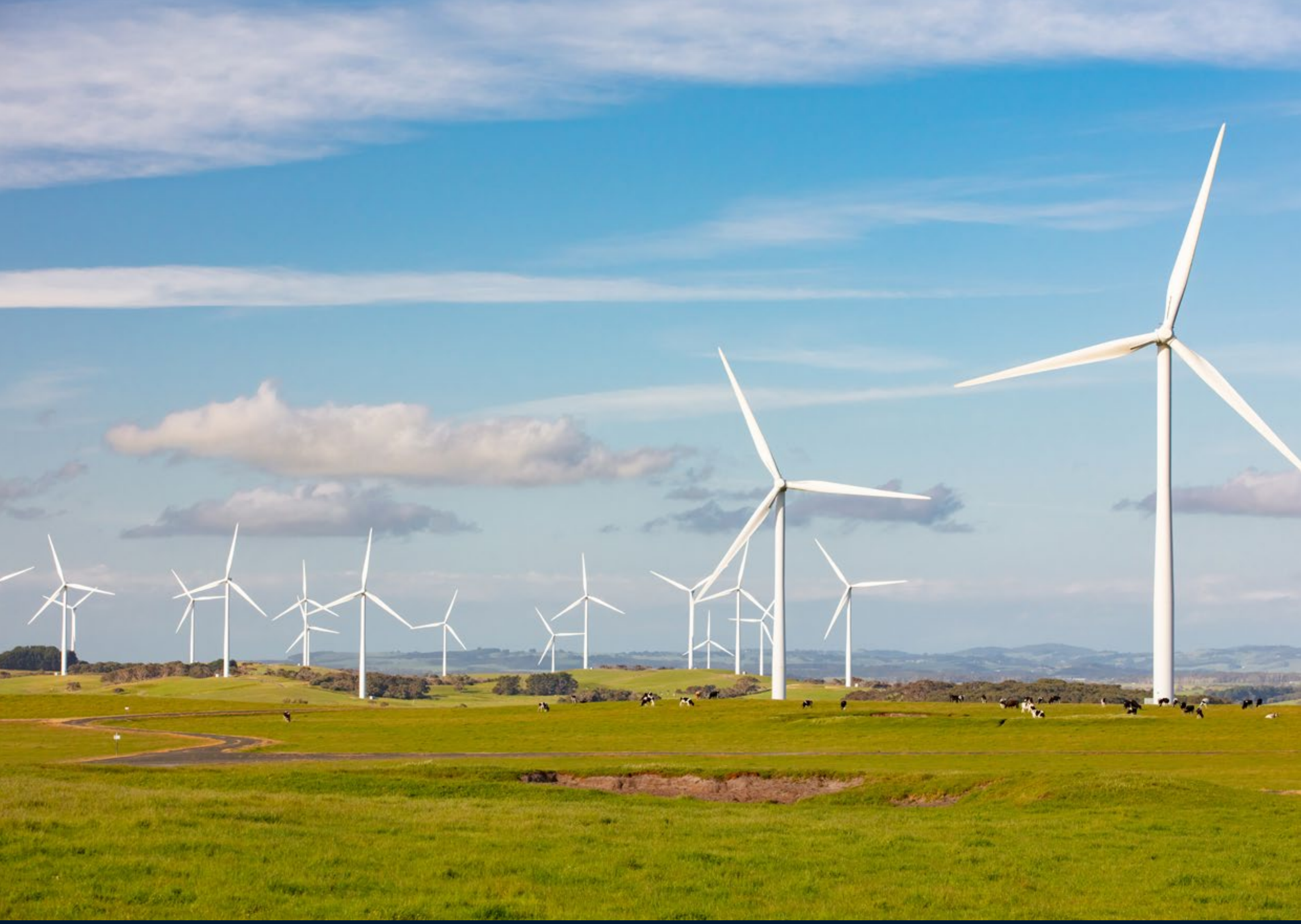
With the growing adoption of renewable energy technologies, the energy grid is becoming more decentralised and variable [108]. AI can **better support the management of renewable energy sources** by improving supply predictions and aligning decisions with forecasted energy needs and weather conditions [108, 109]. For example, AI could be used to automatically adjust solar panels and wind turbines to maximise energy production or identify the optimal location for these systems based on weather conditions [109]. Google's DeepMind has developed an AI algorithm that can predict wind power output up to 36 hours in advance, which has increased the value of its wind energy by approximately 20% [110].

Future climate-related use cases for AI in energy

As the uptake of distributed energy systems increases (e.g. residential solar photovoltaic units, electric vehicles, battery storage devices), the volume of energy-related data will grow too. There are opportunities to use AI to **further leverage the value generated through these data to optimise energy grid management** and provide real-time insights that can be used to detect vulnerabilities or threats in the system (e.g. due to misconfiguration or malware introduced by malicious actors).

Lithium-ion batteries used in electric vehicles and other energy storage solutions are critical to the renewable energy transition. Lithium is a finite resource, however, creating the need to identify other candidate metals that could be used in batteries. AI can play a role in **accelerating the materials discovery and design process for new energy storage solutions**. Emerging examples have used AI combined with physics-based models and high-performance computing to identify other suitable candidates for battery applications [111–113].

Just as AI can be used to optimise the distribution of energy across a network, this technology could also be used to **manage energy supply to electric vehicles based on optimal conditions**. For example, aligning electric vehicle charging times to periods where energy demand is low or when renewable energy sources are high. These AI models could underpin dynamic pricing models for electric vehicle charging to incentivise charging during off-peak (cheaper) periods [114].



CASE STUDY

Alphabet's Tapestry project

Alphabet's Tapestry project aims to improve the management of the electricity grid, shifting from a one-way flow of electricity from fossil fuel plants to consumers to a more distributed network [1].

Currently, electricity grids lack cohesive management and visibility, with information fragmented across various organisations. Tapestry seeks to address these challenges by increasing grid visibility to promote a greener and more reliable system for stakeholders.

Tapestry is developing AI-powered tools to modernise grid management and planning [1]. They include GridAware, which accelerates and automates asset inspections, and the Grid Planning Tool, which simplifies complex simulations of various scenarios (e.g. the impact of low wind on power usage during peak demand).

Tapestry and CSIRO are collaborating to develop advanced smart inverters to improve the integration of renewable energy into the grid [11]. Traditional inverters are often inefficient and costly and can cause grid instability. The Tapestry and CSIRO smart inverters will feature grid-forming intelligence, allowing them to actively manage energy flow, communicate with other grid devices and respond dynamically to real-time conditions.

Water

How can AI help the water sector adapt to a changing climate?

AI can help **anticipate future water demand and optimise water sources**, particularly under a more variable climate with more extremes (droughts and floods). AI algorithms can model complex, non-linear hydrological processes and integrate data from diverse sources, such as ground gauges, remote sensors and Internet of Things devices [115–119]. CSIRO has developed WaterWise, a cloud-based platform that uses data from soil-based sensors and ML to predict future water needs in real time [120]. If this technology was rolled out across Australia's four most water-intensive crops (cotton, sugarcane, tomatoes and almonds), it could generate $1 billion in value by 2030 [120].

Traditional irrigation systems in urban environments operate on pre-set timers. Several research initiatives have explored how AI combined with sensor data and cloud computing can **improve the responsiveness of urban irrigation systems**. Researchers from Central Queensland University used AI to automate irrigation decisions using data from sensors installed in parklands in Cairns, which helped save 583 litres of water per square metre each year [121]. The New South Wales (NSW) Government similarly used ML to optimise water efficiency in parks based on weather conditions [122].

Natural hazards can pose water quality risks through the growth of harmful bacteria and pathogens at higher water temperatures or agricultural run-off from floodings. AI can support the capacity to **monitor water quality risks under changing climate conditions**. For example, Seqwater and the Queensland University of Technology have developed the SAMMI (Seqwater's Autonomous Motorised Monitoring Instrument) robot, which uses AI to autonomously collect water samples from difficult-to-reach locations (see *Case study: SAMMI by Seqwater*). Researchers from Los Alamos National Laboratory are also investigating the use of AI to forecast harmful algal blooms from water sample data, weather conditions and satellite imagery [123].

How can AI help decarbonise the water sector?

AI can be used to **optimise the operation of water treatment plants, reducing greenhouse gas emissions**. An example is the DARROW project, a European research initiative, which uses AI on data collected from sensors that monitor water quality and treatment processes [124–126]. Such models will provide insights that can be used to inform plant operations (e.g. appropriate chemical treatment levels), reduce energy consumption, increase biogas production and recover valuable resources such as phosphorus and nitrogen.

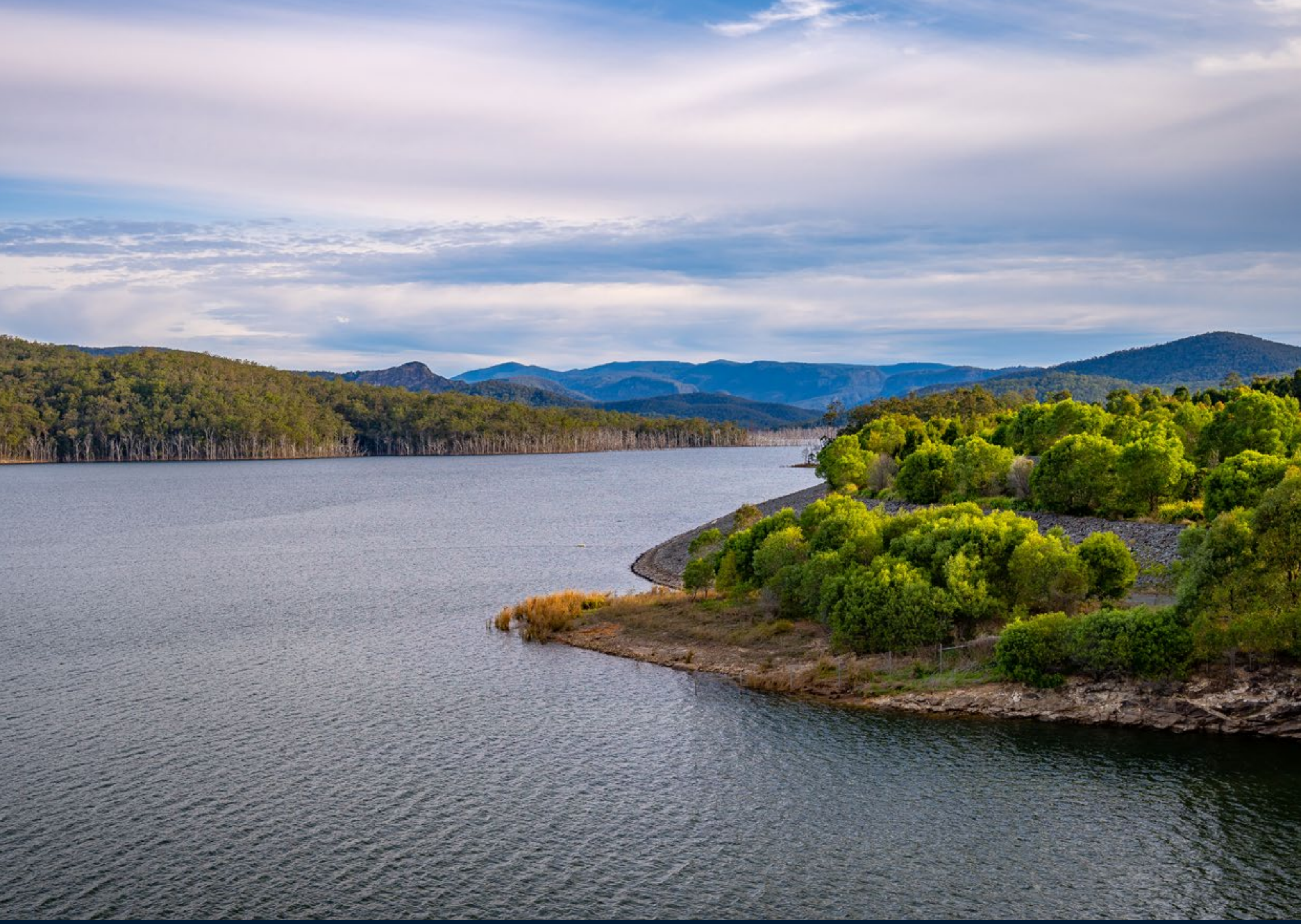
Future climate-related use cases for AI in water

Deciding on which water source to draw from (e.g. dam water, desalination, treated recycled water) is currently a manual process. AI could **support the optimisation of water supply decisions**, taking into account current and forecasted water supply, capacity, pressure within the system and energy use associated with distributing water. AI could also play a role in increasing industrial use of treated recycled water where appropriate, reducing unnecessary use of freshwater sources.

Data centres are a growing source of water demand given that they rely upon water-based cooling systems to manage excess heat generated by servers. There are emerging circular models for repurposing this heated water (see *Responsible AI-for-climate-related applications*) and AI could also **play a role in coordinating water flows as part of circular solutions for data centres**, optimising water use between data centres and other domains that can repurpose the heated water.

Changes in climate conditions can impact water quantity and quality, but current modelling approaches do not integrate climate projections with long-term water forecasting. AI could be used to **integrate climate and water forecasting capabilities** to inform water planning decisions during periods of extreme shortage (droughts) or abundance (flooding). WaterNSW has integrated climate projections with demand forecasting through its NSW and ACT (Australian Capital Territory) Regional Climate Modelling (NARCliM) project as an emerging example of what this capability could look like [127].

While there are promising capabilities for detecting algal blooms in water samples, similar capabilities are needed to monitor the proliferation of deleterious bacteria in water sources [128]. AI tools could be utilised to **efficiently monitor and detect unsafe levels of harmful bacteria in water**. Researchers have trained neural networks to detect specific types of bacteria in water samples with greater precision and speed than traditional methods [129]. Further development of these methods and their application in routine water monitoring workflows could reduce the risk of exposing the population to harmful water sources.



CASE STUDY

SAMMI by Seqwater

The SAMMI (Seqwater's Autonomous Motorised Monitoring Instrument) robot developed by Seqwater in collaboration with the Queensland University of Technology is improving water quality monitoring in South East Queensland [5, 6]. SAMMI is a solar-powered, self-driving robot designed to operate autonomously in waterways.

Since its launch in 2019, SAMMI has demonstrated its ability to collect water samples, measure quality parameters and create sonar maps of reservoirs. These robots enable more frequent measurements of water quality and wider spatial coverage than traditional methods, including hard-to-reach areas.

New versions of SAMMI extend the capabilities of the initial version with multiple AI-based enhancements [6]. For example, SAMMI 2 can autonomously identify and spray weeds that are detrimental to water quality, such as water hyacinth and salvinia. Future versions will focus on collision-avoidance technology to navigate around moving objects and debris.

Healthcare

How can AI help the healthcare sector adapt to a changing climate?

A growing prevalence of extreme heat events heightens the risk of heat-related morbidity and mortality, particularly among vulnerable populations (i.e. those aged 65 years and over, young children or people with existing chronic conditions) [130, 131]. Researchers have used AI to **predict climate-related health risks to help the healthcare sector prepare for surges in demand** [132–135], including heatstroke prediction [133, 135] and forecasting mortality risks related to weather-sensitive cardiovascular diseases [134]. Other modelling approaches have quantified heat health risks across geographical areas to help decision-makers better prepare for extreme heat across Australia (e.g. the Heat-Health Risk Index [136, 137]).

AI can also be used to **monitor for workplace heat stress**, which can lead to work accidents, lapses in concentration, fatigue and poor decision-making [138–140]. AI can analyse physiological data collected from body sensors (e.g. heart rate, temperature and humidity inside clothes, chemical markers in sweat) to detect signs of heat stress [141, 142]. These signals enable managers to intervene early, encouraging workers to take breaks or work indoors when they start showing signs of heat stress [141]. Australian-based start-up EMU Systems has developed an environmental monitoring system to predict heat stress in athletes, with broader application for workers in mining, manufacturing, construction and agriculture [143].

Climate change is also contributing to heightened infectious disease risks and the emergence of vector-borne infections in new locations [144]. Epidemic intelligence systems enabled by AI can be used to **detect early warning signals of disease outbreaks**, mapping these signals spatially, simulating the impact of different interventions and detecting sources of misinformation [145]. These capabilities have been demonstrated through platforms such as EPIWATCH, BlueDot and the Global Biosurveillance Portal, which use natural language processing to analyse social media data and news reports combined with location data to identify and categorise potential disease outbreaks at their precise locations [145–147].

AI can be used to **monitor air quality**, helping decision-makers identify and respond to emerging health risks early. Air pollution and greenhouse gas emissions are often driven by common factors (e.g. burning of fossil fuels via coal-fired power plants), meaning that addressing one of these challenges (reducing emissions) can co-benefit the other (improved health outcomes) [148–151]. BreezoMeter is a platform that uses ML to analyse data from various sources (e.g. air quality monitoring stations, satellite and meteorological data) to create high-resolution real-time heat maps of pollution and pollen levels [152].

Future climate-related use cases of AI in healthcare

A changing climate poses significant risks to populations living in regions that are predicted to exceed the 'human climate niche' (i.e. the climate conditions favourable to sustaining human life and activity) [153]. To support proactive responses to these climate risks, AI could be used to **monitor and identify locations that are trending towards exceeding the human climate niche**, informing community relocation responses. Existing modelling approaches can quantify how global populations might be impacted under differing degrees of global warming [154], which could be used as the basis for such early warning systems.

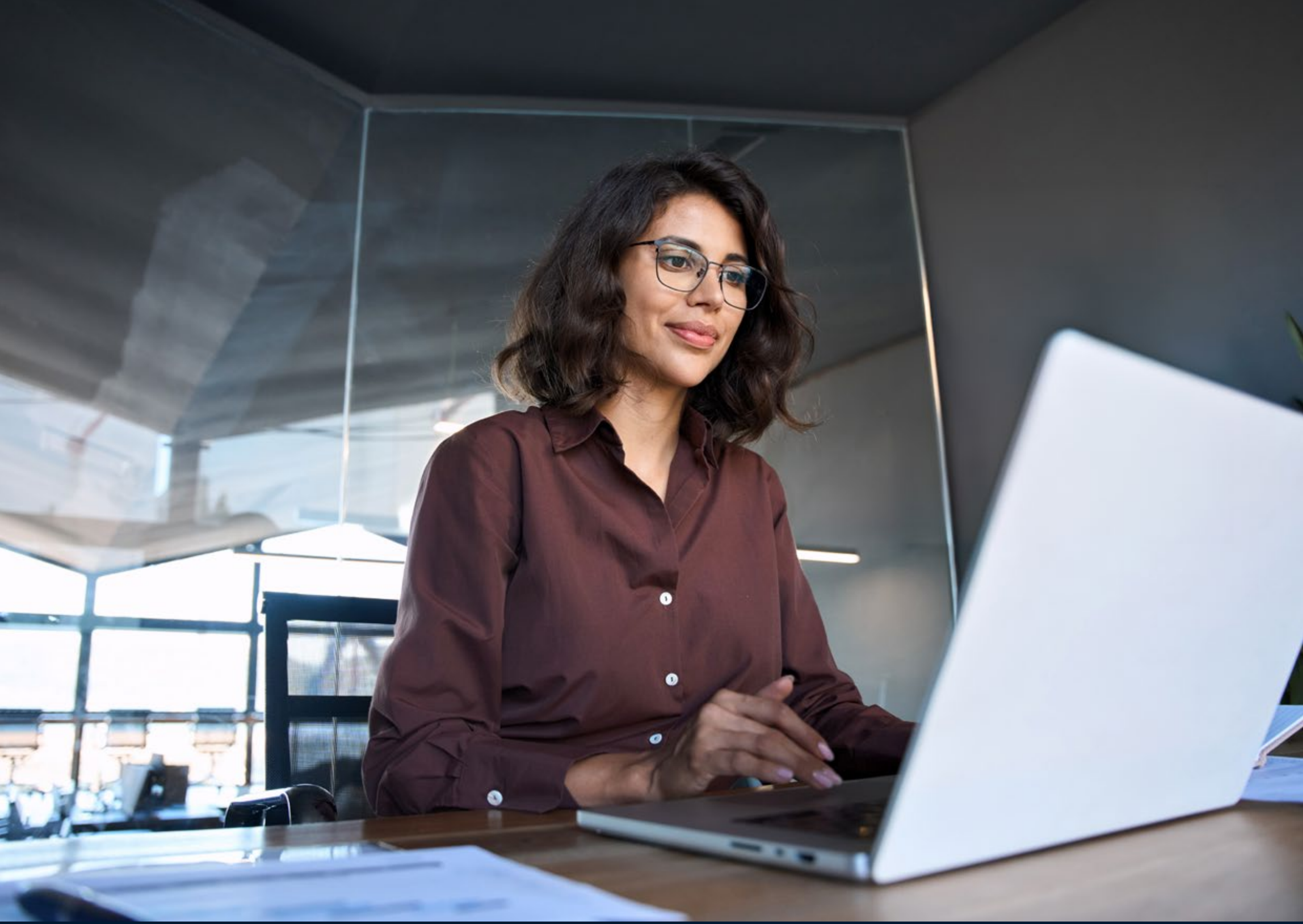
With the increasing digitisation of health records, there are opportunities to expand the use of AI to **predict climate-related impacts on the health system** [155]. Example use cases highlighted by the experts we consulted in developing this roadmap paper include using AI to integrate health system data with climate modelling to provide more precise estimates of the impacts of extreme weather events on healthcare services. There could also be opportunities to factor healthcare-related costs of climate change into existing economic modelling approaches [155] and strengthen the case for investment into climate adaptation measures in healthcare [156, 157].

Global supply chains account for approximately 75% of the Australian health system's carbon footprint [158]. Australia has recently jointly committed with the US and United Kingdom (UK) to decarbonise healthcare supply chains [158] and the Australian Government is developing a health system decarbonisation roadmap (due for release in 2025), which will cover scope 1, 2 and 3 emissions and patient travel [159]. Just as AI has been used to monitor and manage emissions across supply chains in other industries (see *Critical Infrastructure*), AI could be used to **bring together diverse datasets and quantify supply chain emissions in the healthcare sector**.

Other cross-domain applications

AI can **translate and tailor climate insights for a variety of users**. Emerging examples, such as ChatClimate, are leveraging the conversational capabilities of generative AI tools to personalise climate insights to specific queries (see *Case study: ChatClimate*). Another platform, This Climate Does Not Exist, has used AI to generate images that illustrate plausible future climate scenarios tailored to an individual's location to raise awareness and encourage climate action [160]. These capabilities demonstrate how AI could be used as a 'data concierge' to help decision-makers understand climate risks and the actions they can take.

Methane modelling is central to decarbonisation efforts across a range of domains, particularly agriculture, energy and water – the largest anthropogenic sources of methane emissions [161]. The Global Methane Pledge has been established to accelerate global efforts to reduce methane emissions by at least 30% from 2020 levels by 2030 to limit global warming to 1.5 °C [162]. AI has been used to **improve the timeliness, accuracy and granularity of methane emissions monitoring**, including MethaneSAT [163], GHGSat's SPECTRA platform [164] and Climate TRACE [165]. Climate TRACE arguably provides the most comprehensive global inventory of greenhouse gas emissions, including methane, covering over 350 million assets worldwide [165].



CASE STUDY

ChatClimate

ChatClimate leverages advanced natural language processing capabilities to provide timely access to reliable and credible information on climate change impacts [7, 8]. This conversational AI is underpinned by an LLM that was trained on data from the Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC AR6) to produce tailored answers to questions relating to climate change.

The performance of this model has been tested against other current state-of-the-art LLMs (e.g. GPT-4) and a hybrid ChatClimate approach that utilises IPCC AR6 data as well as in-house GPT-4 knowledge to test the value of this potential use case [7]. When evaluated by a team of authors from the IPCC AR6 team, the hybrid ChatClimate solution was found to produce the most accurate responses [7].

These results demonstrate the value of a tailored LLM solution that considers current, domain-specific data [7]. While these tools will not negate the need to translate climate information in complex decision-making contexts, they could support knowledge-sharing in non-expert contexts.

Responsible AI-for-climate applications

AI offers great promise in accelerating climate mitigation and adaptation efforts, but there are potential risks that need to be managed. The design, development and implementation of climate-related AI applications must be done responsibly so that they do not add to, or exacerbate, existing social, economic or environmental challenges. This section highlights key considerations around energy and water use, AI ethics and Indigenous Cultural and Intellectual Property (ICIP) rights.

Ensuring climate-related AI is safe and responsible

Australia, along with other national governments, has developed **ethical guidelines for the safe, secure and responsible development and deployment of AI** [166], and these need to be considered in climate-related AI applications. These include ensuring that AI systems:

- benefit human, societal and environmental wellbeing
- align with human values and rights, including diversity and the autonomy of individuals
- are inclusive, accessible and do not unfairly discriminate against individuals, communities or groups
- respect the privacy, protection and security of data
- are reliable, accurate and reproducible, operating in line with their intended purpose
- are transparent so that people understand when they are engaging with, or impacted by, an AI system
- can be contested when they significantly impact an individual, community, group or environment
- are accountable by those individuals or organisations who are responsible for the outcomes of the AI system.

Some of the use cases presented in this paper highlight specific responsible AI considerations. For example, in the case of emergency management, **respect for the privacy, protection and security of people's data** collected from social media, government services and other sources needs to be considered in the development of AI-enabled evacuation alert systems that can personalise warnings to the public. Providing citizens with the option to opt out of these services could be one way to manage this concern.

The **inclusivity and accessibility of AI tools** also need to be considered. Given that social media data can be influenced by digital access and socioeconomic characteristics, applications that rely primarily on these data may be inadvertently biased towards certain community segments [72]. The broader concentration of AI developments and investments in the Global North – the world's developed and wealthier nations [167] – could lead to geographical biases in AI models and applications and capability gaps in less-developed Global South nations. Targeted efforts, such as dedicated AI-for-climate funding opportunities for the Global South, have been introduced to address these geographical gaps [167].

The establishment of **safe, secure and responsible design and deployment of climate-related AI systems is critical in building trust in these applications**. The spread of misinformation has previously hindered the capacity for climate science to drive climate action [168], so emerging AI applications that aim to communicate climate risks or predictions (see, for example, *Case study: ChatClimate*) must be technically robust, transparent and reliable [169]. Research focused on advancing our understanding of best practices for fostering trust in, and the trustworthiness of, climate-related AI could support the translation of responsible AI principles into practice and the evaluation of trust in such tools [170].

The energy and emissions footprint of AI

The **data centres and transmission networks that underpin AI are energy intensive** [171]. The Electric Power Research Institute estimates that data centres could consume up to 9.1% of electricity in the US by 2030 (compared with 4% in 2023) depending on the pace of future developments in AI applications and energy efficiency measures [172]. If the size of these models and computing demand continue to grow at the current rate, the International Energy Agency predicts that AI-driven energy demands associated with data centres could exceed the existing energy efficiency gains [171].

The **emissions associated with data centres will depend on access to clean energy sources**. For instance, the carbon intensity associated with electricity generation is much less in Norway (30 gCO_2 equivalents per kilowatt-hour) than in Australia (549 gCO_2) [173]. Some of the world's leading technology companies – including Microsoft, Google and Amazon – are exploring nuclear energy as a potential energy source, either by purchasing nuclear power or partnering with a nuclear energy provider [174].

Data centre energy needs are highly influenced by server and infrastructure requirements. A Google-led analysis estimated that its cloud data centre infrastructure was 1.4–2 times more energy efficient than traditional data centres and its hardware specifically designed for ML training and inference was 2–5 times more efficient than generic systems [175]. Importantly, these analyses consider only the emissions associated with operating data centres, but the embodied carbon associated with constructing data centres and server hardware is another key consideration in understanding AI's emissions footprint.

The water footprint of AI

Data centres generate heat, with water-based systems being the most common approach for keeping servers and infrastructure at the optimal temperature. Like energy, **future expansions in AI could place unsustainable pressure on water reserves if not well managed**. There are emerging circular energy models where heated water from data centres has been repurposed for aquaculture production [176] and to heat residential homes [177, 178] and public swimming pools [179]. The viability of circular models associated with data centres will depend on proximity to partners who can repurpose water and other resources.

Recognising and respecting Indigenous Cultural and Intellectual Property

Researchers, developers and other partners **need to consider ICIP rights when engaging and working with First Nations p eople on climate-related AI applications**. ICIP rights reflect the rights of First Nations people to the tangible and intangible aspects of their cultural heritage. The importance of First Nations data sovereignty and ICIP rights is acknowledged in the safe and responsible development and deployment of AI in the Australian Government's proposed mandatory guardrails for AI in high-risk settings [180].

There are existing **examples where ICIP has been misappropriately used** without consent or attribution. These include generative AI tools that have been trained on First Nations artworks without permission and used to create inauthentic AI-generated First Nations art [180, 181]. These practices can pose risks to ICIP and increase the spread of misinformation about First Nations people when false or inappropriate data sources are used to generate AI outputs [182].

To protect ICIP in climate-related AI applications, First Nations people should be involved in the AI design and development to identify where ICIP is used inappropriately or misused and to provide oversight of the information used to train the AI system [183]. CSIRO has previously partnered with rangers and Traditional Owners in the Kakadu National Park to use AI and First Nations knowledge to support the management of para grass – an invasive weed that impacts wetlands [184]. CSIRO is also partnering with First Nations communities in developing digital capabilities under the Climate Services for Agriculture initiative.

Pathways to accelerate AI-for-climate R&D

In addition to identifying *where* AI could be applied in response to climate challenges, this paper serves as a discussion starter on *how* the Australian R&D ecosystem can leverage AI to accelerate climate action. This section presents a series of options, drawing on expert insights and learnings from related local and international examples. These suggestions are intended to stimulate conversations about how industry, government, academia and not-for-profit sectors can work together towards AI-for-climate opportunities.

Bringing together multidisciplinary teams of technical and domain experts

AI-for-climate research requires multidisciplinary teams with expertise and capabilities in climate science, AI and the application domain. 'Knowledge brokers' are also valued team members who can assist with relationship building, cross-disciplinary knowledge sharing and feedback loops between researchers and end users. Embedding these multidisciplinary capabilities in education and training pathways for emerging scientists and engineers could further help build capacity for future AI-for-climate applications.

Experts consulted in developing this paper emphasised that it is insufficient for AI experts to only consult domain experts at the start of the R&D process. The connection between the AI and domain experts needs to be embedded across multiple stages so that the AI experts understand the nuances of the data and the domain experts can understand the assumptions and constraints underpinning the AI model. Through this process, domain experts can also improve their AI literacy around the types of problems for which AI is best suited and its limitations.

> You can't throw things over and expect the AI researchers to understand the intricacies of the dataset… You have to engage in the design process so that the people who are designing [the model] understand what the needs are and the requirements. Also, the knowledge transfer has to happen the other way around. If you are going to consume the model, you need to understand the assumptions made in [its] architecture and design so that you know where it'll work and where it won't work.
>
> – Expert interviewee

WHAT THIS COULD LOOK LIKE	EXISTING EXAMPLES FROM WHICH WE CAN LEARN
Engage a network of Australian and international climate, AI and domain experts to come together (e.g. via a regular annual or bi-annual forum) to share knowledge and learnings on the intersection of AI and climate action	CSIRO hosted an **AI for Climate Symposium** in 2024 that brought together over 120 Australian and international AI and climate experts across industry, government and academia [185]. It included presentations on current AI use cases for climate mitigation and adaptation challenges and a 'design sprint' that encouraged participants to develop novel AI solutions to an emerging climate challenge. This event raised awareness around the need for stronger cross-sector collaboration in AI-for-climate opportunities in an Australian context. The **Climate Change AI Summer Schools** bring together a global network of industry, government and academic participants working at the intersection of climate change and ML [186]. Running since 2022, the Summer School is an annual, hybrid event held over seven weeks and attracting up to 10,000 participants from over 140 countries. It includes lectures on use cases for AI and ML in addressing climate change and hands-on tutorials on applying AI and ML to solve climate-related problems.
Support programs for early and mid-career researchers (e.g. PhDs, fellowships and other professional training programs) that foster the next generation of interdisciplinary experts bridging linkages between AI and climate in different domains	UK Research and Innovation (UKRI) has funded a series of Centres for Doctoral Training that support PhD positions at the intersection between AI and climate, environment and sustainability domains. These include **Intelligent Earth: UKRI AI Centre for Doctoral Training in AI for the Environment** hosted by the University of Oxford [187]; **AI for the Study of Environmental Risks (AI4ER): UK Centre for Doctoral Training** hosted by Cambridge University [188]; and the **UKRI AI Centre for Doctoral Training in AI for Sustainability (SustAI)** hosted by the University of Southampton [189]. In the US, Morgan State University has established the **National Science Foundation (NSF) Research Traineeship (NRT)** program on **Artificial Intelligence for Changing Climate and Environmental Sustainability (ACCESS)** [190]. The program aims to provide PhD students with interdisciplinary training in environmental science, water quality management, climate science, and AI and ML to support the application of AI solutions for climate action.

Supporting research collaboration and innovation across sectors

Partnerships and the coordination of R&D activities are critical when using AI to support climate mitigation and adaptation, given the global nature of climate change and the scale and urgency of climate action required. This type of research requires a diverse combination of resources and expertise that expands the boundaries of any one organisation, sector or region.

For example, as highlighted in the *Critical infrastructure* section, natural hazard risks impacting water, energy, transport, telecommunications and healthcare infrastructure are highly connected. When one node breaks down, these impacts can flow through to other parts of the network. By joining forces across organisations, sectors and disciplines, there could be opportunities to maximise and scale mitigation and adaptation efforts, increase the use of shared tools and approaches, and prevent duplicated efforts .

> What needs to happen is collaborations. AI for science requires collaborations of different groups providing different expertise in [skills] and resources and trying to solve a problem together.
>
> – Expert interviewee

WHAT THIS COULD LOOK LIKE	EXISTING EXAMPLES FROM WHICH WE CAN LEARN
Establish a dedicated AI-for-climate grand challenge or innovation hub for researchers, innovators and end users to collaborate, share resources and develop novel AI-enabled solutions in response to emerging climate challenges impacting Australia and Pacific Island nations	The **AI Innovation Grand Challenge** was held in 2024 as part of the United Nations (UN) Framework Convention on Climate Change's Technology Mechanism Initiative on Artificial Intelligence for Climate Action [191]. This grand challenge was designed to bring together teams of students, entrepreneurs, academics and non-government organisations to pitch an AI solution for climate mitigation and adaptation. All AI applications developed through this challenge were open source, with a strong focus on building capability in developing countries. The **Artificial Intelligence for Decarbonisation's Virtual Centre of Excellence (ADViCE)** initiative – funded by the UK Government and delivered by Digital Catapult, Energy Systems Catapult and The Alan Turing Institute – is focused on the development of AI applications that support the transition to net zero [192]. This virtual centre brings decarbonisation stakeholders across sectors together to collaborate, disseminate information, and identify priority decarbonisation challenges. Other grand challenges and innovation hubs have focused on specific sectors or geographies. These include **AI for Climate Resilience in Rural Areas**, which aims to identify AI-driven solutions that respond to climate challenges facing rural communities in Asia, Africa, Latin America, the Caribbean and beyond [193]. AI for Good, convened by the UN's International Telecommunication Union, the Government of Switzerland and other UN agency partners, hosted a series of **AI/ML Solutions for Climate Change** initiatives in 2023 focused on water management, food and agriculture and 5G network energy consumption [194]. Finally, the USD$100 million Bezos Earth Fund's **AI for Climate and Nature Grand Challenge** aims to create and scale AI solutions and incentivise cross-sectoral partnerships in the areas of sustainable proteins, energy grid optimisation and biodiversity conservation [195]. **Climate Change AI** has systematically analysed 215 past and ongoing grand challenges, competitive grants, 'hackathons', incubators and accelerators, and innovation hubs globally in climate, AI and AI-for-climate domains [167]. While these initiatives have grown exponentially since 2019, most are concentrated in the Global North. Successful initiatives tend to involve heterogeneous participant cohorts, position AI innovations as a vehicle for achieving a climate or nature objective (but not the primary focus), encourage scalable solutions and build in evaluation measures to assess the impact of projects.

Setting the strategic focus with a clear pathway to impact

A large share of current AI-for-climate developments have been opportunistic and lack a clear path to impact or, where relevant, a path to market. There could be **opportunities to develop a set of sector-specific or national priorities or challenges** that consider what is technically feasible, how AI could have maximum impact and where there are 'low-hanging fruit' opportunities.

It is important to acknowledge that some climate challenges that need to be solved may have a strong public interest but limited commercial imperative (e.g. emissions or deforestation monitoring platforms). Such AI use cases could present a **role for government and the not-for-profit sector in supporting the development of AI-for-climate applications where there are insufficient commercial incentives**, ensuring that these developments create opportunities for shared benefits.

> I think there is a lot to be said for programs that are thoughtfully put together and bring together the smartest heads to solve a specific problem and then figure out how you can get that solution a pathway to market where it can have impact.
>
> – Expert interviewee

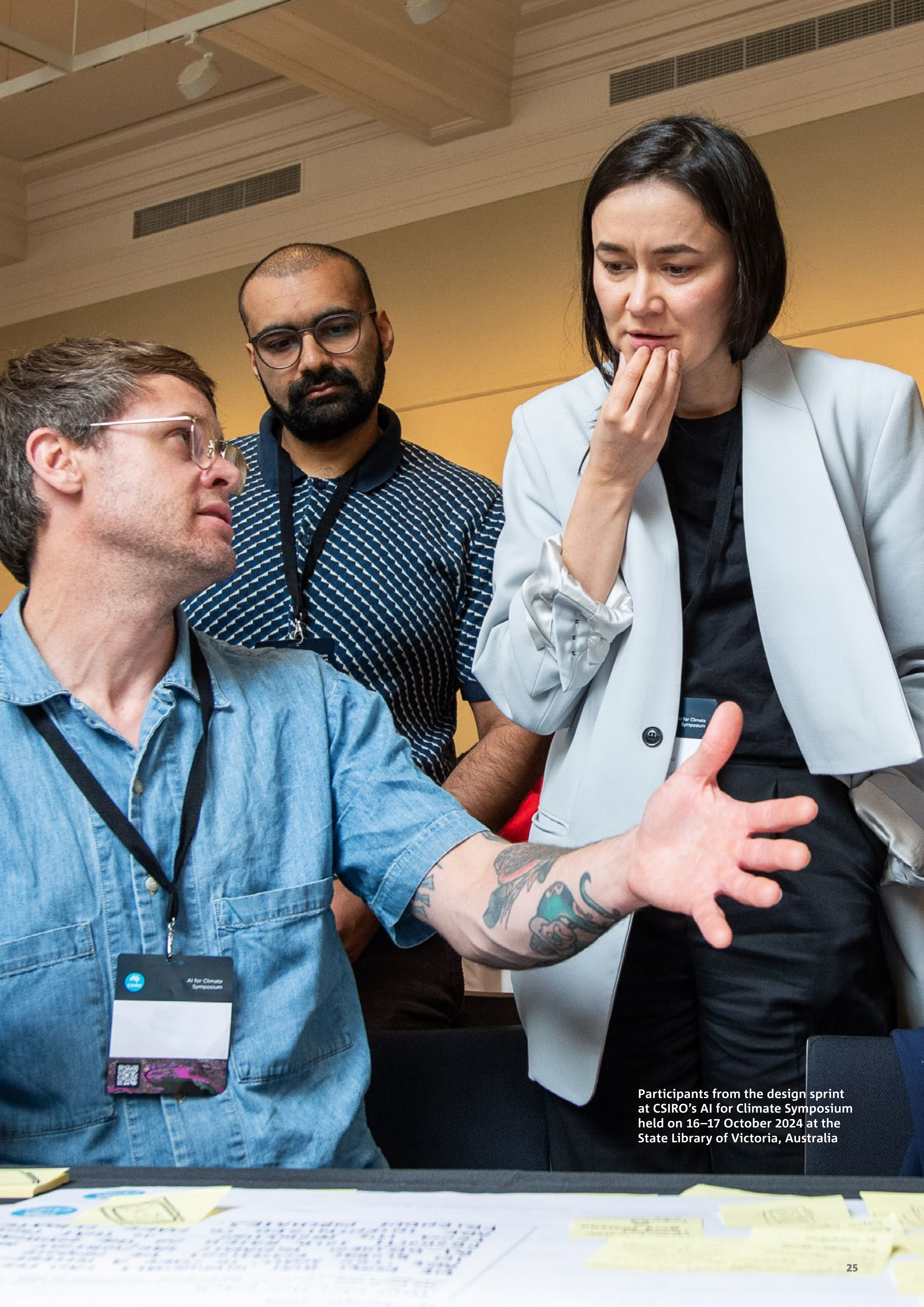
WHAT THIS COULD LOOK LIKE	EXISTING EXAMPLES FROM WHICH WE CAN LEARN
Define a set of priority sectors, national challenges or use cases for AI for climate mitigation and adaptation to coordinate resources across public, private, academic and not-for-profit sectors	The **ADViCE** initiative was defined around four high-emitting sectors, comprising agriculture, the built environment, energy and manufacturing [196]. A set of AI-for-decarbonisation grand challenges was then identified under each of these sectors (i.e. unlocking domestic decarbonisation, enabling net zero infrastructure, maximising flexibility in energy networks, decarbonising manufacturing inputs, improving manufacturing process efficiency, optimising soil management and minimising methane in agriculture [196]). Identifying these priority areas is designed to support stakeholders in connecting with relevant partners and capabilities, improve access to data needed to develop AI solutions and stimulate investment opportunities [196].
Identify pathways and partnerships to support the development and maintenance of AI-for-climate solutions that support public interest, non-commercial datasets, models and applications	The **Lacuna Fund** aims to address the data gaps that commonly exist for low- and middle-income countries, which can lead to biased or harmful outcomes for marginalised populations when these data are used in ML [197]. Funded by public-sector agencies, private organisations and philanthropies, the Lacuna Fund has a specific focus on supporting the creation and maintenance of datasets and ML models to help low- and middle-income communities respond to climate change.

Promoting trusted, safe and responsible AI

In ensuring that AI-for-climate applications are safe and responsible, **there is a need to create trust with users** so that organisations and decision-makers can be confident using the insights generated by such tools [198]. Experts consulted in developing this roadmap raised concerns about relying on AI systems that have not been validated or do not report on the performance of the model. They cited instances where commercial providers claimed that their tools could provide predictions at a level of granularity that is not possible with state-of-the-art offerings.

One way to strengthen trust in AI-for-climate tools is through transparency. Transparency can be achieved through sharing datasets and code, acknowledging the sources of training data, validating and evaluating the impacts of the model, and publishing on the model performance. Experts we spoke to were supportive of the sharing of climate modelling, datasets and AI tools so that they could be tested and improved via collaborations across organisational and national boundaries. Shared resources could include benchmarked datasets, open-source code and results from tests and evaluation exercises.

WHAT THIS COULD LOOK LIKE	EXISTING EXAMPLES FROM WHICH WE CAN LEARN
Create a governance framework that can be used to evaluate alignment between AI-for-climate applications with Australia's AI ethical principles and guardrails	Building on Australia's AI Ethics Principles [166], several resources have been developed to support Australian organisations in aligning their development and use of AI to these principles. The Gradient Institute, in collaboration with the National Artificial Intelligence Centre and CSIRO, has developed a practical set of guidelines for **Implementing Australia's AI Ethics Principles** [199]. These guidelines are designed to raise awareness around Australia's AI Ethics Principles among senior leaders, system owners and AI developers. They also provide practical resources for ensuring adherence to these principles. The Australian Government has released a **Voluntary AI Safety Standard** [198], which specifies 10 voluntary guardrails for Australian organisations to ensure safe and responsible AI use. This standard aligns with emerging international standards and practices around safe and responsible AI use. Federal, state and territory governments in Australia have jointly established a **National Framework for the Assurance of Artificial Intelligence in Government** [200]. This framework is designed to support government agencies in applying Australia's AI Ethics Principles when designing, developing and implementing AI safely and responsibly.
Encourage and incentivise open access to climate-related datasets, models and tools developed across research, private, public and not-for-profit organisations	**Climate TRACE**, mentioned in *Other cross-domain applications*, is a source of timely and granular global emissions information and an example of an open and accessible climate-related data asset [165]. Building on initial funding from Google in 2019 to monitor power plant emissions, this platform has been expanded with other collaborators and partners to now cover up to 75% of global asset-level emissions. All data and methodology documentation housed on this platform are free and publicly available to maximise the extent to which these resources can be used to drive climate action. To help accelerate progress towards addressing gaps in quality and accessible data needed in AI-for-climate applications, Climate Change AI has established the **CCAI Dataset Wishlist** [201]. This platform allows stakeholders across sectors to identify and classify critical data gaps that are limiting their ability to use AI in response to a climate mitigation or adaptation challenge. Users can categorise the current state of available data (e.g. private data that need to be released or public data that need structure).



Participants from the design sprint at CSIRO's AI for Climate Symposium held on 16–17 October 2024 at the State Library of Victoria, Australia

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Note: For brevity, minimal reference details are provided. However, most reports can be readily accessed by copying the information provided into a search engine. All online publications were accessible as of 21 March 2025.

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