INTERNATIONAL CENTRE FOR AI, ENERGY AND CLIMATE

PROPOSAL TEAM

- Peter Clutton-Brock, Founder & CEO, Radiance International & Senior Associate at E3G
- Sims Witherspoon, Programme Manger, DeepMind
- Paul Massara, ex CEO RWE npower, Electron
- Jack Kelly, Founder of Open Climate Fix, ex-DeepMind engineer
- Aidan O'Sullivan, Head of AI and Energy Group, UCL
- Sherif Elsayad-Ali, Director, AI for Climate, Element AI
- George Hackford, Lead Impact Strategist, Energy, Power & Resources, SparkBeyond
- Eleanor O'Keefe, Editorial Director, CogX
- Rafi Cohen, Consultant, BCG
- Ying Teng, Policy Advisor, Radiance

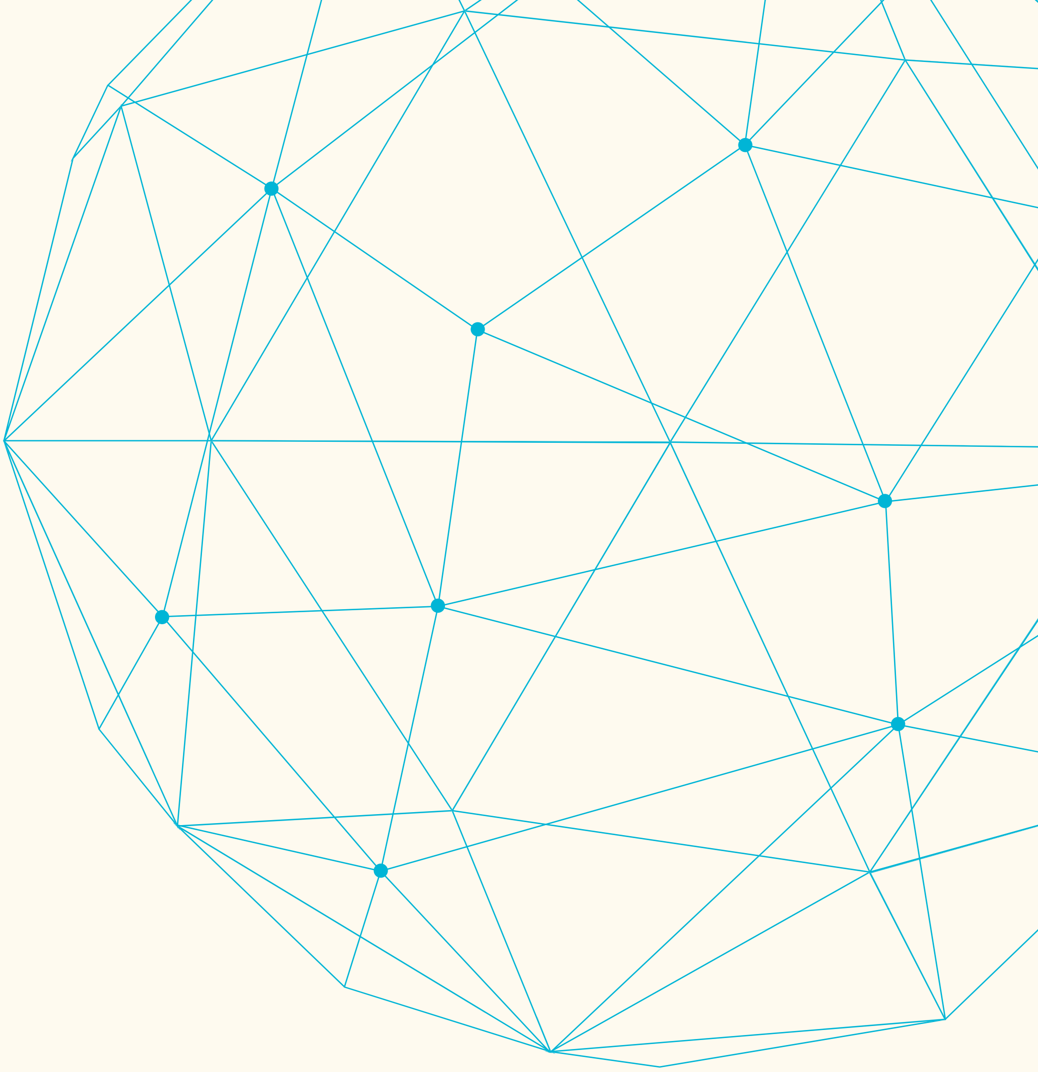


TABLE OF **CONTENTS**

EXECUTIVE **SUMMARY**

Over the last ten years there have been a series of advances in data science and Artificial Intelligence technologies. These advances offer opportunities to rapidly reduce emissions across a wide array of climate change challenges.

Despite the commitments made in the Paris Agreement there remains a gap between the emission reductions pledged, and those needed to achieve the 1.5°C objective. Countries and companies need to urgently look for innovative ways to deliver the rapid emission reductions required to address this gap.

Energy systems are transitioning from being centralised and fossil fuel dominated, to increasingly decentralised and renewables-dominated with new demands from transport and heat. As they do so there will be an increasing need to optimise and manage the many distributed and complex constituents of the energy system including renewable generation, electric vehicles (EVs), battery storage and demand-side response (DSR). AI will not only be a useful tool but will become essential as we manage this much more complex system and the data that it provides, whether it be in relation to solar and wind forecasting, dispatch optimisation, battery management or analysing smart meter data.

Applying AI to climate challenges has the potential to reduce emissions by up to 4% by 2030 against a business-as-usual baseline with a concurrent uplift of up to 4.4% to global GDP[2] as a result of efficiency improvments.

There are opportunities to apply AI to energy and climate challenges that are already being explored. Using AI, Google's DeepMind has reduced the energy consumption needed to cool Google's data centres by 30% and has increased the value of Google's wind farms by 20%.

There are opportunities to apply AI to energy and climate challenges that are already being explored.

Despite the potential opportunity AI offers, a more systemic use of AI for climate is being held back by existing data sharing models, market incentive structures and business models. The heavily regulated nature of sectors key to the transition such as energy and transport creates a series of challenges in applying new technologies, and there is a need to ensure market incentive structures support the application of machine learning and AI. Addressing these barriers could unlock the potential for AI to improve the efficiency of energy systems worldwide and help address wider climate challenges.

To address these barriers internationally, there is a strong case for coordinated muti-government support for the International Centre for AI and Climate Change to advise governments on best practice regulation and to facilitate the application of AI technology to climate challenges.

[1] https://www.unenvironment.org/resources/emissions-gap-report-2018

[2] https://www.pwc.co.uk/sustainability-climate-change/assets/pdf/how-ai-can-enable-a-sustainable-future.pdf

This paper seeks to address the following questions:

1. What is the nature and scale of the opportunity that AI represents in helping to achieve net zero emissions?

2. What barriers exist that are holding back faster adoption of AI to the energy and climate change sector?

3. What is needed to address the barriers identified?

4. What work is already being done in this space, and how can we accelerate adoption?

1. THE OPPORTUNITY

How can AI help address climate change?

In general terms AI can offer the most extensive opportunities in addressing discrete problem areas with clear system boundaries, where it is possible to define unambiguous objectives, and where there are large datasets. In these scenarios AI has the capability to identify complex patterns and advise on how best to optimise system inputs in order to best achieve defined objectives. There are a range of climate change mitigation and adaptation challenges that fit this description.

A recent study developed by Microsoft and PwC estimated that globally AI can help deliver a reduction in GHG emissions of up to 4% by 2030 compared to business as usual, with a concurrent uplift of 4.4% to global GDP[6]. Such estimates are likely to become more accurate over time as the potential of AI becomes more apparent.

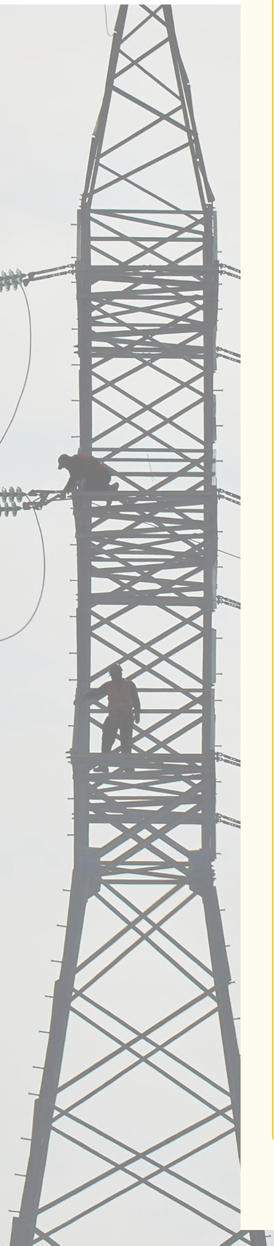
In 2019 Rolnick et al[7] published a paper assessing the opportunities for applying machine learning to climate related challenges. This section seeks to summarise some of the opportunities; however, it should be noted that such opportunities are likely to expand as new data becomes available and new technologies develop.

AI can help deliver GHG emission reductions of up to 4% by 2030.

[3] https://emerj.com/ai-sector-overviews/machine-learning-medical-diagnostics-4-current-applications/
[4] https://www.electronicdesign.com/test-measurement/how-ai-will-help-pave-way-autonomous-driving
[5] https://www.transperfect.com/blog/the-year-of-AI-translation

Energy systems

Energy systems are transitioning from being centralised and fossil fuel dominated, to increasingly decentralised and renewables-dominated with new demands from transport and heat. As they do so there will be an increasing need to optimise and manage the many distributed and complex constituents of the energy system including variable renewable generation, electric vehicle charging, battery storage and demand-side-response. AI will not only be a useful tool in optimising and managing future electricity systems but will become essential in managing the increased complexity, whether it be in relation to solar and wind forecasting, dispatch optimisation, battery management or analysing smart meter data.



Dispatch and scheduling:

One of the most important roles AI could play in energy systems is to optimise grid dispatch. Grid dispatch refers to the process whereby system operators determine how much power controllable generators should produce over a range of timescales. The process is already challenging but will become even more complex as electricity systems include more variable generation, storage, and flexible demand, since operators will need to manage even more system components while simultaneously optimising scheduling more rapidly to respond to second-by-second variations in electricity production. Data science and AI can help improve the optimisation of current grid dispatch processes. In addition, AI will be needed to help develop and optimise control systems for further layers of grid balancing at the distribution network level, and at the individual substation level, which will be needed to allow for greater proportions of variable generation.

Forecasting supply and demand:

A key aspect of optimising dispatch will be the ability to improve forecasts of renewable electricity generation and forecasts of electricity demand. The more uncertainty grid operators have in either electricity supply or demand forecasts, the more back-up power, known as spinning reserve, is needed. Spinning reserve is provided by fossil fuel generation (mostly gas) and comes with associated emissions and costs. AI coupled with improving data collection have the potential to improve short-term renewable energy generation forecasts and demand forecasts allowing for reductions in spinning reserve, and reductions in the loss of expensive excess renewable energy power. AI could therefore help keep electricity costs under control as renewable penetration increases.

Flexibility markets:

To date demand side response aggregators have focussed on aggregating flexible demand commitments from large companies, due to the cost and complexity of analysing the potential flexibility that could be offered by smaller participants. AI has the potential to allow such aggregators to act as market places for thousands of smaller players, including electric car batteries, and rooftop solar, and so help to flatten demand peaks.

Asset optimisation:

Beyond grid optimisation, there is widespread potential for AI to be used to optimise the efficiency of individual assets within the energy system. This could come in the form of optimising renewable energy generation assets or battery assets. Such optimisation is possible both in terms of the operation of existing hardware, but also has the potential optimise the design of new hardware solutions.

Asset location:

Data science and AI can help optimise the location of energy system assets, ranging from identifying optimal locations for solar and wind assets based on solar irradiance and wind speed data, to identifying locations for pumped storage assets based on improved satellite data and AI.

Improving energy access:

Many people living in developing countries do not have access to grid electricity but often rely on wood-burning, diesel generators or kerosene stoves. Supporting access to modern, clean energy sources represents an important development pathway to millions of people. This transition will rely heavily on on-the-ground assessments of needs and working with communities. However, data science and AI can help inform this work by helping to identify optimal locations for microgrids. Microgrids themselves are more challenging to balance than larger grids so connecting microgrids to improved weather forecasting and balancing systems could improve quality of service.

Industry and buildings

Industrial processes are often energy intensive and as a result are one of the leading contributors to global GHG emissions. However, they are often some of the most challenging sectors to decarbonise.

Optimise existing industrial processes:

Data science and AI can help optimise the energy efficiency of industrial processes, by for example optimising the use of energy inputs, increase the efficiency of heating and cooling systems, predict machine breakdowns, and improve production quality. However, due to the rebound effect, where increased efficiency can lead to increased production, such improvements do not necessarily lead to emission reductions on their own and need to go hand-in-hand with policies designed to limit emissions.

Support the development of new industrial processes:

Where large datasets exist for existing industrial processes, it will be possible to use data science and AI to optimise the design of new processes. This will be particularly important for some industries where there may be a need to shift to a completely new industrial process to reduce emissions.

Buildings:

Buildings are responsible for a quarter of global energy-related emissions; however, a combination of simple physical fixes and cutting-edge data science and AI have the potential to reduce emissions for existing buildings by up to 90%. Whether for domestic or commercial buildings, there are opportunities for AI to be used to optimise heating and cooling to ensure energy is not being wasted. AI can help optimise energy use based on combined data on weather and building use patterns.

Flexibility markets:

As the proportion of variable renewable energy is brought onto electricity grids, grid systems are developing flexibility markets to get help from energy users in matching energy demand to variable energy supply. Industrial processes and buildings have an important role to play in these markets and having the ability to amend energy use according to when energy supply is high or low could be financially attractive. Adopting AI to help optimise and automate such energy adjustments will be important in maximising the potential gains available and hence support a lower carbon grid.

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Transport

The transport sector accounts for about a quarter of global emissions, with passenger and freight transportation each responsible for about half of transport GHG emissions. The sector has seen limited reduction in emissions relative to the electricity sector. Data science and AI can help reduce transport emissions in a range of ways.

Informing transport decision making to help reduce demand:

Many areas of transport lack good data, and decision-makers often design policy and infrastructure with limited or poor-quality information. In recent years, new types of sensors have become available, and data science and AI can turn this raw data into useful information. Traditional ground-based traffic counters such as inductive loop detectors or pneumatic tubes are being replaced or augmented with video systems which can use computer vision to monitor traffic. Further application of data science can help determine patterns in traffic to support management decisions. Data science can be especially useful for interpreting information from new data sources, eg, understand the behaviour of public transport users from smart card data.

Freight and delivery optimisation:

Freight consolidation, through the bundling of shipments, has the potential to drastically reduce the number of shipping miles, and therefore the GHG emissions. There is potential for optimisation throughout logistics chains from shipping, rail-freight and long-distance trucking to smaller trucks and last-mile delivery solutions. Data science and AI offer opportunities to optimise freight and delivery decision making to minimise the number and distance of trips needed. In addition to optimising freight and delivery on the basis of existing infrastructure, data science and AI can help inform decision making regarding future infrastructure decisions to, for example, optimise the locations of supply depots and logistics hubs, to maximise efficiency and reduce journey distances.

Vehicle design and autonomy:

Data science and AI are becoming increasingly important in supporting the optimisation of vehicle design, from ML-based surrogate modelling for optimising aerodynamics, to engine design optimisation. Most notably, AI is a critical part of designing autonomous vehicles, although it is uncertain whether autonomous cars are likely to result in lower or higher emissions, or indeed whether they will be widely rolled out any time soon.

Optimising for EVs:

Data science and AI are vital tools for a range of different challenges related to EVs. AI techniques can improve battery energy management, battery design, charging scheduling, and vehicle-to-grid interaction. As the percentage of EVs on the roads increases data science and AI will be critical in helping the system operator and distribution networks to predict EV-related demand and potentially supply, inform decisions regarding charging infrastructure.

New fuels:

Aviation and ocean shipping require high energy density fuels and so are less conducive to electrification. Electrofuels, biofuels and hydrogen could offer potential alternatives. Data science and AI techniques could offer new opportunities for improvement at various stages of research and development of these new fuels.

Bike and scooter sharing:

Bike and electric scooter sharing services can offer low-carbon options for getting around cities that can integrate well with public transport. Data science and AI can help identify usage patterns to optimise bike stations and address the problem many bike-sharing platforms have of uneven demand for some routes resulting in an uneven distribution of bikes. Data science can help forecast demand and inform bike pricing to help create a monetary incentive for users to rebalance bike locations.

By combining satellite imagery, supply chain data, and financial accounts it may be possible significantly improve tracking of deforestation through corporate supply chains.

Forests and agriculture

Combating deforestation:

Whilst robust policy measures must be the focus of efforts to combat deforestation, data science and AI can support policy makers. AI is starting to be used to provide real-time identification of illegal logging from either acoustic monitoring of forests or satellite data. By combining satellite imagery, supply chain data, and financial accounts it may be possible to identify patterns using data science that allow for significantly improved tracking of deforestation through corporate supply chains.

Forest carbon accounting:

Improvements in the resolution of satellite imagery coupled with data science and machine learning now allow for forest carbon to be estimated from satellite imagery at significantly improved accuracy levels. Increasing use of LiDAR will allow for better carbon estimates

Afforestation and forest restoration:

Large scale tree planting will be a key part of achieving net zero, however afforestation projects need to be sited in appropriate locations, to ensure successful tree growth and avoid competition with other land uses. Combining satellite imagery with other datasets, such as soil-type data, land-ownership data, flooding data, rainfall data and applying data science and AI, can help identify optimal planting locations.

Forest Fires:

Large scale forest fires contribute to large quantities of CO_2 entering the atmosphere. They often result from a combination of a build-up of dry biomass and are exacerbated by high temperatures and dry conditions. To avoid very large forest fires, many countries support managed burning on a small scale to avoid large build ups of dry biomass. A combination of satellite imagery, weather system modelling and data science and AI will allow for improved forecasting of areas at risk of forest fire, help determine how fires might spread, inform risk management responses.

Agriculture:

Precision agriculture, using machine learning and data science, will allow for individual plant-level assessments of phenotype and fitness to help optimise farm inputs, and is already receiving significant support and private investment. Whilst these approaches offer significant opportunities to increase growing efficiency, it is uncertain if they will reduce GHG emissions. There are also opportunities however, to focus precision agriculture techniques on optimising regenerative agriculture, a method that seeks to improve soil health, a co-benefit of which is increased soil absorption of CO_2.

Adaptation, Climate Science & Emissions monitoring

Food security:

Food insecurity due to changing climatic conditions represents one of the most acute areas of climate risk, in particular for developing countries. Linking a range of datasets and applying data science can significantly improve food security risk assessments and help inform response measures. Combining improved climate forecasting with high resolution satellite data that can identify crop types, with data science and ML techniques, can help improve spatially localized crop yield assessments, and give both long term forecasting and short-term warning of yield failure. Additional data from social media can also be deployed to uncover early warning signals about crop failure risk. Beyond risk analysis, data science and AI can improve the resilience of food supply chains by identifying supply chain weaknesses and inefficiencies.

Forecasting and tracking extreme events:

New datasets will allow for data science and AI to help improve predictions of climate-related disasters such as floods and hurricanes. For example, improving the prediction accuracy of whether and where hurricanes will make landfall would significantly support response and disaster relief efforts.

Climate Science:

Predicting how the climate will change is a key factor in making policy and investment decisions regarding adaptation and climate risk mitigation. There are opportunities for data science and AI to improve climate science to significantly improve climate predictions. The combination of improved and more affordable satellite data with data science and AI will allow for more detailed and more computationally efficient forecasting. However, there are also significant data gaps, specifically when it comes to regular monitoring of climate tipping point phenomena, such as methane release from the arctic permafrost. Machine learning models are likely to be computationally cheaper and more accurate than other models where there is plentiful data or existing models are too computationally expensive to use regularly. There are particular opportunities to reduce uncertainty in the modelling of clouds, ice-sheet dynamics and sea level rise.

Emissions monitoring:

There is significant uncertainty associated with the GHG emissions in some areas. The application of data science and AI with improving satellite data is offering new opportunities to monitor emissions at a factory or power station level. Such approaches have the potential to support international emissions monitoring efforts.

The application of data science and AI with improving satellite data is offering new opportunities to monitor emissions at a factory or power station level.

Table 1: Climate change solution domains, corresponding to sections of this paper, matched with selected areas of ML that are relevant to each.

	Casual Inference	Computer Vision	Interpretable Models	NLP	RL & Control	Time-Series Analysis	Transfer Learning	Uncertainty Qualification	Unsupervised Learning
1 Electricity Systems									
Enabling low-carbon electricity		✓	✓		✓	✓		✓	✓
Reducing current-system impacts		✓				✓		✓	✓
Ensuring global impact		✓					✓		✓
2 Transportation									
Reducing transport activity		✓				✓		✓	✓
Improving vehicle efficiency		✓			✓				
Alternative fuels & electrification					✓				✓
Modal shift	✓	✓				✓		✓	
3 Buildings and cities									
Optimizing buildings	✓				✓	✓	✓		
Urban planning		✓				✓	✓		✓
The future of cities				✓			✓	✓	✓
4 Industry									
Optimizing supply chains		✓			✓	✓			
Improving materials									✓
Production & energy		✓	✓		✓				
5 Farms & forests									
Remote sensing of emissions		✓							
Precision agriculture		✓			✓	✓			
Monitoring peatlands		✓							
Managing forests		✓			✓	✓			
6 Carbon dioxide removal									
Direct air capture									✓
Sequestering CO_2		✓						✓	✓
7 Climate prediction									
Uniting data, ML & climate science		✓	✓			✓		✓	
Forecasting extreme events		✓	✓			✓		✓	

Source: Rolnick et al; (2019), Tackling Climate Change with Machine Learning

2. CHALLENGES

Despite the clear benefit that data science and AI can offer to energy and climate change challenges there remains a significant risk that the application of AI over the coming years will fall short of what is needed to support the transition to a zero carbon economy at the required pace. The combination of a number barriers is constraining application of AI in a range of instances. This section describes the different types of barriers that exist in this space.

1. DATA

Machine learning algorithms require large amounts of good quality data, often working across multiple datasets requiring common formats and standards. The current processes for collecting, storing, cleaning, sharing and standardising data need significant improvement.

70-80% of any machine learning project is spent on cleaning and labelling data

Data discovery and access:

The starting point for many data science projects involves an extended process to ascertain what datasets are available, from where, whether they are publically available and if so on what license. This process is time consuming, inefficient and creates barriers to entry in each sector.

Datasets are often held privately which limits the potential for achieving efficiencies by making it hard to combine or link datasets from different private actors. There are limited mechanisms for data sharing or purchasing across the sectors relevant to climate change. There is currently no market for energy and climate change data and as such there is no mechanism for addressing the illiquidity of data in an economic way.

Data collection:

- Across all sectors identified data is often unavailable because data collection and availability is not being incentivised by the market. Data on everything from energy system topology (where grid wires and assets are), to high resolution forest logging data are needed to address some of the challenges in the sectors identified.

Data quality and standards:

- There are substantial costs associated in cleaning and labelling datasets to allow for them to be used by machine learning algorithms. Approximately 70-80% of time spent on machine learning projects is spent on cleaning and labelling data. The market inefficiencies caused by a lack of applied data standards results in substantial inefficiencies.

Data monopolies

- In any sector there is a risk of some companies building up a closed monopoly of data in that sector, creating barriers to entry and so reducing competition and innovation.

POLICY AND MARKET STRUCTURES: I

The market structures and incentive structures in the sectors most relevant to climate change, such as energy, transport, land-use are often defined in legislation and regulation rather than by the market itself. These legislative frameworks and market structures were designed in an analogue era and have yet to be adapted for the digital age, let alone AI.

Market structure:

- Energy and transport are examples of sectors where systems are often managed by either heavily regulated or state-owned monopoly companies. In the energy sector these include companies that manage transmission & distribution networks, system operation, interconnector companies and others. In the transport sector transport network operators are often either publicly run or involve monopoly contracts. These monopoly companies have their incentives set by regulation or legislation. Further, the ability for startups and tech companies to support these companies is often limited as the business model innovation that might allow for the sharing of value created by innovations may be restricted by regulatory requirements.

Cooperation incentives:

- AI offers opportunities to optimise systems, however such optimisation often requires market participants to cooperate, and the incentives for this are often ambiguous. For example in the electricity sector there would be considerable benefits in developing a system-wide digital twin on which it would be possible to run machine learning algorithms, however in most electricity systems there are limitied incentives for system operators to collaborate to effectively deliver such a model.

Data sharing:

- Stipulations regarding data sharing in regulated sectors such as energy and transport are often set out in regulation. These regulations are not always designed in a way that incentivises data sharing and access, even where there are no security, privacy or commercial sensitivity issues.

Market structures:

- In some regulated markets the types of organisation, and the requirements for these organisations are set out in legislation or regulation. For example, in the UK electricity sector the 1989 Electricity Act defines electricity 'suppliers' and sets out a series of requirements for them. This has a negative impact on innovation as it is not possible for small, innovative companies to offer part of the role of the 'supplier', which, for example, some demand-side response aggregators may want to deliver.

FUNDING: There is a higher risk in funding startups of AI-for-climate startups than in other sectors as due to the embedded position of monopoly incumbents.

Finance Risk:

- Because the route to market for AI startups in the energy and transport sectors is more complicated than other sectors due to the incumbent market structures, despite seeing huge opportunity for value creation early stage investors are wary about investing as startup success or failure may rest on a small number of high-value contracts.
- Whilst there has been increasing interest in the application of AI in the agriculture sector, this has focussed on optimising existing farming systems. There may be some climate and environmental benefits from this, but there has been limited focus on the application of AI for helping farmers shift to new, lower emission production methods. This is largely due to the fact that incentives for farmers are determined by subsidy schemes, which to data haven't prioritised emission reduction. Whilst new subsidy schemes may increasingly support emission reductions, there will still be a need to support innovation to help de-risk new, lower emission production methods.

Investor opportunity costs:

- Other sectors offer higher returns and easier market access for AI. Investors have focussed on sectors where the potential returns are highest. The returns in the energy and climate space are not perceived to be as high as in fintech, adtech and healthtech. As a result there has been a less interest in climatetech. There is a competitive market for data science talent. The higher available returns in fintech, automotive, adtech and healthtech have resulted in a reduced availability of data science capacity and expertise in the energy and climate space.

Public services:

- In some areas there are no private sector incentives for investment and as a result a requirement for public funding. There is no private sector incentive to develop AI applications to reduce deforestation, support climate resilience and adaptation, and to improve climate science. The application of AI in these sectors will require public funding. Whilst there have been some instances of the application of data science and AI in these areas it has been sporadic and nascent. A well funded programme to apply AI to these sectors has the potential to crowd in AI talent and dramatically accelerate progress in each field.

KNOWLEDGE SILOS: Successfully applying data science and AI often requires combining knowledge, data and skills held by sector incumbents, tech companies, policy and academia. Ensuring the combination of data from these various silos is critical to successful project delivery.

- Applying data science and AI, and overcoming the various challenges in doing so, requires an in-depth understanding of a series of areas of knowledge that are currently often held in silos, currently with limited mixing.
- In some of the more straightforward contexts in which it is possible to apply machine learning there is a need for people who have strong technical data science skills coupled with a strong understanding of the sector in which you they looking to deploy a particular solution.
- The sectors that are most relevant to climate change often have additional challenges, where it is also important to understand the policy frameworks that shape the sector a project is operating in.
- To guide academic progress and the underlying development of new computer science techniques, there is also a need for close coordination with the academic community.
- Combining the skills and knowledge of the incumbent players in each sector, together with the tech sector, the academic sector and policy makers has the potential to rapidly advance adoption of AI in key sectors.

RESEARCH & SKILLS: Improved research coordination has the potential to accelerate the academic support for AI-for-climate applications.

Research Coordination:

- There is a wide range of academic work that is relevant to the application of data science and AI for climate-related challenges. However this research could benefit from improved coordination to ascertain more precisely what research has already been conducted, where the important gaps are that need to be filled, and to build coalitions of research bodies to help address them.

Data science skills:

- One of the most significant constraints to faster adoption of AI to climate-related challenges is the limited talent pool of data scientists who have both strong data-science skills and a deep understanding of a particular sector relevant to climate change. Improving the talent pipeline coming through universities will be a key part in addressing this. Developing specific skill areas that are relevant to deployment of solutions will need to be conducted in close coordination with the private sector to ensure the skills being developed are needed.

Digital literacy:

- Whilst improving data science capacity is clearly important to delivering data science projects, equally it is important to build the digital literacy throughout the sectors relevant to climate change to ensure that there is an understanding of the potential for data science and AI.

3. INTERVENTIONS NEEDED TO **ADDRESS BARRIERS**

In seeking to address the market failures identified, five key intervention pillars are likely to be required:

Pillar 1:

POLICY DESIGN: to address some of the policy barriers, a locus of expertise is needed to advise government on how to upgrade energy and climate-related policy to be AI-friendly and to align the incentives of market incumbents to support its adoption. Specific areas of advice would include:

- Energy and climate data collection, access and standards
- Incentives for market incumbents to apply AI
- Market integration and system flexibility
- Project specific regulations
- Ethical / responsible application of AI in energy / climate sector

Pillar 2:

DATA AND TOOLS LAB: to facilitate the application of AI to key energy and climate challenges, there is a need for a group with technical data science expertise to develop processes and tools that make it easier for the wider AI community to engage in the sector. Interventions could usefully include:

- Hosting an international energy and climate data platform / index / market
- Coordinate the development of public interest models on which new applications could be built such as digital twins
- Hosting machine learning competitions and ongoing collaborations
- Incubating new research initiatives and/or start-ups

Pillar 3:

ACCELERATOR: The under-investment in R&D projects in this area, can addressed with bespoke innovation funding to support initiatives and crowd in private investment. Interventions will include:

- Proof of concept challenge grant-funding
- Semi-commercial seed equity in collaboration with VCs
- Developing collaborations with start-up accelerators and incubators
- Incubator space for early stage projects
- Match-making for founders

Pillar 4:

RESEARCH & SKILLS: This pillar recognises the need for improved academic research coordination, and a coordinated approach to improve the talent pipeline for AI-for-climate.

- Focused academic workshops, conferences to support knowledge sharing and research coordination.
- Building the talent pipeline for the sector through multi-university doctoral training centres to pool collective UK expertise to support PhD students
- Applied training to support incumbent industries in developing the capabilities needed to adopt AI

Pillar 5:

MARKET FACILITATION: this pillar involves building coalitions, conferences, workshops, tech delegations to connect industry with tech and academia.

- Coalition building to deliver a series of flagship projects focussed on key opportunities
- Supporting knowledge sharing on the opportunities for AI to support decarbonisation in a range of energy system contexts, via industry events, country engagement, tech delegations, MOOCs, jobs/projects board and engagement at international fora.

5. CONCLUSION

The international community have ten years to halve global emissions. AI, whilst not a silver bullet, is a powerful tool we can deploy in helping to rapidly reduce emissions.

There is an important role for the International Centre for AI, Energy & Climate to deliver across a wide spectrum of disciplines, from policy advice, to AI technical facilitation, to data discovery and standards. Beyond this, the creation of an international ecosystem of start-ups, universities, tech companies, energy companies and policy makers will be critical in overcoming the identified barriers and supporting investment and job creation in this sector.

The Centre's success will hinge on its ability to build powerful partnerships, collaborations and coalitions of organisations with a strong interest in deploying data science and AI to help accelerate action on climate change.

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