

Artificial Intelligence & Climate Change: Supplementary Impact Report

AI Solutions for a 1.5°C Future

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This document will provide an overview of the challenges presented by the climate crisis and the scope for AI-based solutions to those challenges. Specifically, it will provide several examples of ways in which AI has already been applied in the field, as well as areas where it promises to have useful application. This document is a supplement to the Challenge Statement for the AI and Climate Change Impact Weekend 2020. It is intended to provide students with essential preliminary topic information and context, as well as serve as inspiration for ways in which AI could be successfully employed in tackling climate change.

The first section of this paper outlines the problem of climate change and the challenges involved in climate action (§1). We then outline opportunities for AI application to climate solutions (§2). In particular we highlight examples of application within energy systems and climate engagement. Finally we address several further considerations that should be taken into account when designing AI-based climate solutions (§3).

1 Climate Change: An Urgent Problem

The primary cause of anthropogenic climate change is net emissions of “greenhouse gases” (GHGs). Excessive GHG emissions create a power imbalance in the atmosphere: more energy enters the Earth’s system than is emitted, resulting in global heating. The rapidly warming atmosphere behaves quite differently, exhibiting significant changes in weather patterns — we collectively refer to this as ‘climate change’.

As of 2018, human activities have already caused approximately 1°C temperature increase above pre-industrial² levels [1]. At current warming rates, and assuming business as usual continues, it is estimated that warming will reach 1.5°C by 2030-2052 [1]. The consequences of even a 1°C rise have already been

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² ‘pre-industrial and industrial refer, somewhat arbitrarily, to the periods before and after 1750, respectively’, corresponding to the beginning of large-scale GHG emissions [71]

observed. We have witnessed increased frequency and severity of extreme weather events, rising sea levels and species extinction [2], as well as a rise in societal harms including increased displacement [3], deaths [4], damages and costs [5]. In addition, these physical changes are occurring at speeds unprecedented in Earth's history, and impacts on humanity are projected to continue increasing.

The IPCC 1.5°C report demonstrates the substantial benefits of keeping warming to 1.5°C compared to 2°C, including limiting irreversible damages [6]. To achieve the Paris goal of 1.5°C we must bring the planet's collective GHGs emissions down by at least 45% from 2010 levels by 2030 and down to net-zero emissions by 2050³ [1]. Reaching this goal will require rapid, far-reaching and unprecedented changes in all aspects of society [6].

In order to meet the challenges that climate change presents, we must focus on both mitigation and adaptation:

- *Mitigation* constitutes emissions reductions via radical changes in areas including, but not limited to land-use, agriculture, energy, industry, buildings, transportation and cities-design.
- *Adaptation* encompasses preparations for the environmental and societal degeneration that wasn't prevented with mitigation, and so involves climate modelling, risk prediction, and planning for resilience and disaster management.

Despite the wealth of scientific understanding, resources and high stakes, there has been little progress on climate change. There are four key properties of the physical climate system that interact with human psychology in such a way that action is made difficult — all show potential for novel ways to bridge gaps between human perceptions of climate change and reality and present opportunity for AI applications:

1. *Scale*: physical processes outside the anthropic scale are deeply unintuitive. For example, 2°C colder is a regular occurrence in daily experience, whereas global averages of just 5-6°C colder is an ice-age state [7]. Comparably extremes states are expected to result from a 4°C warmer world. It is difficult, or potentially impossible, to comprehend the impacts of climate change due to their extreme scale (e.g. populations impacted, mass extinction, damage to settlements) and length in time that these impacts will remain (e.g. changes lasting for thousands of years, if they aren't entirely irreversible). [8]
2. *Risk and uncertainty*: most consequences can only be predicted with associated uncertainties and risk⁴. Work in psychology about behaviour in relation to risk shows that, even when uncertainties are smaller, consequences are nearer (in space and time) and stakes smaller, most people do not

³ Note: In addition to limiting emissions to net-zero by 2050, many of these projections require further net negative emissions in the second half of the century.

⁴ "Risk", here, refers to the potential for adverse climatic effects on individuals, societies, non-human life, the environment, etc [72]. "Uncertainty", to a 'cognitive state of incomplete knowledge' resulting from a lack of, or inability to obtain, information [72].

appear to behave in a rational manner. Risk is often difficult to understand, manage, and make decisions in relation to. Further, the complex causal networks in the social and physical systems of climate change exacerbate this issue; extracting insights and understanding of relationships between action and consequence from the huge amounts of data can be challenging or impossible without technological innovation.

3. *Remote Consequences*: climate consequences are remote from their causes in both space and time. For example, significant and serious changes in extreme weather patterns develop subtly over decades, slower than human perception, often occurring in different locations to their causes (e.g. emissions source). Typically, people wait to experience the negative consequences of actions to motivate a change in behaviour. The later we act, the larger the atmospheric carbon stocks, and the more locked-in high-carbon infrastructure we have. There is additionally an empathy gap at play here; the most impacted people are disproportionately poorer and in the future, far removed from those most contributing to the issues, who are disproportionately richer and living now. In particular, we tend to discount or undervalue future generations, withholding them the same ethical considerations that we give to the living [9] [10] [11]. Can we, as decision makers (directly and as voters), imagine, or see representations of, what climate change will do on a human level, and can they use this to motivate their decision urgency?
4. *The Public Nature of GHGs*: CO₂ emissions are well mixed in the atmosphere and therefore public; it is total emissions volume that matters to the atmosphere, not the details of individual sources. This leads to the challenges associated with collective action, presenting global game theory scenarios of unprecedented scale and complexity [12] [13]. "I won't act if you won't" behaviours result from the idea that climate action will harm me now, at the benefit of helping others (or me) later; therefore if I act and you don't, simultaneously the goal won't be achieved and I will be worse off than you. Studies have repeatedly seen that such decisions will prioritise "me, now", and we see this played out at personal, corporate, national and geopolitical scales. In fact, despite limited media coverage, climate action does help "me, now". For example, switching from ICE vehicles to greener alternatives immediately and significantly improves local wellbeing and boosts local business [14]; insulating your house saves you money [15]; and reducing meat consumption has personal health benefits [16] [17] [18]. These results suggest that targeted education, campaigning and social marketing (areas that AI has had some success) focussing on this understanding may be useful to help lower emissions.

2 Opportunities for AI Application

Developments in ML and AI has fuelled major breakthroughs with far-reaching consequences in society. Driven both by rapid advances in high-throughput hardware, as well as an explosion of available and accessible data sources made possible by high-bandwidth internet connections and the sensor connectivity provided by the internet of things, the rising economic value of AI, predicted at as much as \$16 trillion by

2030 [19] has turned it into a powerful agent of change. AI not only has the ability to transform public perception, but also, for example, forms an important part of the UK's post-Brexit industrial strategy [20]. Global media activity surrounding prestigious breakthroughs, such as DeepMind's AlphaZero winning against Go-champion Lee Sedol in December 2017 [21], has certainly contributed to the rapid growth of the AI community and its popularity far beyond the gaming scene.

These developments coincide with an increasing urgency to address climate change. The pervasiveness of both climate change and AI means that they form a complex web of interdependencies, ranging from governance to technology. It is conceivable that one might not be successfully dealt with without the other.

The AI community is now turning its attention towards how their methods can help us tackle climate change [22] [23] [24] [25] [26] [27] [28]. In particular, the authors of "Tackling Climate Change with Machine Learning" [22] argue that ML 'can be a powerful tool in reducing greenhouse gas emissions and helping society adapt to a changing climate', in part because ML has the capacity to lead to 'massive efficiency gains' and to 'improve public services, help gather data for decision-making, and guide plans for future development' to name a few. Yet, despite this enthusiasm to apply AI to climate solutions, there remains a challenge in the form of a lack of interdisciplinary collaboration, which can leave AI practitioners unaware of how to best apply their methods to climate solution [22].

Below, we provide two examples of areas where AI has been and could be fruitfully applied to climate change — (i) energy systems; and (ii) climate engagement. Note: these examples are by no means exhaustive of the ways in which AI could be productively utilised in climate solutions. For a range of other areas please see Rolnick et. al [22].

2.1 Energy Systems

Radical transformations in energy systems will need to take place in order for us to limit warming to 1.5 °C. Fossil fuels are the main driver of climate change; they are also currently our main source of energy [29][30]. To reach net-zero emissions by 2050, we therefore need to rapidly reduce fossil fuel production, emissions, use and dependence. How might AI help with this task?

'Energy systems' refers to both: (1) energy production and supply; and (2) energy use and demand:

1. *Energy Production and Supply*: Energy production and supply entails energy source — be it fossil fuel or renewable — as well as distribution and grid supply. Emissions from this sector can be lowered in multiple ways. For example, renewables can be strengthened (improvements must be made in reliability, storage and intermittency caused by fluctuations in wind, water and solar patterns) enabling a faster transition to a greener energy grid with less fossil fuel reliance; fossil fuel emissions can be reduced and sequestered. AI and ML practices have started being applied to this sector [31]. Google's DeepMind, for example, has begun applying ML to improve wind generation and predict power output. Use of AI and ML in Google's own wind farms has already increased the value of their wind energy by 20% [32]. Key considerations in production and supply

include energy security (stability, reliability, etc), equity (equal access to energy, fair cost, etc), environmental impacts (the climate and environmental impacts of production and supply).

Note: not all implementation of AI within energy production is without contention. AI is being adopted by the fossil fuel industry, such as by Rockwell Automation and Schlumberger [33]; Microsoft and big tech companies, offering data storage and AI tools for such tasks as improved drilling location detection and faster refinery production [34]. AI employed in these efforts threaten to perpetuate 'carbon lock-in' (fossil fuel reliance and domination in energy production) [35]. However, AI can also help reduce dependence on fossil fuels. Carbon Tracker utilises AI to monitor coal plant emissions via satellite imagery, employing this data to help prevent against the development of new coal plants, track air pollution sources, encourage divestment from the financial sector, and assist in placing an accurate prices on emissions in carbon tax proposals [23].

2. *Energy Use and Demand:* Energy use and demand encompasses the ways in which energy is used, be it in households, cities, industry, transportation, etc. The energy demands of transport as well as buildings and cities present opportunity for significant climate gains via the introduction of AI methods [22].
 - a. Transport: Transport emissions account for approximately $\frac{1}{4}$ of global energy CO₂ emissions [6]. Transportation is often regarded as hard to decarbonize, due to vehicles' high-density fuel requirements and controversy over salient, intrusive transport policies [22]. ML and AI, however, offer promising developments in lowering transport emissions. ML can assist in understanding transportation data, such as traffic data; SVMs and neural networks, (ML methods) in particular have helped classify traffic patterns; ML optimised ride-share services can decrease the amount of vehicles usage as well as monitor and explain efficiency gains and savings emissions to consumers; AI and ML can also assist in optimising trade and shipping routes, helping to lower emissions of shipment transportation [22] [36]. These ML and AI developments can also assist planning and infrastructure, ultimately helping to reduce emissions. However, despite promising developments, we must be wary about potential negative and unintended consequences that may lead to inadvertent emissions increases. Take the Jevons paradox: a situation where increased efficiency nonetheless results in higher overall demand. For example, autonomous vehicles could cause people to drive far more, so that overall GHG emissions could increase even if each ride is more efficient [22].
 - b. Buildings/Cities: within the European Union, buildings account for 40% of energy consumption and 36% of the areas CO₂ emissions [37]. Building emissions can be reduced in multiple ways, including: increasing carbon efficiency (switching to renewables/low-carbon fuels/alternatives, etc); increasing energy efficiency (reducing waste, improving heating/cooling, switching to energy efficient appliances, etc); increasing system and infrastructure efficiency (better urban planning, introduction of passive energy houses,

heating/cooling, etc); and reducing service demand (via behaviour/lifestyle changes) [22] [37]. AI and ML will be extremely useful in lowering emissions in these domains. For example, ML can assist in tailoring the energy demands of individual buildings (building management) and implement solutions via “smart control systems”; ML can help us understand where and how energy is being used within a building; ML data analysis can inform policy regarding buildings (urban planning) and building design; smart buildings with “intelligent control systems” can help reduce energy emissions, control heating and cooling and interact with energy grids [22]. At the level of urban and city planning AI can be used to predict city-wide building energy usage [22]. In a recent case, ML used disclosed energy data from New York City residents to predict the energy usage of its 1.1 million buildings, analyse demand, and developed a ranking system for energy efficient buildings [22] [38] [39].

2.2 Climate Engagement⁵

Climate engagement is crucial for climate progress: individual action has the potential to reduce emissions by changing personal actions and institutional behaviors, as well as providing pressure and political capital for governance systems to act. This is especially true in democratic systems, which are conservative by design in order to filter out extreme policies or views, and therefore can struggle to handle the radical changes required. Thus, widespread engagement is key in the transition to a net-zero future and increasing attention is being given to how we can more effectively engage the public in this arena [40] [41].

Climate engagement has historically been quite limited in scope. Awareness was mainly held by climate and environmental experts, and early public awareness was built predominantly by news coverage of activism by groups such as Greenpeace. Such academic and radical communication is often not conducive to mainstream uptake and is often presented in a way that can threaten to marginalise certain audiences.

Alignment of values with the nature of an issue, and self-identification with a movement, are important for people to act, in whatever capacity they have agency. In particular, it is well known that values influence one’s disposition towards environmental issues [40]. This understanding highlights the importance of the context within which information is framed (intentionally or unintentionally) [40]. For example, consider the framing of cases for preserving nature: some frames prioritise the intrinsic value of the environment (the value nature has in and of itself) [42]; others highlight the instrumental value of nature (eg. our economic relationship with the environment and its resources [43], or the health benefits of protecting access to green spaces [44]). Different frames resonate more strongly with different sets of people. In light

⁵ This section is focused on the history of environmental engagement in Western cultures, particularly the anglosphere. Discourse and engagement in the countries most affected by the impacts of climate change seem not to have suffered such political polarisation or decoherency, perhaps in part because the realities of climate change and the need for action are so much more present, and there exist fewer conflicts between self-enhancing and altruistic values.

of this, two primary and complementary trends have emerged in values-based climate change campaigning [40]:

1. ‘to promote messages primarily oriented towards self-transcendent values (which are likely to resonate with the membership of environmental organizations, but may not have broader cultural transfer)’ — ie. to encourage people to act for the sake of others.
2. ‘to identify the values that target populations actually hold (whatever they are - even if they include values known to be incongruent with environmental engagement, [eg] materialism) and try to match campaign messages to those values (a strategy known as ‘social marketing’) [45] — ie to mobilise action on the basis of values that people already hold.

It is understood that ‘values are relatively stable across the adult lifespan’, therefore, over the short term it is important to widen pro-climate engagement by reaching new and often ‘hard-to-reach’ audiences [46]. Approaches typically segment audiences into different groups based upon values predisposing them to pro-climate sentiment, such that different narratives for embedding climate action messages can be tailored for them. Use of AI methods allow hyper-personal targeting of messaging based upon personal data, similar to the role that Cambridge Analytica played in recent political campaigns in the US with the election of Donald Trump [47], and the UK with the pro-Brexit leave campaign [48].

A less controversial example of the intersection between AI and social media is the use of natural language processing (NLP) techniques (including ‘sentiment analysis’) that were used to investigate advertising networks and social media discussions on ‘fake news’. Social platforms have long been used by climate denial groups, and techniques from social network analysis have revealed numerous structural relationships between different agents within the climate denialism space [50]. A recent project clearly demonstrates the links and vested interests between climate denial groups, fossil fuel companies, and both pro-Brexit and pro-Trump groups [51]. Similar tools and techniques might be employed to stimulate and monitor climate engagement. [52]

When developing AI-based climate solutions, it is important to take the possible ethical and social implications into serious consideration. This may include the ethics of methods such as such as the privacy of personal data, national-scale manipulation, and the impacts of the backlash against such methods [49]. Where do we draw the boundaries between climate engagement and climate manipulation? Evidently people don’t appreciate feeling that they are being influenced, or campaigned at (or against), and poorly judged attempts at such methods is likely to only fuel climate denial rhetoric. Also of interest is the counterintuitive possibility of framing climate action in terms of ‘values known to be incongruent with engagement on climate change’ [40], for example materialism.

Tension and disagreement in relation to climate action, whilst often framed as challenges to the science and input from experts [53], may in part originate from differences in underlying values. Climate change challenges common perceptions of what it takes to be a ‘good person’. Suddenly, actions that were once considered morally acceptable or neutral, such as a preference for a more convenient lifestyle (travel by

private car, plane, etc), have become morally problematic given their generation of emissions and harms. We are left with the choice between expressing a preference for personal freedom (autonomy to choose certain, albeit polluting, lifestyles) over fairness and respect for the freedoms of others (vulnerable people impacted by climate change). This may create decoherence of thought and identity and presents a challenge to communication and engagement. Thus, to avoid such discomfort, debate around value-based responses to climate change often uses denial of the science as a proxy. If ways can be found to facilitate healthy dialogue between people of various tacit beliefs, then we might go a long way to remedying the impasse on climate action in much of the anglosphere, and perhaps to resolve deeper issues of increasingly fragmentary societies, of which climate change is but one symptom.

How might AI methods be used to encourage and increase climate engagement? Opportunities for AI to support climate engagement involve a wider variety of resources and methods than social media, including analysis of more standard political polling [54] [55], prediction [56] [57] and attribution of climate related extreme weather events. Further, it could be used to help vulnerable people in informal settlements to adapt by identifying settlements from satellite data [58] [59] [60] and predicting and visualising the risks of climate change, as well as to monitor disasters remotely and in real time to aid relief efforts [61].

In attempting to reduce the psychological distance to climate impacts, and thus stimulate action without the need to wait for real negative consequences, recent attempts have been made to visualize climate impacts by training adversarial networks on historical disaster imagery and then generate images of places that have yet to experience those impacts [62] [63]. This area seems to promise more emotive engagement than earlier attempts at visualising the effects of (for example) sea level rise [64]. In making more local visualisations of climate impacts, careful consideration of the implications of such knowledge (especially if inaccurate projections are created) are needed. For example, the effect on housing prices and insurance of certain settlements may dramatically change, and lead to a buying race where the wealthiest people are able to purchase the safest regions, widening the inequality gap as disadvantaged people are increasingly pushed towards higher-risk areas. None of this knowledge is new, so negative impacts of AI here will primarily serve to exacerbate rather than cause these problematic dynamics. Nevertheless, AI allows for a dramatic upscaling of communicating this information, the visual impact of which will be stronger than preceding map-based data. On the other hand, information similar to this is already influencing insurance companies to not support new fossil infrastructure.

3 Further Considerations for AI Climate Solutions

Any AI-based solution to climate change would need to consider the wider implications and unintended consequences of using AI technology. Consequences such as poor solutions (eg an AI optimising a problem using an exploitative mechanism) are difficult to identify or understand. This is due to AI algorithms being an opaque black-box, ie they provide no explanations for their conclusions. We expand below:

One of the challenges of a globally connected industrial economy that leads to environmental damages is that, in many cases, it is difficult to be aware of the full scope of the consequences of one's actions. This might be because the impacts occur in a space that was excluded (accidentally or deliberately) from consideration as an externality (one has no data for these impacts), or because the causal relationship between your action and an impact might be complex enough to be invisible to you in the data (you have data but no insight). Optimising actions for a restricted set of parameters (profit, job security, etc) without consideration of these wider impacts can lead to consequences for others, including one's future self as well as future generations.

As an example, consider that the cost of agricultural business does not contain the full social and environmental costs of the industry: short term personal profit is optimised by excluding from their accounting the effects dumping waste into public systems [65]. In some cases the farmers pay for none of the damages (e.g. fertilisers, pesticides and effluent flowing into water supplies, antibiotic overuse driving up the costs to health care as antibiotic resistance builds up), and in some cases the farmers' future selves are also impacted (e.g. carbon emissions contributing to climate change [66], and soil abuse leading to topsoil eradication [67]). Consider also the example that economic models knowingly omit many of the worst climate impacts. They are either designed to operate within a narrow set of "normal" conditions, unable to handle step changes (eg. crossing the threshold where return time for extreme weather is shorter than affected communities' recovery time), or economists are unable to quantify the effects of damages and so leave them out entirely (eg mass climate migrations estimated with high uncertainty as up to a billion people by 2050 [68]).

Clearly the decision spaces for larger climate actions (eg national policies) are more complex still, and we may not fully understand all the dynamic feedbacks between the systems involved. Further, there is such significant time pressure to act that we may not have time to understand all these relationships academically before we would have needed to act. ML methods can provide improved decision making by assisting with both these challenges: ML algorithms can handle much larger domains, within which we may train algorithms to optimise for a wider set of parameters (including environmental ones). ML methods can demonstrate the "optimal" action to take, even if we don't understand precisely how it has decided that; this saves time required to comprehend and consciously design better practices and can lead to step-change benefits [32] [69].

In the above agricultural example, ML methods have been used to both reduce the impacts of current practices [74], as well as to transition practices towards environmentally positive practices such as regenerative farming [75]. This does however point to a difficulty with using such methods to aid decisions with such significant impacts on the world: if we do not yet explicitly understand the dynamics of a system, how much can we trust the suggestions that an algorithm generates?

We have seen in the past that optimisation of our methods for only a subset of all parameters that are important to us can lead to significant damages to excluded parameters, and similar risks of unintended consequences are associated with methods that an algorithm employs to reach the goal that we have given

it. We have repeatedly seen AIs generate wholly unexpected or exploitative mechanisms for maximising goals we explicitly set them. Safety research of such methods must be central to any sustainable and ethical business tool, especially given the huge consequences of applying insights to large scale social and environmental systems.

On a less dramatic note, clients are likely not to trust an algorithm just because you say it's working [76]. Significant waiting periods to validate whether an ML technique is working are either necessary or need viable workarounds without compromise to safety and validation of expected outcomes. Models that have some explanatory value in them are likely to fair better from both a safety and business perspective.

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