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Artificial intelligence for climate change adaptation

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Abstract

Although artificial intelligence (AI; inclusive of machine learning) is gaining traction supporting climate change projections and impacts, limited work has used AI to address climate change adaptation. We identify this gap and highlight the value of AI especially in supporting complex adaptation choices and implementation. We illustrate how AI can effectively leverage precise, real-time information in data-scarce settings. We focus on supervised learning, transfer learning, reinforcement learning, and multimodal learning to illustrate how innovative AI methods can enable better-informed choices, tailor adaptation measures to heterogenous groups and generate effective synergies and trade-offs.

This article is categorized under:

Application Areas > Government and Public Sector

KEYWORDS

AI, climate change adaptation, machine learning

1 | INTRODUCTION

Climate change adaptation is complex, as most solutions require balancing synergies and trade-offs that stem from interdependencies among social–ecological systems and sectors involved in adaptation. Adaptation as the process of adjustment to actual or expected climate change is typically local or sector specific (Field et al., 2014), and can overlook transmission of climate risks across sectors and regions (Challinor et al., 2018). Heterogeneous actors also adapt differently, and have varying capabilities and choices for adaptation measures. Furthermore, unprecedented climatic events and the time lag of climate change impact generate unknown consequences that are difficult to adapt to. The result is a complex, uncertain, and rapidly shifting matrix of adaptation challenges (Helmrich & Chester, 2020) which traditional climate change adaptation tools and strategies are not prepared to address. With increasing availability of new data streams and analytic capabilities, new opportunities emerge for artificial intelligence (AI) to help tackle these adaptation challenges. Though AI has been deployed in climate change science, this has largely been confined to climate change modeling, impact, and mitigation (Huntingford et al., 2019; Jones, 2017; Monteleoni et al., 2013; Rolnick et al., 2022) with less attention to adaptation. The value of AI increases for adaptation especially when it facilitates the analysis of aforementioned complexities such as synergies and trade-offs, heterogeneous actors, and unknown consequences of climate change impact. Furthermore, AI is advancing rapidly to handle the data-scarce problems that are pervasive in adaptation research. This article highlights these roles with key applications relevant to adaptation.

2 | OFF-THE-SHELF AND INNOVATIVE AI TECHNIQUES FOR ADAPTATION

AI is a set of techniques that simulate human cognition and reasoning using machines supported by higher computational power and large scale data sources. Machine learning, a subset of AI, is particularly good at detecting patterns and extrapolating information to predict future trends and support decision-making. Standard AI applications require data where major input features are clearly specified in advance and manually curated by domain experts to accelerate data processing and improve human performance on complex tasks. They can automatically prepare semantically meaningful labels and identify novel patterns from raw data. This efficiency of data processing is valuable given the urgent timelines for climate change adaptation (Orlove et al., 2020). It may be the difference between evaluating an adaptation question in 1 month versus 1 year by accelerating data annotations and applying supervised learning.

Off-the-shelf, standard AI methods and techniques, however, may not be suitable in instances where the data required are rare or take too long to materialize; or they require costly expert labeling to transform raw measurements into meaningful data. For example, online sellers often build AI models on surrogate outcomes such as customer page views or clicks, instead of purchases; while purchases may be the final outcome of interest, they are often rare and take longer to observe, making the data sparse. Similarly, climate change impact (the final outcome of interest) takes time to materialize, whereas the impact assessment needs to be done in advance to protect the population from potential harm. These data scarcity challenges worsen in poorer regions where data collection and analysis are difficult.

AI techniques increasingly demonstrate ways to solve limited data problems. Transfer learning leverage existing data to transfer knowledge or learned representations to other similar settings; semi-supervised learning extends partially annotated data to the entire dataset; and multimodal learning triangulates different data sources to delineate multidimensional adaptation processes. We explain briefly how these techniques are used in relevant domains, and list them with examples from related fields such as sustainability and health in Table 1.

TABLE 1 Relevant AI techniques

AI technique	Adaptation-relevant examples	Description
Supervised learning	Wildlife surveys for ecosystem change, infrastructure monitoring, predictive maintenance	Supervised learning can help provide meaningful annotation to raw data streams. It can turn camera trap images into species population estimates, and elevation maps with weather forecasts into flood risks.
Transfer learning	Urban planning, early warnings for floods, crop yield monitoring	Transfer learning repurposes existing models to new contexts, often by reusing parameter estimates across tasks. This supports annotation of raw data when prior labels are scarce. For example, it can be used to tailor a model from one urban center to another.
Reinforcement learning and multiarmed bandits	Relocation	Reinforcement learning and multi-armed bandits estimate the long-run values of possible actions to learn optimal policies in heterogeneous, evolving environments. For example, they can be used to identify personalized incentives for relocation.
Semi-supervised Learning	Crop yield monitoring	Semi-supervised learning leverages unlabeled data to supplement training on small, labeled datasets. Deep network classification or Gaussian process regression come with semi-supervised variants.
Multimodal learning	Multifaceted impact of extreme heat, drought and food supply, resilient infrastructure planning	Multimodal techniques make it possible to integrate information across multiple modalities, like images and text. For example, they can help combine social media feeds with environmental sensor data in disaster management.
Multiobjective techniques	Agricultural and water management, response to heat island effects	Multiobjective methods optimize several competing objectives simultaneously, either through introduction of constraints or by reweighting goals. They ensure that model-guided improvements in one aspect of a system do not result in unintended losses elsewhere.

Much of the initial model development for *transfer learning* is likely to take place in regions where extensive data are already available—for example, Google's flood risk system (Nevo et al., 2020) was trained on data from the Brahamputra basin, and Deines et al.'s (2021) model crop yield was trained on data from the U.S. Corn Belt. Once these base models are developed, they can be transferred across contexts. While models must be trained in data-rich locations, they can be applied anywhere as long as the requisite features (based on street or satellite imagery) are available. Transfer learning is especially useful in contexts with limited institutional record-keeping (e.g., no relevant government records) and helps generalize context-specific adaptation planning. Challenges of applying models to new yet related settings include differences in structures across data types and content (He et al., 2021). Ways to transfer trained models to new domains are still being actively developed (Koh et al., 2021; Yang et al., 2021). More sophisticated techniques use *reinforcement learning* and *multiarmed bandits* (Lai & Robbins, 1985) to dynamically allocate limited resources by exploiting validated options as well as exploring new ones efficiently. This allows the system to navigate the exploration–exploitation trade-off, gravitating toward treatments that past measurements suggest are optimal while continuing to explore treatments for which little data are available.

Semi-supervised learning is useful when a large volume of historical data is available, and only a subset is annotated. While it may be possible to train a supervised model using only the annotated subset, accuracy gains can be achieved by leveraging the database of unannotated examples. It is widely used in satellite image analysis for ecosystem monitoring, food security assessment, water management, and public health studies that are part of climate proofing and mainstreaming. *Multimodal learning* merges varying data sources, and necessitates interfaces that require specifically designed algorithms and transparent data processing in interoperable formats (Morency & Baltrušaitis, 2017). There are important advantages to combining data sources in a climate adaptation context. First, this allows new data sources to be integrated into existing systems. Second, multiple data sources can be complementary, as when social media messages can be linked with geolocated events (Chowdhury et al., 2013).

3 | EXAMPLES

We have identified critical areas of adaptation to which AI techniques can add value, and highlight several examples that reflect both the application of off-the-shelf/standard and innovative uses of AI for informing adaptation choices and implementation. The examples focus on knowing more about what we are adapting to; customizing adaptation to fit the specific needs of varying populations; and identifying synergies and trade-offs across sectors and localities.

3.1 | More information on the current status of adaptation

Providing more information in an accelerated manner is valuable to monitor climate change impact and protect people from climate risk leading to informed decisions about adaptation choices. For example, ecosystem adaptation often requires detailed, precise, and up-to-date information to monitor ecosystem health as climate changes. Climate change impacts wildlife populations either directly (e.g., through weather-related ecosystem changes) or indirectly (e.g., through climate-change-induced changes in human settlement patterns and agricultural land use). AI can distill more information by expanding the rate at which data can be collected and processed from camera traps, aerial imagery, and acoustic sensors routinely used to survey species populations (Simpson et al., 2014). Data from these sensors can be transformed by AI into usable quantitative information with image classification, object detection, and instance counting. With a labeled training set, the AI system can learn to annotate new records (Norouzzadeh et al., 2021), and reduce the human labor and time in the identification of wildlife populations. The data generated by these systems can also potentially provide more precise information as AI can allow the processing of data from more sensors in the same amount of time, allowing higher-resolution surveys.

Evidence of adaptation choices can be also found in text, such as laws, project descriptions and policy documents that natural language processing (NLP) can assist with. Topic modeling is often used to discover relevant themes with or without supervision from extensive text-based datasets including speeches given at climate negotiations (Lesnikowski et al., 2019) and automated classification of scientific abstracts and documents. They can generate evidence maps using geoparsers, and determine the status of observed climate change impact and the implementation of adaptation policies (Biesbroek et al., 2020; Callaghan et al., 2021).

3.2 | Tailored adaptation measures

There is considerable heterogeneity in terms of the ability of individuals and societies to adapt because of demographic, economic, institutional, and health factors that vary among individuals, households, communities, and nations. Adaptation will be more effective if policies are tailored to these differences. Machine learning techniques can be particularly well-suited to identify different effects of a policy on different groups. This enables decision-makers to customize policies to specific groups of individuals to maximize efficient and equitable allocation of resources rather than following a one-size-fits-all approach. Techniques such as reinforcement learning and multimodal data are already being applied in health and sustainability fields. For example, Greece maximized the efficiency of limited COVID-19 testing by targeting tourist profiles that were most likely to test positive for the disease (Bastani et al., 2021); and an integration of geo-located text data with satellite imagery estimated socioeconomic indicators and assessed the level of poverty in Sub-Saharan Africa (Sheehan et al., 2019).

Such techniques can be applied to the problem of relocation, tailoring adaptation measures to different population needs. Policymakers can provide different incentives to individuals to move to a safer location because of increasing climatic events such as wildfires and flooding. Some individuals might respond to information about the risks, whereas others might respond to monetary incentives. Because adaptation is relatively new, large-scale observational datasets from different policies are not available to support a non-experimental approach. Traditional experimental design would randomly offer different treatments to different individuals, collect outcomes data, and then fit a machine learning model to the results. Importantly, this model would identify *heterogeneous* treatment effects (see, e.g., Chernozhukov et al., 2018), informing subsequent decisions about what treatment to offer to each individual. Reinforcement learning can significantly boost the efficiency of traditional experimental design by dynamically allocating resources to the most promising treatment effects.

3.3 | Synergies and trade-offs

A significant absence of cross-sectoral or regional/global interactions in models of adaptation has been identified (Harrison et al., 2016). This absence leads to the lack of information on the ways these interactions alter the long-term impacts of climate change and the subsequent scope of adaptation (Holman et al., 2019). Knowledge on these interactions is, therefore, important to understanding synergies and trade-offs of adaptation decisions and investments. Mathematical programming and scalarization that readily utilize AI techniques, for example, can be applied to assess multiple, often competing goals. Multiobjective techniques fit this role by ensuring that performance is balanced across multiple groups. They go beyond traditional machine learning algorithms that focus on a single objective to typically test accuracy. Instead they seek choices that lead to satisfactory results across all objectives, rejecting solutions that may be optimal for one set of objectives and not for others.

In climate change adaptation, multiobjective techniques can be employed to model jointly water and food security or predict heat island effects that design and promote equitable interventions. A system trained to optimize regional crop yield alone may attempt to increase yield by increasing the amount of irrigation in a locality, potentially straining community water resources. A multiobjective approach instead guides the search for solutions that benefit both food and water security by ensuring that community water needs are not neglected. Similarly, in the absence of multi-objective techniques, a system to predict heat island effects may achieve high overall accuracy in an urban setting without guaranteeing accuracy of each neighborhood. This may lead to inequitable distribution of resources such as tree planting or placement of cooling centers to mitigate the heat effect. A solution with lower overall accuracy, but with more evenly distributed performance across neighborhoods, may be preferred to assess neighborhood specific heat island effects.

In this sense, multiobjective reasoning improves fairness and transparency of machine learning systems (Kusner et al., 2017; Liu et al., 2018). However, nontechnical challenges exist with the practical translation of these methods to the climate change adaptation context. Multiobjective optimization requires accurate measurement of all relevant metrics. While we have seen that AI can help transform raw data into more usable metrics, managing multiple metrics creates additional complexity. It will become important to build harmonized datasets across subpopulations, sectors, or localities and collect metrics that may previously have been only of secondary interest.

4 | CONCLUSION

Understanding what and how we are adapting to climate change, within the complex, dynamic system in which adaptation strategies are made, will be critical to the successful management of the climate crisis. Adaptation is not readily reducible to simplified factors that can be fed as an input to standard machine learning methods. It will be important to have AI augmented systems that generate algorithms to identify novel, subtle patterns in biophysical and social responses to climate change impacts; generate targeted behavioral intervention strategies; and devise "adaptive" multi-objective planning and implementation. We can also combine physics-based models with machine learning to ensure predictions that obey the laws of physics (Bolton & Zanna, 2019; Zhao et al., 2019).

Going forward, raising the interpretability of AI generated results and removing implicit bias are important areas to consider. To this end, AI-driven analyses must be able to provide explanations that characterize how each feature contributes to a given decision and incorporate feedback of the domain expert. These explanations enable domain experts to identify issues in the underlying model, including training set bias (Ribeiro et al., 2016) or dependence on non-causal relationships (Bastani et al., 2017; Lou et al., 2012). They allow the domain expert to incorporate feedback into the model to ensure it is making decisions in a meaningful way. Moreover, evaluating the performance of the algorithms across different demographics and locations can reduce the risk of overfitting and help remove unintended AI bias (Wu et al., 2021).

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CONFLICT OF INTEREST
The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS
So-Min Cheong: Conceptualization (equal); supervision (lead); writing – original draft (lead); writing – review and editing (lead). **Kris Sankaran:** Conceptualization (equal); writing – original draft (supporting); writing – review and editing (equal). **Hamsa Bastani:** Conceptualization (equal); writing – original draft (supporting); writing – review and editing (equal).

DATA AVAILABILITY STATEMENT
Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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