The Algorithmic Planet

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To ensure a sustainable future, we need to understand how Earth's climate has changed over time, how different factors have contributed to those changes, and how human action will impact the climate in the future. Developing this understanding involves a continual process of model refinement, calibration, validation, and evaluation against available observations. These tasks present the core opportunity and challenge of applying artificial intelligence to climate: AI is enabling a revolution in the ability to represent the functioning of complex systems, but while the sheer volume of data available to help us understand the earth system is growing at an unprecedented pace, this observational record is often ill-suited to provide robust benchmarks for AI-driven models. In this essay, we present examples that illustrate this tension, focusing on the AI tractability of different applications, with tractability linked to the availability of metrics and benchmarks to guide model development. We also describe a future when developments in AI will accelerate improvement in models used to support climate action and resilience, enabling us to tackle the currently "intractable" frontier.

We, the authors of this essay, have up to this point spent our careers in different worlds – namely, academia and technology – but we share two things in common. The first is that we have both been working to understand and address the climate challenge for many years. The second is that we are both strong believers in developing and using tools that are firmly grounded in data. In fact, for both of us, some of our earliest papers dealt with constrained optimization, which is the process of finding the best solution of a function, called the objective function, while adhering to certain limitations or constraints.[1]

The idea of constrained optimization, very broadly defined, is central to understanding Earth's past and future climate (climate science), to identifying and scaling solutions that limit the climate impact of human activity (climate mitigation), and to identifying and scaling solutions that reduce the negative impacts of climate change on societies and ecosystems (climate adaptation). In each of these cases, the goal is to maximize how much we understand about how the earth system functions under specific conditions, and act on that understanding, while dealing with the uncertainty that stems from the fact that we have limited observations on which to base that understanding.

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Central to climate science, for example, is the need to understand how Earth's climate has changed over time, the degree to which different factors have contributed to those changes, and how climate will continue to change in the future as a result of what we do as humans.

Addressing even the simplest questions within the broad scope of climate science requires us to build models of Earth's functioning. For example, how do we know that Earth's temperature has risen by almost 1.5 degrees Celsius since the preindustrial era?[2] We can't take the temperature of Earth, as a physician would of a patient. Instead, we rely on a combination of instrumental records (like thermometers and weather satellites) and proxy data (such as ice cores and tree rings) that are unevenly distributed in space and time. Our best estimate of the global temperature is based on interpolating and extrapolating instrumental records and using models of how the earth system functions to convert proxy data into temperature estimates.

Developing models that can reconstruct historical climate conditions and anticipate future conditions, such as those used as part of the Intergovernmental Panel on Climate Change (IPCC) process, involves a continual process of model refinement and model calibration, validation, and evaluation against available observations.[3] The data and observations that we have to inform projections and reconstructions are limited, however, which makes model evaluation against a comprehensive set of metrics and benchmarks challenging. As a result, even basic aspects of climate science, such as quantifying the effect of a doubling of carbon dioxide concentrations on global average temperature (known as the climate sensitivity), are still debated among climate scientists.[4] This is because, unlike in a laboratory setting, we cannot run an experiment in which we increase the concentration of atmospheric carbon dioxide on the whole planet while keeping all other factors constant (we only have one Earth!), and our understanding of how different factors have changed concurrently over time (such as carbon dioxide concentrations, temperature, cloud cover, land cover, and ocean circulation) is limited by the lack of observations. Identifying and scaling solutions for climate mitigation and climate adaptation is similarly predicated on leveraging limited observations of the real world to constrain models of how the earth system responds to human action.

This sets up both the core opportunity and the core challenge of applying AI to climate science, climate mitigation, and climate adaptation. As described throughout this issue of *Dædalus*, artificial intelligence is enabling a revolution in the ability to represent the functioning of complex systems and in deriving understanding from massive troves of data. In many fields – such as in weather forecasting, where AI models are outperforming traditional dynamical models, and in medical imaging, where AI models are enhancing diagnostic accuracy, efficiency, and accessibility – AI is already revolutionizing science and its applications.[5] This presents a growing opportunity for climate science, too. The challenge, however, is that the fields in which AI has made the greatest mark are those that provide massive volumes of data on which to train models and clear benchmarks for evaluating model performance. In the case of weather, data from constellations of satellites and *in situ* instruments can be used both to train models and to assess whether forecasts were accurate. In the case of medical imaging, diagnoses can be evaluated against patient outcomes.

How does this apply to climate? While the sheer volume of data available to help us understand the earth system and our role in it is growing at an unprecedented pace, this rich observational record is often insufficient to provide robust benchmarks for AI-driven models. For example, the limited duration of data records is incompatible with the multidecadal timescales represented by climate models, the spatial and temporal scales of observations are often incompatible with models used to support climate mitigation and adaptation, the parameters that we are most interested in are often the most difficult to monitor at scale, and observational uncertainties are often too high to support model evaluation.

In what follows, we use several case studies to illustrate the opportunities and challenges associated with using artificial intelligence to inform climate action. These examples fall on different points along two axes: AI tractability and the spectrum of climate adaptation to mitigation.

The success of artificial intelligence in advancing solutions depends substantially on the tractability of specific problems and applications. AI tractability ranges from highly tractable applications, characterized by well-defined problems and supported by good data and clear benchmarks, to problems with low tractability, where the problems are harder to define, where data are sparse, where there are deep uncertainties, or where systems are nonstationary. In effect, AI tractability expresses how well suited a problem is to current AI methods. We find that tractability is linked to the availability of metrics and benchmarks to guide model development.[6]

The second axis represents the climate adaptation-to-mitigation spectrum. This axis ranges from applications focusing purely on adaptation (that is, responding to the effects of climate change to minimize impacts), to applications focusing purely on mitigation (that is, reducing increases in radiative forcing, typically through the reduction of greenhouse gas emissions) to slow or halt climate change.

The first case study focuses on power generation and grid management. The global energy landscape is undergoing a profound transformation, moving away from centralized, fossil fuel–based generation toward a decentralized, dynamic system powered by renewable sources. This transformation is key to successful climate mitigation. However, the intermittent nature of solar and wind power – dependent on weather – poses significant challenges for grid stability and reliability. AI models are being used for optimizing power generation and enhancing grid management, making it possible to integrate high levels of renewable energy while maintaining a stable, efficient, and resilient grid.[7]

AI models are used to forecast the output of renewable energy sources by leveraging historical weather patterns, satellite imagery, and sensor data from wind turbines or solar panels.[8] The forecasts range from hours to days in advance. This predictive capability allows grid operators to anticipate fluctuations and adjust other energy sources, such as hydropower or battery storage, to ensure a continuous supply.

In the context of grid management, AI models can perform real-time load balancing by analyzing data from smart meters and other grid sensors to predict electricity demand. This allows the grid to dynamically shift power to where it's most needed and to manage energy storage systems by charging batteries during periods of high renewable output and discharging them during peak demand. This process of demand-response management reduces reliance on "peaker" plants – fossil fuel generators that are typically fired up to meet sudden spikes in demand.

Both applications lend themselves well to the use of AI tools because actual renewable energy production and actual energy demand are monitored throughout the system, making the problem highly tractable. This means that benchmarks to evaluate models are readily available at timescales and at locations that are relevant to the models' performance.

Another area in which short-term forecasts are advantageous is near-term impact assessment and resilience. Climate adaptation is about building resilience to the unavoidable consequences of a changing climate. This resilience spans timescales ranging from hours (for example, during evacuations or emergency aid deployment) to decades (for instance, when planning for sustainable development in the face of a changing climate). Applications of AI models have been especially promising with shorter timescales ranging from hours to seasons. Such applications have focused on anticipating and responding to extreme events such as heatwaves, floods, droughts, and wildfires through early warning systems and dynamic risk assessment for infrastructure and communities.

AI models are being deployed to enable more accurate and timely early warning systems.[9] Traditional meteorological models, while powerful, are often computationally intensive and struggle to capture local-scale, rapid-onset phenomena. AI, particularly deep-learning models like neural networks, can process vast, multimodal datasets in near real time to make highly localized predictions. For example, by analyzing satellite imagery, radar data, and ground-based sensor readings, AI can predict the path and intensity of a hurricane, the likely locations of a flash flood, or the spread of a wildfire with greater accuracy than ever before.

This short-term impact assessment goes beyond simple weather forecasting. AI models can integrate meteorological data with other datasets – such as topographical maps, urban infrastructure layouts, and population density information – to predict the specific impacts of an event. For instance, a model can forecast not only that a river will flood but also which specific streets will be inundated, how many homes are at risk, and where vulnerable populations might be. This information is invaluable for emergency services, allowing them to pre-position resources, issue targeted evacuation orders, and optimize response logistics.

AI tools can also be used to optimize resource allocation for disaster response and recovery.[10] After a flood or earthquake, AI-powered image recognition can quickly analyze satellite or drone imagery to assess damage to buildings and roads. This allows relief agencies to prioritize aid delivery to the most affected areas.

What makes many of these short-term applications highly tractable is the availability of historical data on the precise variables that the AI models are trying to predict. For example, the spread and evolution of historical fires, as captured through satellite imagery, can be used both to train and to evaluate models that aim to predict the evolution of future fires. This means that rich benchmarks are available, and those benchmarks are well matched with the responses that the models aim to predict.

Two aspects make applications in these areas somewhat less tractable than in power generation, however. The first is that many applications related to adaptation focus on predicting and responding to extreme events, which are, by definition, relatively rare. This means that the availability of historical data for training and evaluation can be limited, especially over the relatively brief period during which high-resolution satellite imagery and meteorological data have been available.

The second is that for applications related to disaster response, it is less clear which benchmarks are most appropriate for model evaluation. For example, if an AI model is used to optimize deployment of resources in disaster recovery, how should one evaluate the recommendations of one model versus another, or the overall performance of one specific model? Without access to hundreds (or thousands) of similar events, or the ability to provide counterfactual examples where different approaches were used under the same circumstances, evaluation metrics are difficult to define or quantify. Synthetic data based on simulated events can be used to some extent, and the use of synthetic data makes it possible to generate thousands or even millions of scenarios, but determining whether the synthetic scenarios are sufficiently representative of real-world applications is not trivial.

Contrail (condensation trail) avoidance presents an interesting opportunity on the climate mitigation side of the opportunity space. Contrails are the white line-shaped clouds that are sometimes left in an aircraft's wake. If the ambient air is very dry, these trails dissipate quickly. If the contrails form in regions of ice supersaturation in the upper atmosphere (near the tropopause), they persist and spread. In this case, the small amount of soot and water ice produced by an aircraft acts as condensation nuclei and can draw ten thousand times as much water vapor out of the atmosphere.[11] This causes a thin cirrus cloud that can last for many hours over a wide region.[12]

Contrail cirrus is a notable contributor to climate change because it absorbs outgoing infrared radiation from Earth and reradiates some of that energy back to the planet. In addition to this warming effect, contrail cirrus reflects a small amount of shortwave sunlight back out to space, producing a cooling effect. During the day, the two effects roughly cancel, but at night when there is no shortwave radiation reflection, contrails add net forcing to the climate system.[13] If one measures climate forcing using the GWP 100 metric (global warming potential over one hundred years), then contrails contribute approximately one-third of the total climate impact of today's aviation.[14]

Rerouting air traffic to avoid contrail cirrus is thus a cost-effective method for combating the climate impact of aviation, often requiring only small adjustments to flight altitude or routing that incur minimal fuel penalties.[15] The rerouting is highly effective because approximately 5 percent of flight kilometers produce persistent contrails, and of those, 15 percent produce 80 percent of the positive climate forcing.[16] An AI system could therefore assess the current weather and the flight plan data and predict whether a contrail will form. Such a system can be applied at space-time locations that are likely to produce highly-warming contrails and avoid a large fraction of the climate forcing attributable to contrails.[17]

Building such an AI system is highly tractable because we can detect contrails from satellite images.[18] This satellite imagery provides a large, labeled dataset for training machine-learning models. Therefore, the input and output of such a system are dense and well determined, with a clear metric for the AI to use.

Knowing the climate forcing produced by contrails at a given space-time location, as opposed to using long-term averages, would allow us to potentially reduce the number of diversions twofold by focusing on those flights for which the resulting contrails would have the most impact on radiative forcing (that is, warming).[19] However, estimating the contrail cirrus radiative forcing is a much harder problem for AI than simply predicting the formation of contrails because we cannot directly measure the forcing due to a contrail (since we cannot observe the counterfactual atmosphere where the plane did not fly). The current state of the art is to use approximate physical models to estimate the radiative forcing.[20] Because of unknowns due to ice microphysics, upper atmosphere humidity, and wind fields, such physical models have large uncertainties. How to apply artificial intelligence in such a scenario is an open research problem.

Quantifying greenhouse gas emissions and sequestration is central to broader efforts in climate mitigation. Indeed, progress toward a net-zero global economy is predicated on the ability to track emissions of greenhouse gases (GHGs) such as carbon dioxide (CO_2) and methane (CH_4) into the atmosphere across the many sectors of human activity. In parallel, there is a need to track removals of carbon from the atmosphere, whether by the natural components of the earth system (such as plants, soils, and oceans) or by engineered approaches to carbon capture. This is because the natural components of the carbon cycle have been removing approximately half of the carbon that has been emitted through human activity over the past several decades, but the details of where, why, and how this "natural sink" operates are still unclear, as is the degree to which this sink will continue to function as climate change intensifies.[21]

Traditionally, this movement of GHGs into and out of the atmosphere, collectively referred to as "fluxes," has principally been tracked through one of three approaches. The first is inventories, which rely heavily on generalized activity data and established emission factors. The second is mechanistic models of the natural components of the earth system, which rely on parametric representations of processes like photosynthesis to estimate fluxes. The third is atmospheric inversions, which couple observations of the concentrations of GHGs in the atmosphere with a model representing atmospheric dynamics to trace back the location and magnitude of fluxes. These traditional approaches have strengths and weaknesses, but they are all fundamentally limited by their inability to integrate information across the vast quantity and diversity of atmospheric and Earth surface observations that have become available through major advances in the ability to monitor Earth from space.

Artificial intelligence and machine learning have emerged as pivotal technologies, offering a path toward quantification of all constituent human and natural components of the global carbon budget. This opportunity is thanks to AI's ability to process vast, heterogeneous datasets and to discover and leverage the interrelationships among variables.

One example of where these tools have already had a large impact is in the development of models that can use small-scale observations of GHG fluxes from trees, plants, and soils, and extrapolate them in space and time to obtain estimates of biospheric activity everywhere, all the time. These tools infer relationships between observations from what are known as eddy covariance flux towers (that can represent fluxes for an area of approximately one square kilometer with meteorological data and satellite observations of Earth's surface and atmosphere. Once those relationships are captured by the model, meteorological and satellite observations can be used to quantify fluxes where no towers exist.[22]

A second example is the use of deep-learning algorithms and convolutional neural networks applied to satellite imagery to enable detection and attribution of point-source and diffuse fugitive plumes, such as those from the oil and gas sector, agriculture, and landfills.[23] These AI systems identify and characterize plumes at a high spatial resolution, significantly reducing the latency of detection and providing actionable data to operators.

The challenge with many of these applications, however, is the dearth of benchmark data to train and evaluate models. This is because fluxes of greenhouse gases cannot be measured directly at most spatial and temporal scales that are directly relevant to climate action. In the case of methane leaks, for example, if the goal is to spot unknown leaks, and if known leaks are fixed, where does one come up with the thousands or millions of example leaks on which to train an AI model? Here again, synthetic data, if carefully designed to mimic real-world situations, can in some cases be used for model development and evaluation. In the case of biospheric GHG fluxes, while AI models can be trained on observations from eddy covariance flux towers, there are only about a thousand such towers globally, with some regions and ecosystems very poorly represented, making it difficult to assess how models perform across vast areas. This presents a fundamental contrast with applications such as weather forecasting, in which tomorrow's weather can be used to assess today's forecast.

Overall there is incredible potential for AI to enable a transition toward substantially more robust emissions measurement, reporting, and verification (MRV) and effective assessment of both nature-based and technological approaches to carbon capture and sequestration in support of climate mitigation. These applications present challenges in terms of their tractability, however, and there is a need to develop sophisticated new approaches for leveraging the data and information that we do have to inform these critical applications.

At the far end of the tractability spectrum lies the problem of using AI for long-term climate projection to support multidecadal planning for climate mitigation and adaptation. This application represents the frontier of intractability because it is fundamentally an out-of-distribution generalization problem, for which the historical record is an increasingly inadequate guide to a future, nonstationary world.[24] Purely data-driven AI models, which excel at learning statistical patterns from vast amounts of data, are poor at out-of-distribution extrapolation. AI models may have low skill when confronted with future climate states that involve novel physical dynamics or the crossing of critical thresholds not represented in their training history. To further complicate this, information on historical climate conditions spanning timescales of decades to centuries is severely limited by the relatively short period of the record of observations with high spatial and temporal detail, such as those provided by space-based observations.[25]

This intractability is rooted in three core properties of the earth system. First is nonstationarity: anthropogenic forcing is actively changing the underlying statistics of the climate. The relationships between variables, such as temperature and precipitation patterns, are not fixed over time, violating the core assumption of many machine-learning algorithms that the training and testing data are drawn from the same distribution.[26]

The second property is internal climate variability: the climate system possesses natural chaotic fluctuations on different timescales. The atmosphere itself erases information in its initial conditions within roughly fifteen days.[27] The entire climate system has multiyear fluctuations, such as the El Niño–Southern Oscillation. The inherent variability of the climate system makes it difficult to isolate the forced "signal" of climate change from the limited historical record. Disentangling this internal variability requires large ensembles of simulations, a task for which AI-based emulators are beginning to show promise.[28]

Third is the existence of potential tipping points within the climate system. The climate system may contain thresholds or bifurcations at which a small additional forcing can trigger a large, abrupt, and potentially irreversible shift in the state of a subsystem, such as the collapse of an ice sheet, a sudden change in ocean circulation, or the breakdown of the biospheric carbon sinks discussed earlier.[29] By definition, such unprecedented events are absent from any training data that one might use to develop models, making them nearly impossible for a purely data-driven model to anticipate. Further, any demonstration of a tipping point in any simulator (either AI- or physics-based) is often very difficult to distinguish from numerical artifacts (or even simple programming bugs!) in the model itself, making such tipping points difficult to validate.

These properties force us to conduct a deeper examination of AI models versus traditional, physics-based earth system models (ESMs). ESMs are often presented as the transparent, physically grounded alternative to "black box" AI. This view, however, is an oversimplification. ESMs are highly complex computational artifacts, comprising millions of lines of code. Crucially, they depend on hundreds of parameterizations – simplified, often empirically derived equations used to represent critical processes like cloud formation and atmospheric turbulence that occur at scales too small to be explicitly resolved by the model's grid.[30] The complex, nonlinear interactions among these parameterized components give rise to emergent behaviors that are not always fully understood or predictable, making the ESM difficult to interpret in its own right. Both ESMs and AI models are complex systems, and the goal should not be to find a perfectly transparent model but to develop a rigorous suite of tools to validate, interrogate, and understand the behaviors and limitations of all our models. This set of tools could be improved by incorporating the latest AI techniques.

The successes and challenges illustrated by the five case studies above hint at how the use of AI is likely to evolve in the future. To anticipate how it will support climate science, climate mitigation, and climate adaptation over the next decade and beyond, we need to look at the cutting edge of today's artificial intelligence, such as the large language model (LLM)–based systems that can generate complex code or models. One such example is the recent LLM and tree search system designed to create expert-level scientific software that can be scored using a given quality metric and that searches for code that improves it, including through AI-assisted web or literature searches.[31] Going forward, AI coding systems will make the creation of models much less expensive than at present, which reduces the need for centralized models or libraries that cover many possible cases.

One of the issues with the current use of machine learning–based models in climate is that they are largely black boxes. Domain experts don't know the limitations of such models *a priori*. However, if climate models were actually generated by LLM systems, then we could use another LLM to inspect the model code and create hypotheses for why the model behaves the way it does. We could generate new diagnostic or experimental code to test these hypotheses. There are early signs of this behavior in the tree search system, whereby the system automatically generates explanations of why a model had a sudden jump in performance while the LLM is searching for alternatives.[32]

Casting forward to 2036, we can imagine the use of such model-generating tools in the climate field. Climate models of all sorts will be built by AIs, not just by researchers in academic departments. The AIs will ensure that the models both reproduce current observational data and obey physical laws and long-term qualitative measures of reasonable models. There may be a shared foundational model that is a coarse but full model of the earth system, vetted by the scientific community.[33] Fine-grained predictions would be built via AIs on top of the shared model. Researchers would then spend most of their time understanding observations and models, rather than writing software, sourcing observations, and contending with the limitations of legacy models. Our hope is that such support from artificial intelligence will accelerate scientific progress in all fields, including models used to support climate action.

Three additional outcomes are likely once such future models are possible. First, the ease of assimilating diverse data into AI-created models will increase the utility of observations and thereby incentivize globally coordinated observational programs. More data will constrain the future models and will rapidly improve them (since building the models will be so much easier). Second, the concept of "data science at the singularity" suggests that rapid scientific progress is enabled by frictionless reproducibility and public metrics.[34] If artificial intelligence can easily generate models, they can be more easily shared and measured. This will likely lead to an increase in the rate of progress. Third, rather than replacing scientists, such future models will free researchers to focus on their core scientific expertise and use it to guide the AI to do the grunt work needed to support scientific breakthroughs. In other words, AI coding systems will allow scientists at all levels of seniority – from graduate students to senior faculty – to concentrate on the true creative and analytic work of science, rather than getting bogged down in processing data and developing software.

Looking into the future, we must also recognize that the rapid proliferation of machine learning and artificial intelligence presents a critical paradox for climate science: while AI offers essential tools for climate action, the computational infrastructure supporting it carries a significant, accelerating environmental burden.

The most obvious climate impact of AI stems from the energy required for model training and inference.[35] While the computational demands associated with training state-of-the-art LLMs, which often involve billions of parameters, result in substantial electricity consumption, they are dwarfed by the energy used for inference: that is, the energy consumed by queries by the end users.

The rise in the number of queries is driving construction and power demand of global data centers. The International Energy Agency (IEA) has projected that data center electricity consumption could more than double by the end of the 2020s. Since a large portion of this electricity is still currently sourced from fossil fuel–based grids, the result is a potential growth in global GHG emissions. Conversely, this also increases the benefit of decarbonizing electricity production, a key step toward climate mitigation.

Interestingly, however, the use of AI for climate science itself does not put a substantial burden on the climate due to electricity usage. Assuming that scientists are using a tool similar to the tree search system, we can estimate the total energy demand by conducting a back-of-the-envelope calculation based on one hundred thousand atmospheric scientists who are each issuing ten thousand typical Gemini queries a week (assuming that each scientist is calling on the AI coding tool on average once per week).[36] At 0.24 watt-hours per Gemini query, the weekly energy burden would be approximately 1.4 megawatts, or roughly the same as twelve hundred average U.S. households.[37] The overall carbon burden, assuming the typical U.S. carbon intensity of 384 gCO_2/kWh, would be approximately five thousand metric tons of CO_2 per year. This amount is less than one ten-millionth of total global greenhouse gas emissions.

The convergence of climate urgency and the AI revolution has given us a dual mandate. On the one hand, the next era of climate science, mitigation, and adaptation will be powered by algorithms capable of extracting understanding from the planet's immense, complex, and heterogeneous data streams. Artificial intelligence offers an attractive scalable path toward robust measurement, reporting, and verification; grid stability; and near real-time disaster resilience. On the other hand, this very tool carries a significant and growing environmental footprint.

Moving forward requires a collaborative, humble, and clear-eyed approach. Defining the landscape of climate challenges along the axes of tractability and the adaptation-to-mitigation spectrum can serve as a guide. We must vigorously pursue AI solutions where problems are highly tractable, such as in power grid optimization and short-term impact forecasting, and where clear benchmarks and dense data records accelerate progress and yield immediate climate benefits.

However, we must also focus on the "intractable" frontier. To do so, we should not treat physics-based and data-driven models as mutually exclusive. The future lies in fusion: utilizing physics-informed AI and LLM-generated models that accelerate discovery while remaining subject to physical laws and community vetting. Critically, we must address the challenge of scale incompatibility: that is, the mismatch between the scales at which we can measure key climate variables and the scales at which we need models to represent them. The scientific community must collaborate to build the benchmarks and comprehensive observational infrastructure necessary to constrain models.

Ultimately, returning to where this essay began, the goal of constrained optimization is not just to find the best possible solution, but to define the true limits within which action can succeed. By being clear eyed about both the immense potential and the inherent limitations of artificial intelligence, we can successfully navigate the challenges ahead and begin to realize the promise of an Algorithmic Planet working in service of a sustainable future.

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