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WHERE GREEN MEETS MACHINE

EDITORIAL

Harnessing digital technologies for environmental stewardship

In the 21st century, digital technologies like artificial intelligence (AI) and machine learning are reshaping many sectors, including the environmental sciences. As these tools evolve, their potential to address environmental challenges becomes increasingly apparent. Yet while there are many benefits, we must also acknowledge the challenges they present.

Digital technologies offer unprecedented capabilities in environmental monitoring, analysis and management. Machine learning algorithms can analyse vast datasets to identify trends and anomalies in environmental data, and remote sensing technologies coupled with AI can provide real-time ecosystem monitoring, offering the potential for a rapid response to environmental threats. AI-driven agricultural practices can optimise water usage and minimise pesticide application, promoting sustainable farming.

However, the integration of digital technologies into the environment sector is not without its challenges. One significant concern is the environmental footprint of the technologies themselves. The energy consumption of data centres required for AI and machine learning processing is substantial and growing. There is also a risk of over-reliance on technology at the expense of traditional, community-based knowledge and practices. Indigenous and local communities have long been environmental stewards, possessing invaluable knowledge that should complement digital advancements, not be overshadowed by them. A holistic approach that integrates modern technology with traditional wisdom is essential for sustainable environmental management.

Digital technologies hold great promise for addressing some of the most pressing environmental challenges of our time. Their potential to revolutionise climate modelling, resource management and ecological monitoring is immense. But their design and outputs need human guidance to ensure they remain on track to tackle the issues we need them to address. It is vital, therefore, to approach the integration of digital technologies into our systems and processes with awareness – balancing innovation with sustainability and ensuring that technological advancements enhance, rather than replace, traditional environmental stewardship practices.

Editorial: This edition of environmental SCIENTIST was guest edited by ChatGPT, an AI chatbot with natural language processing. It suggested authors and themes for several of the articles included. ChatGPT also wrote this editorial. This was done through a short prompt, and edits were made for accuracy and readability. A full discussion of our motivations for doing this and reflections on the process are available in an online interview with the human editors of environmental SCIENTIST at: **the-ies.org/chatgpt-editor**

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The future of clean technology

Sam Goodall and **Sylvie Russell** consider the complex relationship between environmental technologies, ethics and the marketplace.

We have reached a moment in time in which novel technologies and artificial intelligence (AI) are rapidly developing. With these developments, ultimately, comes the imperative to establish new rules and regulations. It goes without saying that this can be a difficult journey. One of the core responses to challenges like these is working together to establish frameworks for uplifting and scrutinising new technologies.

TECHNOLOGY AND ETHICS

The agenda for new clean technologies varies widely depending on the kinds of governance and policies that apply nationally and internationally. Currently, it is not clear in which political direction Europe is moving. In light of these geopolitical differences, looking for new and improved ways of working that respond to this is essential, as is ensuring that investors are dedicating their time, money and resources in the right places.

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For this to happen, there needs to be a paradigm shift. This needs to take the form of ecosystem engagement rather than just open innovation; an ecosystem engagement, by its nature, facilitates interaction with different parts of the clean technology sector's ecosystem. There are five key elements to the ecosystem: entrepreneurs, investors, universities, public sector and corporates, which are all required for a functioning innovation ecosystem. Others might include companies or the media, but ultimately the ecosystems are effective once the entire set of participants is working productively together.

If cohesive international policies do not exist, we must consider how clean technology innovation and development might be regulated. The market is increasingly seeing investors who are specifically seeking out startups that effectively monitor where their raw materials are coming from, and the complexities of their impact on the environment.

There are also other areas of contention in the clean technology space; specifically, different ethical standards or viewpoints. A solid, pluralistic approach should give new and different technologies the space to flourish. If a new technology comes to light and has credible climate-positive claims, we should support exploring its potential.

SYSTEMS CHALLENGES

One of the biggest barriers in the development of clean technology is the implementation of relevant policies to support innovation and to regulate the use of novel products. The gap between intention and action plays out visibly in the sector. All kinds of policy ambitions, claims, targets and objectives exist, but the true challenge arises in bringing together different stakeholders to achieve these goals. We have had access to the appropriate technologies to achieve specific environmental goals for years – yet the technologies are rarely used to their full potential. While funding is also part of this story, there is also a strong sense of system inertia in utilising technologies to the best of our advantage. The traditional problem-solving paradigm does not best equip people in the environmental sector to handle the implementation gap, as a complex multi-stakeholder problem involves effective multi-stakeholder system solutions.

Regulation and implementation of policies relating to new technologies must also remain cognisant of the raw materials that need to be extracted to enable their use. The ethical implications of sourcing raw materials from countries that do not have satisfactory labour regulations or adequate supervision are fraught, and this is an increasing concern for both investors and consumers in the clean technology space. Guidelines that consider both the environmental and social impacts of new technologies, and that work towards better ways of accelerating development, are sorely needed.

In certain aspects of the green technology industry, there are risks embedded in the transition to automation. This is seen in sub-sectors such as agritech, where there is naturally some replacement of manual jobs through advances in robotics. However, claims that this will be a widespread effect of the development of clean technology in general are often exaggerated, and AI and other digital technologies can support decarbonisation of energy systems, particularly in relation to microgrids and distribution networks for energy. AI or computer modelling can handle vast quantities of data compared to how we might have handled them in an analogue fashion, and this is where AI can make its most promising contribution to environmental sector issues: whole-system analysis and intervention.

However, one of the more immediate and visible environmental risks around accelerating AI deployment is the ever-increasing use of servers and data centres, and

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the energy (and significant amount of water) that powers them. In the global race to lead AI development, there is significant investment in server infrastructure, yet even in recent years this kind of expansion has been unprecedented. While some companies, such as Bloomberg and Nvidia, are beginning important research into the environmental implications of AI and energy consumption, we need greater understanding of the complexities and trade-offs of these risks in relation to the benefits of these fast-evolving technologies.

CLEAN TECHNOLOGY NETWORKS

Successful innovation in technology for environmental purposes is essential, but there are limited opportunities for cross-pollination of ideas and cross-disciplinary work in the sector. Cambridge CleanTech (CCT) is an innovation network, which was established 13 years ago. As a company, CCT is primarily focused on the functional economic area of the technology in the Cambridge technology cluster, which has had a long history of expertise in life sciences and the digital and IT sectors. There are various network organisations that support and bring people together around these domains, but CCT's goal was to specifically create a pipeline of emerging technologies. In its early phase, we quickly realised that there was no critical mass of emerging technology and commercial activity in the two dominant sectors of climate and clean technology; six years ago, CCT began to network across the UK and internationally.

Alongside its sister organisation, Oxfordshire Green Tech, which follows the same kind of business model and innovation network proposition, CCT has extended its network across northern Europe, the Netherlands, Scandinavia, northern France and parts of Germany. CCT's mission and theory of change are that there are nascent technologies that can have a positive impact on climate change and the environment, which need investment, support, and scaling partners, something CCT seeks to facilitate and provide.

One of CCT's core roles is to help organisations navigate the clean technology ecosystem, while propagating the ecosystem itself in positive ways. For example, CCT is soon hosting its annual flagship investor event: CleanTech Venture Day. This year, it is aligned with a new initiative called the Climate Tech Super Cluster, which defines a functional economic area within about four hours of London, including Birmingham, Manchester, Edinburgh and Glasgow, alongside Paris, Amsterdam and Cologne. The underlying goal for this event is to take the CCT model, which has been successful in the last 10 years, and scale it up, ultimately creating a new Silicon Valley for climate tech.

Something else that CCT has explored for this purpose is the need for more structured and integrated facilitated workshops. While this is by no means a novel approach, and at first glance does not appear to be particularly revolutionary or exciting, it is one of the best ways to allow embedded systems thinking – from design of products and development to securing investment.

CCT has therefore worked to pioneer a specific kind of systems thinking in this area, called 'embodied cognition'. This involves bringing people together from different professions and disciplines in a physical space to co-design solutions for particular issues. While this is ultimately a basic approach, by implementing it, CCT brings together, for example, people who work in start-ups and in distribution and network organisations, investors and university employees.

Naturally, these professionals speak different languages and might have an entirely different vocabulary when discussing challenges and solutions, but bringing them together physically to approach a solutions-focused task allows them to build a shared model and understanding of what they are respectively aiming to achieve. This is a structured and positive kind of facilitation, and demonstrates that multi-sector, multiagency network events and workshops are a truly effective way of driving innovation.

Revisiting our overall mission, this method follows the ecosystem-first approach, with an emphasis on curating a meeting that is representative of different professions and enabling others to understand new ways of thinking that go beyond their own understanding of the problem, which can be limited by siloed approaches. By focusing on framework improvement and rejecting linear and narrow problem-solving, we can create change that is informed by a broader cross-section of professionals.

CLEAN TECHNOLOGY: PAST, PRESENT, FUTURE

It is unsurprising that clean technologies spend much of their lifespan in the potential space, before they have attained the necessary traction, funding and interest to fully materialise in the present.

One company that CCT works with has developed an AI-designed process for electrical motors, which could allow up to 90 per cent energy efficiency, benefits which have come directly from the AI design aspect. AI enables this company to produce multiple design iterations and can respond to specific queries that relate to motor efficiency or longevity. If we have a 90 per cent energy efficiency improvement in these electric motors, this could in theory be applied to every single electric motor in the world, with an unprecedented positive environmental impact. Without AI, a development such as this may not have been possible – or, at least, it would not be anywhere near as rapid.

CONCLUSION

As demonstrated by the spread and depth of articles in this issue, embracing digital technologies in the environmental sector comes with both risk and enormous opportunity. Through facilitating cross-disciplinary workshops, allowing new ventures the space to bring their innovations to market, and embracing the possibilities of AI and machine learning in the sector we can support a just transition to a future defined by exciting new pathways in clean technology. ES

Sam Goodall is Chief Executive Officer of Cambridge Cleantech, the UK's first clean-tech innovation network and a leader of climate innovation in Europe. With over 20 years' experience in project management, regeneration and economic development, Sam builds and connects national and international innovation ecosystems for climate-positive technology.

Sylvie Russell is the Chief Operating Officer at Cambridge Cleantech and has over 20 years of experience in senior roles in international companies, from small and medium-sized enterprises and charities to large multinational brands. She manages the Cleantech Venture Day, a flagship pitching event and a meeting place for innovators, investors, large enterprises and economic development partners.

https://www.cambridgecleantech.org.uk/

The CAETÊ algorithm: assessing vegetation and climate change in the Amazon

Bárbara Cardeli and **Bianca Fazio Rius** set out how a new generation of models can more accurately represent hyperdiverse environments.

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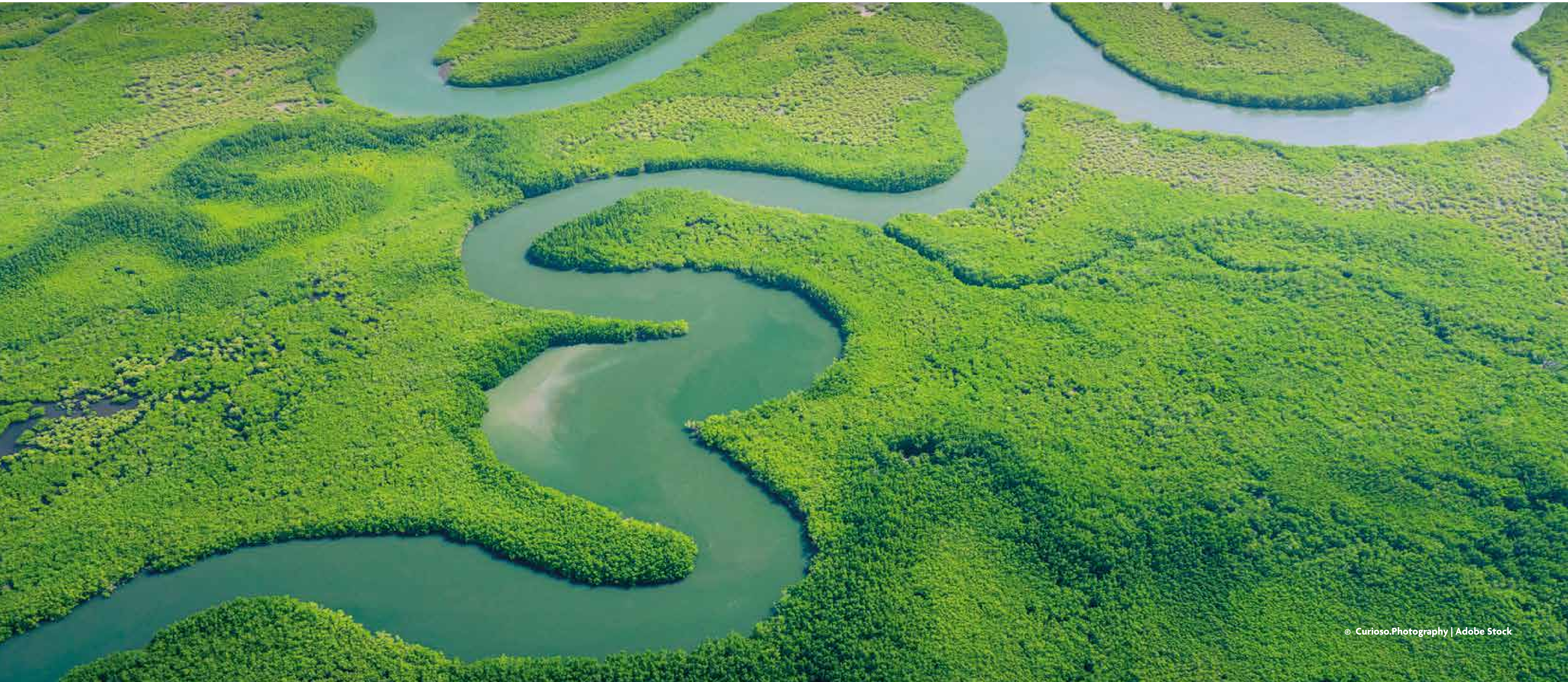
Studying the Amazon rainforest can be tricky. It harbours an incredible diversity of plant species, with many still awaiting discovery and formal description. Although the Amazon is often described as a 'green carpet', it is far from homogeneous; rather, it is composed of a diverse mosaic of vegetation formations.[1] The Amazon's complexity makes it one of the most important ecosystems in the world, and one which provides an immense number of globally significant ecosystem services.[2,3] This same diversity and complexity make it incredibly challenging to study and understand.



Simultaneously, the Amazon faces the challenge of resisting, adapting to and recovering from the numerous effects of climate change that have affected it, which are predicted to continue and to potentially worsen.[4] According to the latest Assessment Report (AR6) by the Intergovernmental Panel on Climate Change, climate change is already affecting ecosystems, including the Amazon, and human societies.[5] This underscores the urgency to comprehend these processes and to pursue solutions to mitigate their effects.

VEGETATION MODELS

To improve our understanding of earth and climate sciences, algorithms known as vegetation models have become increasingly employed to investigate the impact of climate change on various aspects of the biosphere. These models are excellent tools that combine technology, ecology and climatology to explore urgent issues related to climate change. However, one of the biggest challenges for these models is the complexity of representing the vast diversity of plant strategies found in hyperdiverse ecosystems such as tropical forests, given, among other aspects, the computational limitations inherent in any algorithm.[6,7,8]

Researchers at the University of Campinas in São Paulo, Brazil, have developed the CAETÊ vegetation model to better represent the plant diversity found in tropical forests.[9] This algorithm is designed to investigate the effects of climate change, such as reduced precipitation and drought events and increased carbon dioxide (CO_2) concentrations, with a focus on the Amazon rainforest and to incorporate plant diversity.

DIVERSITY WITHIN VEGETATION MODELS

CAETÊ stands for carbon and ecosystem functional trait evaluation model. It also means 'big forest' in Tupi-Guarani – one of the most important language families in South America, which encompasses various Indigenous languages, the most representative being Guarani.

CAETÊ is an innovative trait-based dynamic vegetation model (DVM) designed to simulate vegetation dynamics and their associated ecophysiological processes through measurable plant characteristics (see **Box 1**). These plant characteristics, known as functional traits, are key to understanding how individual plants perform within their ecosystems. The focus on functional traits is what classifies CAETÊ as a specialized subset of DVMs known as trait-based models.

Unlike conventional vegetation models that categorize plants into broad plant functional types (PFT), trait-based models like CAETÊ provide a more nuanced and detailed representation of plant functional diversity in which the entities simulated are life strategies rather than PFTs. Trait-based models enhance our ability to understand how diversity determines ecosystem processes and properties. Beyond this, the approach is more precise in simulating vegetation responses to environmental changes under different biogeochemical variables. Importantly, such models allow the investigation of impacts of functional diversity and functional traits on forest responses to these changes, which is not feasible in non-trait-based models.

As a vegetation model, CAETÊ uses a series of mathematical equations to simulate a plant's ecophysiology. To incorporate climatic conditions, representative equation parameters are used, such as for as solar radiation, temperature, relative humidity, precipitation rates and atmospheric CO_2 concentrations. By accounting for these factors, CAETÊ can effectively simulate the impact of climate change on vegetation dynamics.

Using CAETÊ, researchers can estimate a wide range of ecosystem processes. For example, the model can simulate photosynthesis rates – crucial for understanding plant growth and carbon assimilation. Furthermore, the model can evaluate biomass accumulation and distribution, carbon sequestration, and the storage capabilities of different ecosystems.

Overall, CAETÊ – and trait-based models more widely – represent a powerful tool for ecological and climate research, enabling scientists to explore and predict the effects of environmental changes on vegetation and ecosystem functioning. Its trait-based approach offers a detailed and accurate framework for studying the complex interactions between plants and their environment, ultimately contributing to a better understanding of global ecological and climatic patterns (see **Figure 1**).

AMAZON BASIN CASE STUDY USING CAETÊ

To understand one of the main projected effects of climate change in the Amazon (the increase in severity and occurrence of drought) an experiment was conducted

BOX 1. GLOSSARY OF TERMS

Plant functional types. Plant functional types (PFTs) refer to a grouping or classification system used by ecologists and climatologists to categorize plant species based on their similar functions and performances in an ecosystem. PFTs simplify the complexity of plant diversity by grouping plants into categories that share common functional characteristics, such as leaf type (e.g. needle-leaved, broad-leaved), growth form (e.g. tree, shrub, grass), phenology (e.g. evergreen, deciduous) and resource acquisition strategies (e.g. nitrogen fixation, mycorrhizal associations).[10,11]

Functional traits. A functional trait is a morphological, physiological, phenological or behavioural feature of an organism that influences its performance and fitness, determining its response to environmental factors and its effects on ecosystem processes.[12,13,14,15,16,17,9] In plants, examples of functional traits include leaf size, plant height (morphological), photosynthetic rate, water use efficiency (physiological), flowering time and leaf-fall timing (phenological).

Functional diversity. Functional diversity quantifies the functional traits present in an ecological community or system, determining how that system functions and operates. As a component of biodiversity, functional diversity encompasses the range of these traits within an ecosystem, highlighting the different roles organisms play and their contributions to ecosystem processes.[18,19,20,21,22,16,23,9]

Life strategies. In functional ecology this refers to the functional traits, behaviours and resource allocation patterns that organisms exhibit to survive and reproduce in their environment.[24,25]

Net primary productivity. This is the rate at which primary producers (such as plants) store energy as biomass in an ecosystem. It is calculated by subtracting a plant's energy for metabolism and maintenance (respiration) from the total energy captured during photosynthesis (i.e. gross primary productivity).

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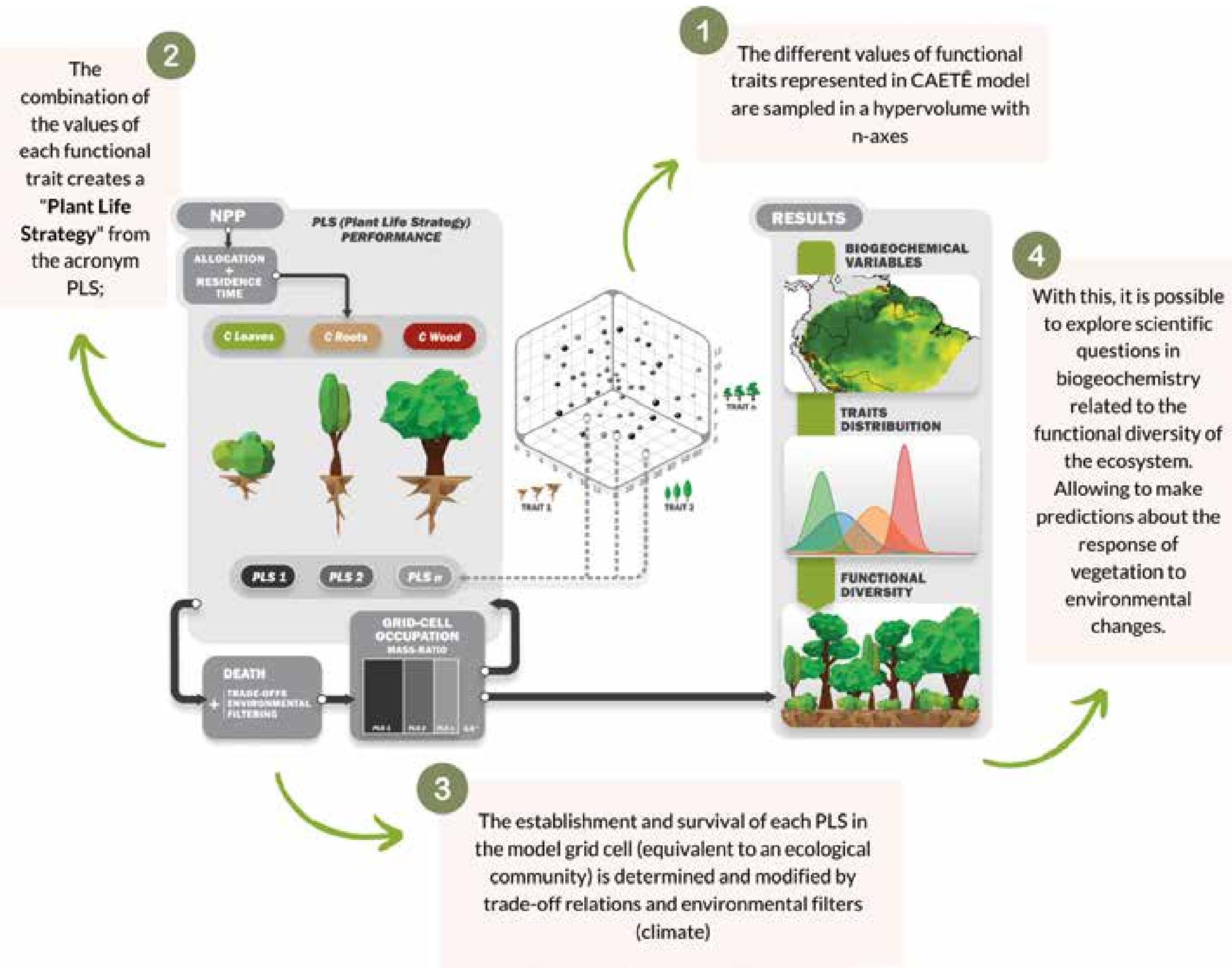
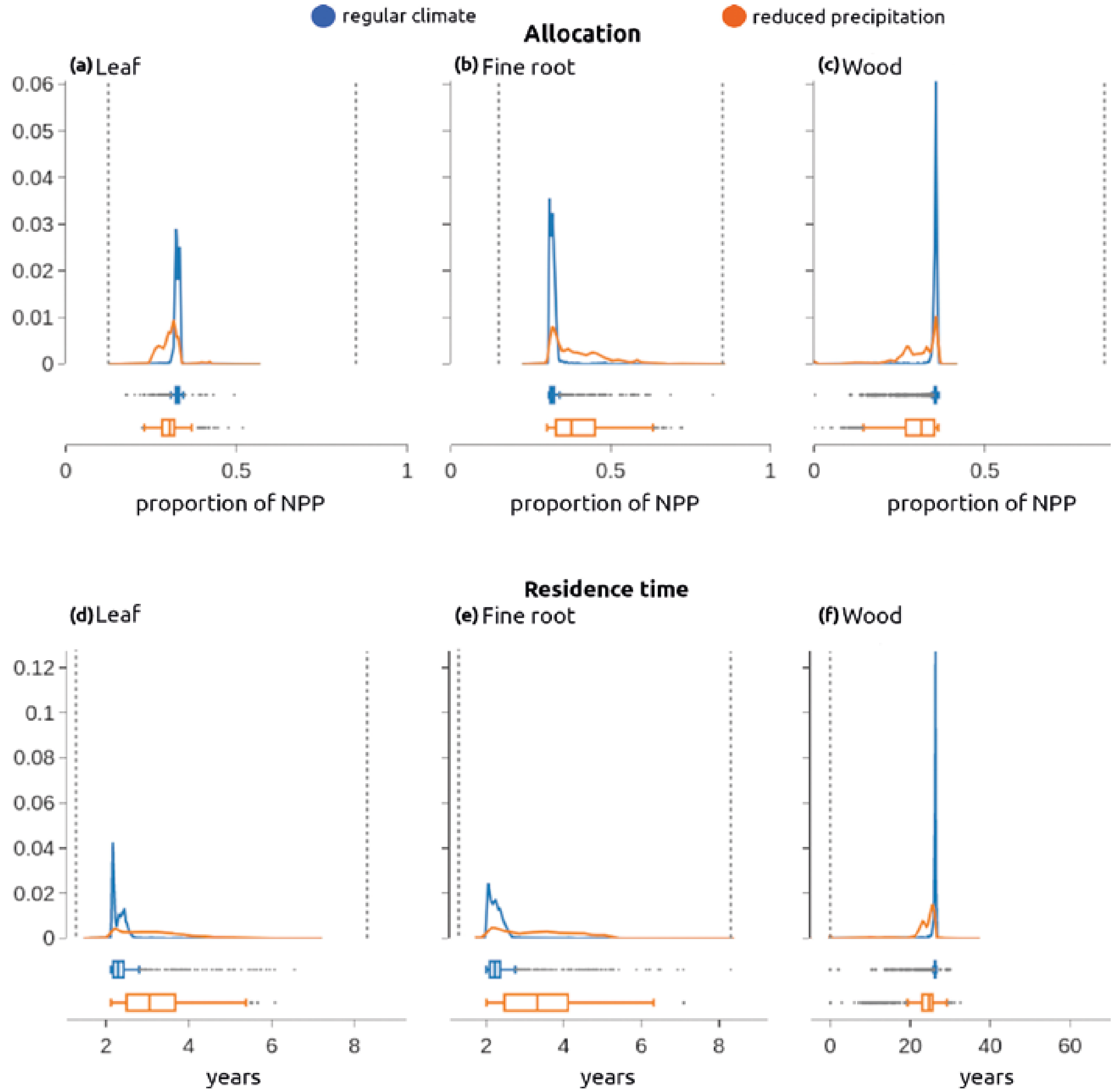
using the CAETÊ model.[9] A precipitation reduction of 50 per cent was applied across the entire Amazon basin. The results showed significant changes in ecosystem functioning and functional diversity, including an unexpected increase in the latter and changes in plant trait composition, indicating a reorganization of the plant community in response to the new climatic conditions.

Specifically, life strategies that invest more carbon in root systems were favored and an increase in root abundance was seen, as roots are crucial for the uptake of the most limiting resource in this scenario: water. Because an investment in roots would limit the carbon allocation to other organs, a decrease in carbon investment in woody tissues, such as stems, was seen. Due to its structural



▲ **Figure 1. Schematic diagram of the CAETÊ model and its trait-based approach. From the initial plant functional trait ranges (the axis of the hypervolume), values are uniformly sampled and combined to create hundreds of thousands of what we define as plant life strategies (PLSs). The set of all created PLSs composes a hypervolume that represents the potential functional trait space in which each point inside the volume is a unique combination of functional trait values. Environmental filtering, the trade-offs between functional traits and the physiological processes determine the performance of a PLS (abundance) and whether it survives (positive carbon balance) or dies and is excluded from the grid cell. Then, the grid cell is filled as a mosaic of PLSs, in which each occupies an amount of space proportional to its abundance, calculated from the PLSs' relative contribution to the total carbon storage in that grid cell. From the PLSs' occupation, the ecophysiological variables are updated and return to the model for iteration. This modelling framework allows us to assess the model's results regarding biogeochemical variables and trait distribution and, therefore, the different components of functional diversity. (Source: Modified from Rius *et al*., 2023[9])**

Notes: [a]NPP: net primary productivity; [b]C Leaves: amount of carbon allocated to leaves; [c]C Roots: amount of carbon allocated to fine roots; [d]C Wood: amount of carbon allocated to wood.



▲ **Figure 2. Density distributions of functional traits using the trait probability density method for the trait-based approach.[16] The curves correspond to the probability density distribution of trait values across the Amazon basin. Each boxplot represents the median value and variance for each trait under each climatic condition. The boxes extend from the first to the third quartiles, and the whiskers extend from the minimum and maximum data. The outliers are shown as grey dots. The orange curves/boxplots represent the results with the applied low-precipitation scenario, and the blue curves/boxplots represent the results concerning the regular climate conditions. Plots (a)–(c) show the results concerning the allocation traits, and plots (d)–(f) display the results for the residence time traits. (Source: Rius *et al*., 2023[9])**
Note: [a]NPP: net primary productivity.

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and physiological characteristics, the stem has the greatest potential for carbon accumulation, in addition to being a large supporting tissue. Thus, the reduction in precipitation was shown to decrease the overall carbon stock in the ecosystem (see **Figure 2**).

Unexpectedly, the lower precipitation scenario showed increased functional diversity – that is, the variety of plants present in the community. Importantly, this shows that diversity does not always maximize ecosystem functioning. Even under conditions where plants can adapt, important processes such as carbon storage can be negatively affected. In this scenario, there was an increase in plant diversity but a decrease in carbon storage capacity due to the reduced plant biomass. In short, the greater diversity shown did not necessarily improve ecosystem functioning. Effects like these exert strong feedback on climate change, as the process of carbon sequestration and storage is directly related to one of the main climate change mitigation mechanisms provided by vegetation: acting as carbon sinks.

Furthermore, the greater representation of diversity using variant functional strategies, rather than fixed functional types, also demonstrated improvements in ecosystem representation, especially in key processes such as productivity (e.g. net primary productivity).

CHALLENGES, ADVANCES AND LIMITATIONS

Prior to CAETÊ, trait-based vegetation models did exist. Which raises the question: why create another one?

Most of the ecosystem models available today were developed in the context of temperate vegetation. Therefore, the representation of tropical and megadiverse ecosystems, like in the Amazon, is not accurate enough in these models. The development of CAETÊ aims to improve the representation of tropical ecosystems, focusing on the Amazon rainforest and its diversity. Additionally, the proposal to create a new model offers the advantage of training and empowering scientists in this nascent field of modelling, especially in Brazil.

However, developing vegetation models presents several challenges. Representing nature through computer algorithms involves delicate processes, requiring precision and a series of complex procedures.

The new era of trait-based model development has brought significant advances in the representation of megadiverse ecosystems. However, as with any other

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model, weaknesses and underrepresented processes in DVMs are still found. From generalising important parameters and characteristics to simplifying processes like mortality – especially for hydraulic constraints – and growth, the need for model improvement is ongoing. For example, defining which traits to use, how to sample their values, correlations, and the precise linkage to ecophysiological processes still represent challenges for both the models and their developers. The understanding of these relationships is still new, even in the field of functional ecology.

As science develops our understanding of how functional aspects affect ecosystem responses, their relationship with environmental changes and the deep mechanisms of ecosystem functioning, model development also continues to improve. It is an ongoing effort of advancements, understanding weaknesses and seeking improvements. ES

Bárbara Cardeli, MSc, is a PhD student in Ecology at the University of Campinas, Brazil. Bárbara is part of the experiment-modelling integration component at the AmazonFACE programme and contributed to the development of CAETÊ-DVM. Her research seeks to understand the impacts of climate change on the functional diversity and ecosystem services of the Amazon rainforest.
barbara.r.cardeli@gmail.com

Bianca Fazio Rius, MSc, is a PhD student at the University of Campinas, Brazil. Bianca researches the effects of climate change on the resilience of the Amazon rainforest, mediated by functional diversity. She is part of the experiment-modelling integration component of the AmazonFACE programme and contributes to the development of CAETÊ-DVM.
biancafaziorius@gmail.com

AmazonFACE is a research programme that investigates how the increase in atmospheric CO_2 affects the Amazon rainforest, its biodiversity and ecosystem services. The experiment exposes an area of the forest, located 80 km north of Manaus at an INPA (National Institute for Amazonian Research) station, to a CO_2 concentration 50 per cent higher than the current level, using Free-Air CO_2 Enrichment (FACE) technology. The goal is to generate knowledge about the forest's resilience to climate change, essential for guiding mitigation and adaptation policies in the region.

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Artificial intelligence and the environmental professions

Peter Humphrey, Gary Kass and **Victoria Ward** report on a collaborative inquiry exploring the promises and perils of this technology.

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THE POTENTIAL OF ARTIFICIAL INTELLIGENCE

How might artificial intelligence (AI) support progress towards environmental improvement and nature recovery? How might AI affect the work we do and how we do it? How might we engage more widely and constructively in how we govern AI? These are just some of the questions we are exploring through a collaborative inquiry involving Jigsaw Foresight, Natural England, The Law Society, a scientific publishing organisation and a global pharmaceutical company.[1]

This eclectic group is interested in the implications of generative AI (genAI) – a suite of tools such as ChatGPT that can generate text, numbers, images, audio and video from a few prompts, drawing on vast quantities of data. The focus of the collaborative inquiry is on the implications of genAI for knowledge professionals – those engaged in work grounded in the creation, curation, analysis, interpretation and application of knowledge in various forms. Within the inquiry, perspectives from scientists, lawyers, business managers, publishers, educators and innovators are explored. Environmental scientists spanning many disciplines are involved, sharing their expertise and experience in specialist areas and cross-cutting topics ranging from monitoring to modelling.

Much has been said about the promises and perils of AI: at one extreme, it could save the world; at the other, it could wipe out humanity. As ever, these caricatures are unhelpful, and the collaborative inquiry is drawing out more realistic and practical implications across knowledge professions. Issues raised include whether the environmental costs of using genAI (in terms of carbon and embedded water) might create an ethical dilemma over using AI at all – especially for low-level and general-use cases, such as carrying out simple analytical tasks that only save small amounts of time. How can you be sure about the various claims being made about the promises and perils of AI in the current climate, where it is hard to tell real from false – for example, in the use of deep fake imagery – to skew debates? How can you tell whether genAI has true potential, whether it is just the latest pyramid scheme from untrustworthy big tech, or whether the hype is just idealistic, magical or apocalyptic thinking?

The inquiry has focused deeply on the human aspects, exploring the implications of AI for the work we do, for how we act and learn as workers, and for our workplace settings. A key issue here is the potential dangers of rushing. As we envisage a future that pulls us towards it, do we run the risk of not giving ourselves breathing space to wonder about the impacts of today's choices? Have we taken the time to notice the effects of genAI on us or on how our knowledge-working practices are changing at deeper levels? While we may encourage innovation in AI to secure benefits for the environment, are we doing this with our eyes wide open? What trade-offs are we making and are we innovating responsibly? Are we aware, for example, of the water and energy demand required to cool the servers that deliver the AI outputs? Are these costs justified by the potential benefits we envisage?

Two critical points are helping to frame the discussion. Firstly, we recognise that AI is not a single thing: it encompasses a range of tools, techniques and applications. This starts with machine and deep-learning algorithms and includes everything through to the most recent text-to-video genAI applications such as Invideo or Synthesia. Secondly, we acknowledge that the range and applications of AI are not yet settled – evolution is continuing at pace. So what we are talking about in the here and now is not the final word. Yet we are having to face these issues in the present, learning from the past but with an eye on the possible futures.

THE COLLABORATIVE INQUIRY PROCESS

The future is unpredictable, the more so the further ahead you look. Therefore, at the heart of this inquiry is a foresight process involving a team of researchers scanning and searching for articles in newsfeeds, foresight resources, online journals and blogs around AI technology developments that are pertinent to the knowledge professions. Articles are added to a database and tagged with the core driver behind the change using the PESTLE-V framework (political, economic, social, technological, legal, environmental and values). Scanning huddles are held as informal idea-sharing meetings between selected groups of people to review the main articles of interest, share perspectives and raise questions. Articles are grouped around ideas and concepts based on themes gathered from horizon scanning and the research questions, generating a series of change cards.

Change cards are a way to communicate various threads of emerging change that are gathered in the horizon-scanning stage, often incorporating insights from scanning huddles. Each card is given a title that sums up an identified emerging change (see **Figure 1**). A repeated format is used for each card with sections that explain what it is, how it could change things and what could impact this change, providing reference material for each topic at the bottom of the card. Change cards from this project covered specialised topics within environmental science, such as the use of digital twins for modelling environments, as well as more general themes such as the potential for AI technologies to increase the speed of future workplaces. In this collaborative project, change cards have proved effective in connecting workshop participants with the research process and have fostered engagement during foresight exercises. They become important project artefacts that could be taken beyond the initial projects for which they were designed to prompt ongoing conversations around change and potential actions that may be needed in response.

An online whiteboard is used as a gathering space for conversations and ideas generation – a virtual campfire around which discussions can evolve. These workshops are held with the inquiry collaborators and with participants from a variety of backgrounds, including operational, strategy, regulatory and technical staff. Participants use the 'futures wheels' foresight tool with different groups, exploring a variety

▲ **Figure 1. Example of a change card. (© Jigsaw Foresight)**

of prompts based on the change cards that describe one aspect of a potential future. As an example, the prompt for this change card was: AI tools informed by micro-sensors monitor the health and welfare of wildlife (see **Figure 1**). Participants then think through the different layers of consequences based on the future change assigned to them, later exploring other groups' futures wheels to highlight similarities and differences.[2]

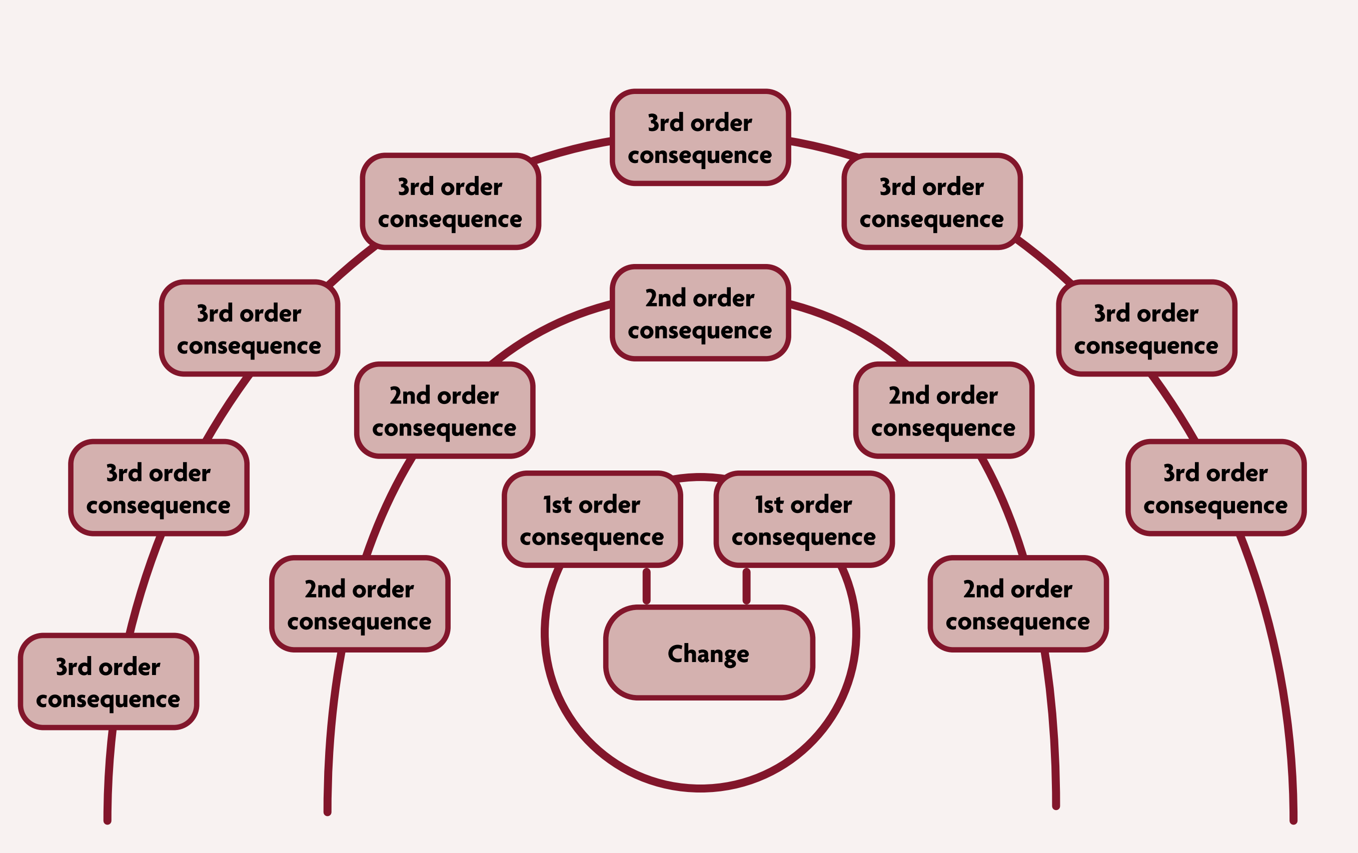
FROM FORESIGHT TO INSIGHT

The foresight process generates a broad range of insights, spanning diverse themes that are shared with project members through change cards and bespoke reports. Issues may be related to data ownership and accessibility, or to bias in the data and how data gaps are handled, affecting confidence in the veracity of AI-generated data, especially where the data sources used are unknown or unclear.

A fascinating issue raised to date has been that of the Habsburg Effect, where AI-generated data distort future AI models, raising implications for the validity of environmental models in all fields – from climate to pollution, and from ecology to oceanography – giving an erroneous sense of how the environment is changing and how it may continue to change.[3] Through one exchange, it is recognised that if AI models are 'too good', it might lead to a phenomenon known as social loafing, where humans do not bother to question them.[4] Instead, they approach AI as a black box or truth engine, and take its outputs at face value, affecting the credibility and legitimacy of decision-making.

Three main themes have emerged from this analysis to date.

Power. Issues are emerging related to who has power in the system, questioning who the winners and losers are in the development and use of AI models, whom they benefit and what counts as 'good AI'. However, there is a sense among the collaborators that AI could also empower more people and democratise the expert space, potentially challenging institutional power. This line of inquiry extends into discussions around the regulation of AI systems and the various ways that human rights could be upheld or ignored as AI models are implemented in society and the workplace. Concerns are being raised that AI use could increase burnout among staff due to the increased speed and quantity of information. As AI technology continues to evolve,



▲ **Figure 2. Futures wheels template (© Jigsaw Foresight)**

it is seen as necessary to regularly engage a wide group of stakeholders to critically assess and gather perspectives on the ground, including from within an organisation's workforce.

Opportunities and threats. There is a lively ongoing discussion on a very wide range of opportunities and threats, related not only to practical-use cases but also to how AI technology is perceived among workers and how organisations might be encouraged to become more digitally mature. While it is widely recognised that the increased scope afforded by AI tools includes unlocking more creative work when mundane tasks are automated, it is also recognised that the opposite effect could arise, where human work shifts from creating meaningful impact to merely being 'factory checkers' and quality controlling the AI outputs (see **Table 1**). The ramifications for expertise feature widely in these conversations, raising questions about what knowledge, skills and behaviours people would need to develop and continue to evolve when working with AI.

Systems complexity. The final theme focuses on the implications arising from the complexity of systems brought together through AI technology. Here, an important emergent point is the potential conflict between different AI systems. AI models are not identical and each could produce different data and results on the same problem or field of research. For example, in ecological management, different AI tools could generate different outputs related to assessing damage to habitats. As such, this could open up a wealth of claims and counterclaims about the validity of a particular set of findings, perhaps with parties cherry-picking models that generate results to suit them. This in turn creates a significant threat to the ambition of evidence-informed decision-making.

REFLECTIONS AND PROSPECTS

Drawing together the breadth and depth of questions emerging and insights being generated through the collaborative inquiry, the project team currently sees a number of overarching issues.

Framing risks and benefits. Clearly, the use and ongoing evolution of AI are opening up a new agenda and asking new questions. But it is also worth noting some themes familiar from previous technological and social disruptions. AI is not a single thing but a plurality of concepts and tools and is not inherently good or bad. There are many shades of grey between risk and benefit, with both intended and unintended consequences. Here, the beholder's eye is critical: one person's risk may be another's benefit.

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How these issues are framed, what narratives are told and what metaphors are used within them has enormous power. It matters not only what is said, but by whom and why. The Royal Society's motto *Nullius in verba* (take nobody's word for it) reminds us to hone and exercise our powers of critical thinking and self-awareness, and not to fall into the trap of seeing AI as a truth engine. In seeking to use AI to help halt and reverse environmental harm in fair and just ways, it is critical that good decisions are made and implemented across different integrations of AI technology. This requires clarity on what matters; acknowledging and attending to the range of different values in play; and the appetite for or stance towards understanding, agreeing and responding to risk and opportunity that different stakeholders may have. Again, we cannot assume that everyone thinks and values the same things in the same ways. Fostering collaboration to seek out and bring to the surface multiple perspectives, to collectively anticipate the future and to consider the wider system becomes key to setting sound strategies and enabling integrated problem solving.[5]

Innovating responsibly. One key factor is how innovation happens. In the context of AI, the collaborative inquiry is recognising that innovation is a continuous process, not a one-off event, requiring ongoing scrutiny and assessment of risks and opportunities. Part of that is being clear about the purposes of innovation and focusing on what needs to be done, not just on what can be done. The inquiry is finding a helpful way to think about this through the framework of responsible research and innovation based around innovation systems that exhibit a culture of continual and iterative anticipation, interaction, reflection and response.[6] The inquiry provides scope for anticipation (through foresight), interaction (through participatory and deliberative processes) and reflection (through discussion groups and working papers). But in the end, this will be effective only if those capable of acting can and do respond in responsible ways.

Preparing for emerging change. We are still at the start of the AI journey. Its evolution continues apace and there is no pre-defined path ahead. The Spanish poet Antonio Machado put it well when he wrote 'We make the path by walking'.[7] While the future of AI is unknown, we can anticipate possible changes. Some of these may be incremental: we can save time by asking genAI to prepare some PowerPoint slides for us. But others may truly be transformative – such as using AI to identify innovative materials with a significantly lower environmental footprint. As we make the path by walking, we would do well to travel with our eyes wide open. Ensuring that organisations are agile and flexible in the face of such rapid and largely unpredictable changes is critical to being well-prepared when those changes unfold. Futurist Maree Conway pointed out in 2018 that 'AI will change the world but it will change the world in different ways depending on what else happens around it'. The future we will not see is one in which everything is exactly the same as it is now, except with AI.[8]

▼ **Table 1. Opportunities and threats of artificial intelligence tools**

Artificial intelligence capability	Opportunity	Threat
AI[a] technology becomes capable of mundane, repetitive tasks unpopular with most workers.	Human workers are liberated to do more meaningful and creative work.	Human workers become quality checkers for AI tools' outputs leading to less-rewarding work.
AI tools become primary sources of workplace expertise.	Workers have better access to information and can upskill quicker.	Human workers are augmented by AI co-workers with increased efficiency and accuracy.
AI agents work alongside human workers in various workplaces.	The detachment of professional knowledge from the human experience adversely affects quality.	Hybrid teams of humans and AI agents disincentivise human workers to work to their full potential.

[a] AI = artificial intelligence

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Building, governing and maintaining the infrastructure system. While data scientists and computer engineers develop increasingly sophisticated technology, we must be able to shape those developments in responsible ways through effective governance and decision-making. It is key that people should have ready access to fundamentally useful and reliable technology.

But even as we see better technology we also need better humans and more empowering views of humans and how we approach the work we do – not just as drones waiting to be replaced or to be absorbed by an AI algorithm. In the end, AI is human intelligence. If we wish to actively shape and use AI to fulfil its promises and to avoid its perils, we need to become more active in our own learning and development. We need to be setting out, teaching and adopting a broad suite of competencies, and to be promoting equity and inclusion as we shift to a new working paradigm.

Underpinning all this is the need to devise better governance: linking needs, knowledge and capabilities through a purpose- and values-led approach across technical, social and legal issues; embedding traceability and accountability; and transforming data and information into knowledge and insight. We know from bitter experience that, despite our best intentions, technology can go wrong and can be used for nefarious purposes. As such, the systems we develop to enable responsible use of AI need to be resilient, enabling us to prepare for shocks and surprises and to counter the influence of bad actors intent on harm through deliberate actions such as spreading disinformation.

It is worth noting that the emergence of AI has happened hard on the heels of a shift to remote working due to the pandemic, which means that the longer timelines needed for responsible innovation have been lost in the turbulence of the recent past. There is merit, therefore, in taking the time to look further back and to look further forward into a range of possible futures to deepen and broaden our appreciation of the context for the choices we make today.

ES

Peter Humphrey is a research director and creative producer at Jigsaw Foresight. He has a PhD from the University of California, Berkeley in musicology and new media and has been leading research and creative projects for Jigsaw Foresight around technology and media.

Gary Kass is a Fellow of Jigsaw Foresight, a Vice President of the IES and chair of the IES External Policy Advisory Committee. He is a visiting professor in environment and sustainability at the universities of Surrey and Royal Holloway. Until September 2023, he was Deputy Chief Scientist and Deputy Director for Foresight and Innovation at Natural England.

Victoria Ward is the co-founder of Jigsaw Foresight and has worked at the forward edge of organisational change, narrative at work and knowledge management for over 25 years. With a background in finance, she has held roles such as head of research, chief operating officer and chief knowledge officer and has done terms on the FTSE 100 Index Steering Committee, the board of the London International Financial Futures and Options Exchange, and the Financial Services Tribunal.

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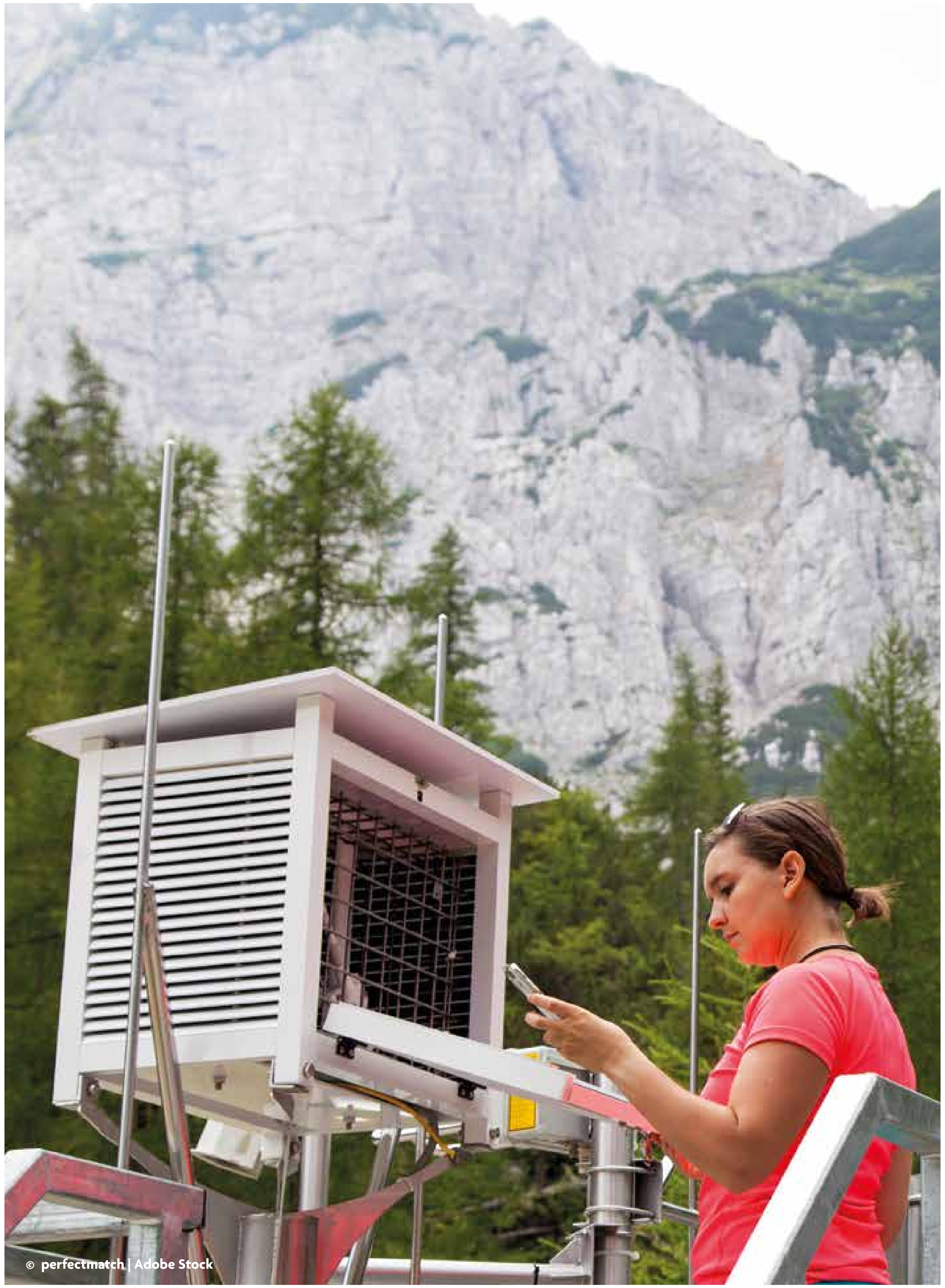
TECHNICAL

An introduction to artificial intelligence weather forecasts

Kieran Hunt reveals the ways in which technology is tackling the complexities of forecasting for cheaper and more accurate results.

Humans have a natural affinity for the weather and have speculatively predicted it for as long as they have observed it. Unfortunately, accurate weather forecasts – once we move beyond fail-safe lore around red-sky timing or St Swithin's Day – require computers that can ingest current weather conditions from global observational networks and evaluate a list of complicated differential equations at thousands of grid points in order to wind the clock forward.



TECHNICAL

THE FIRST WEATHER FORECASTS

It has been a little over a hundred years since the first serious effort to do this by hand: it took L.F. Richardson six weeks to produce a six-hour weather forecast for Central Europe, and it was a catastrophic failure.[1] In his 1922 book, Richardson envisaged a future where 64,000 human 'computers' would manage this task, passing endless slips of paper to each other under supervision.[2] Fortunately, the invention of the transistor prevented this, and Richardson's ideas, which were ultimately correct, could be automated in a process that came to be known as numerical weather prediction (NWP).

This process remained – albeit with many subsequent methodological tweaks and improvements – state-of-the art in weather forecasting for the next century. Until about 18 months ago.

THE RISE OF ARTIFICIAL INTELLIGENCE

The recent, swift rise of artificial intelligence (AI) has come about from remarkable and coincidental advances in hardware, through the rapid production of high-specification graphics processing unit (GPU) chips that neural networks run on; software, including transformers that drive large language models like ChatGPT; and diffusion models that drive image generators like Midjourney.

Few areas of research have been immune from AI during this revolution, and weather forecasting is no exception. But why is AI relevant to weather forecasting? After all, we know the equations that govern the fluid motion of the atmosphere and we have supercomputers that can integrate these equations forward in time with typically very high accuracy (despite the common refrain about UK rainfall forecasts).

As is usually the case with AI, the answer lies in the data. Weather observation networks have global coverage and are dense in both space and time. For historical weather, these are conveniently blended in a dataset known as a reanalysis, which in effect uses a physics-based model to fill in the gaps between heterogeneous point-based measurements taken at the surface or in the atmosphere (e.g. weather stations, weather balloons, research aircraft) and asynchronous but broader observations from satellites.

The most widely used of these reanalyses, ERA5, which was developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), has an hourly output on a 0.25° (approximately 25 km) grid, with 137 atmospheric levels, for each quantity of interest (e.g. temperature, humidity, wind speed).[3] Running these numbers comes to about 3 billion data points per hour for data that stretch back decades. This is a big-data puzzle, perfect for AI models or, as they are synonymously known, data-driven models.

We therefore have all the ingredients necessary – hardware, software and an enormous high-quality dataset – to make this a potentially workable problem for AI. Through recent initiatives such as WeatherBench, we now even have a universal set of standards through which we can compare relative model performance.[4]

This only explains why we can use AI, not why we should. Fortunately for the sake of scientific endeavour, NWP models are flawed. They are extremely expensive to run, with global 10-day forecasts requiring many hours of supercomputer time to compute. This means they cannot be run frequently, are (often) carbon intensive and are ring-fenced – for instance, only one of the world's top 500 supercomputers is found on the African continent, effectively preventing African forecasters from running cutting-edge models.[5] Yet once trained, AI models require only a minuscule fraction of these resources to produce a forecast.

NWP models are also limited by their resolution: any process that occurs at scales smaller than a single grid cell (i.e. 10–20 km) must be parameterised. In other words, the accumulated effect of such 'sub-grid' processes must somehow be estimated for each grid cell since they cannot be explicitly resolved. Even in high-resolution NWP models, this includes many important processes, such as convection, turbulence, water phase changes, and the interaction between the atmosphere and incoming solar radiation. Many parameterisations are heuristic or empirical, requiring approximations that lead to forecasting errors.

AI models are not decoupled from this problem, but as heuristic solvers they offer an opportunity to improve the representation of sub-grid processes beyond the current limit of human insight. This begins at the artificial neural network (ANN) level (which is synonymous with deep learning) and is further refined through the specific architectures that current state-of-the-art AI models use.

ARTIFICIAL NEURAL NETWORKS

ANNs consist of layers of units that process information sequentially. This starts with the input layer in which each unit represents an individual feature of the input data (e.g. surface temperature at a particular grid point). There is then at least one hidden layer, where every unit receives input from each of the previous layer's units, adds them in a weighted sum and does a quick computation on the final value. This is known as an activation. If a network has many hidden layers, then it is referred to as deep. Finally, the output layer receives input from the last hidden layer and, using the same method, converts it into a value or set of values that we are interested in (e.g. surface temperature in six hours' time).

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But what are activation functions, and how does the model know what weighted sums to use to achieve a useful output? Each connection between units in neighbouring layers is associated with a weight, and each unit in each layer is also associated with a bias. Each unit multiplies the outputs from the previous layer by their respective weight and adds them together with the bias to produce a pre-activation value. If the process stopped there and did not include an activation function, it would only be able to find linear input–output relationships; in other words, it would be little more than a glamourised best-fit line. The activation functions can take a range of forms, but one of the most common in regression tasks, such as weather forecasting, is the rectified linear unit – which is zero if the input is negative, and equal to the input if positive.

All the model has to do is find the right set of weights and biases (these are the only things that can change during training) in order to get an output as close as possible to the right answer. There is a very large body of research on the optimal way to find the right set, but at its core, it hinges on a premise from high-school calculus: the chain rule. Effectively, the model runs and produces an answer; we measure how far away it is from the truth, then apply the chain rule to determine which weights and biases are needed to adjust and by how much to get a little closer to the truth.

ANNs are remarkably powerful tools – they can approximate any mapping between the input and the output. This is a crucial result in machine learning theory, known as the universal approximation theorem, which states that a neural network with at least one hidden layer can approximate any continuous function to any desired level of accuracy, given sufficient neurons in the hidden layer. However, in weather forecasting it is not just the input data themselves that are important, but the relationships between them in time and space (which can be easily checked by looking at the underlying equations). Basic ANNs are very poor at using information about these structures, and therefore require more advanced architectures.

TRANSFORMERS

Transformers rely on two innovations: embedding and attention. Embedding is a way of representing something defined by a huge number of data points by effectively using a much smaller number of data points (the terms dimensionality reduction and latent space have similar meanings in this context). For example, imagine you had an unlabelled photograph of every animal species in the UK and you wanted to use a computer to find a frog. Rather than writing software to look at every pixel to find frog-like structures, it is much easier to embed the image and look for green animals smaller than six inches with webbed feet and protruding eyes.

Attention is a mechanism that allows a model to dynamically focus on specific parts of the input data, improving its ability to understand relationships between different parts of the input. Consider two slightly different sentences: 'the squirrel jumped into the pond; it was cold and wet' and 'the squirrel jumped into the pond; it was running away from a cat'. A regular ANN would (incorrectly) treat the 'it' in the same way in both cases, whereas an attention mechanism can learn the context: that it is related to the pond in the first instance and to the squirrel in the second.

By stacking (often many) transformers together, they become powerful context engines that can learn complex relationships within the input data. They have been most widely used for language tasks (e.g. in translation and as chatbots) but have recently been applied to vision tasks (known as vision transformers), where they can learn information about the spatial structure of the input. Vision transformers apply a special embedding (patch embedding), which encodes local regions and their structures in a similar way to conventional embedding for words (as in the squirrel example). It is this feature that makes them potentially very useful for weather forecasting.

GRAPH NEURAL NETWORKS

Graph neural networks (GNNs) comprise nodes (e.g. people in a social network), edges (e.g. friendships or family relationships in a social network) and features (e.g. characteristics of the people in the social network, such as age). Like transformers, this information is usually embedded, such that the representation of each node contains information on the characteristics of the node itself, its relationship to its neighbours and even the structure of the graph as a whole.

Subsequent layers of the GNN then allow the nodes to pass messages to their neighbours and update accordingly, much like the units in a conventional ANN, except that information about the edges and graph structure are also used and distant nodes cannot communicate unless it is done across many layers.

In contrast to a transformer, where the structures within the input data are learned, a GNN represents these structures explicitly. This architecture is conveniently analogous to a weather forecast, where the weather depends on its local neighbourhood in the short term but on the whole globe in the long term.

THE BIG THREE

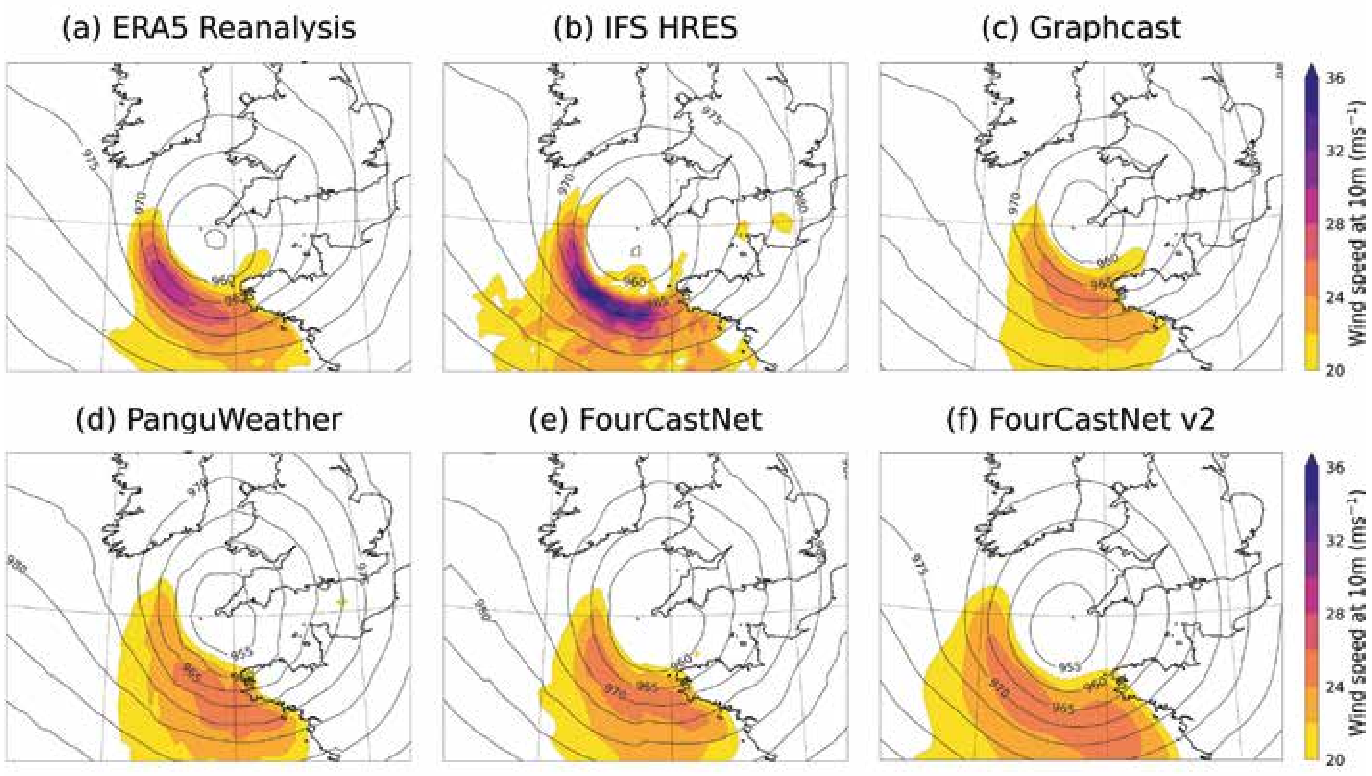
There were several early efforts to develop a global forecasting model using AI.[6,7] However, due to hardware limitations, these models had much coarser resolutions (around 200 km and 600 km between each grid point, respectively) than contemporary operational NWP models and, therefore, could not resolve many types of weather events or beat the skill of conventional systems. The problem attracted interest from large private sector companies with significant computing resources. This led to the emergence of three competing models that could leverage the full resolution of the ERA5 training dataset (at a resolution of 25 km), each showing comparable skill to the physics-based market-leading forecasting model: ECMWF's high-resolution (HRES) Integrated Forecasting System (IFS).

FOURCASTNET

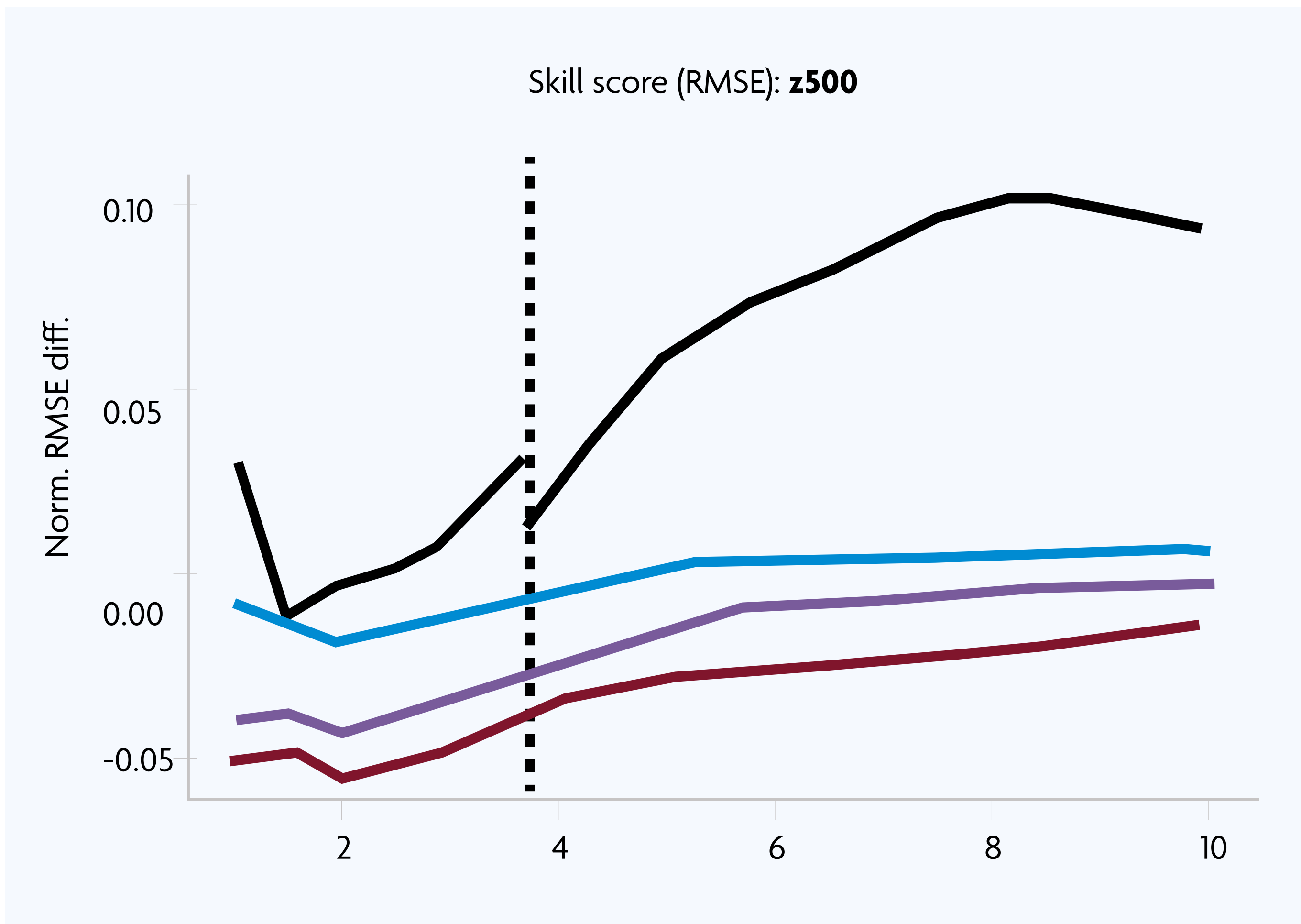
Released in early 2022 by a team largely led by scientists from GPU manufacturer Nvidia, FourCastNet was the first AI global forecasting model to pose a genuine challenge to state-of-the-art physics-based models.[8] 'Four' stands for Fourier transform, a process that converts signals in time and space into information about all the different waves needed to build that signal, and that is ingeniously used here as an embedding.

Put simply, the FourCastNet model encodes the input in a patch embedding, runs a Fourier transform, applies a conventional ANN, then unpacks the Fourier transform and embedding to produce an output. This method, in a like-for-like comparison with contemporary physics-based models, computes forecasts 45,000 times more quickly and with comparable skill.

However, if the model were trained to first predict the weather six hours in advance, then to run a 10-day forecast, the model's own output would have to be applied a further 39 times, resulting in rapidly growing, compounded errors. To mitigate this, the model was trained on both six-hour (i.e. running the model once) and 12-hour (i.e. running the model again on the six-hour output) forecasts. A recent update (FourCastNet v2) improves the way the Fourier transform is computed, more accurately reflecting the spherical geometry of the Earth.



▲ **Figure 1. Maps of 10 m wind speeds (shown as shaded areas) and minimum sea level pressure (shown as contours) at 00:00 UTC on 2 November 2023 from (a) ERA5 and from forecasts initialised at 00:00 UTC on 31 October 2023 from the (b) Integrated Forecasting System high-resolution model and (c–f) artificial intelligence models, as labelled. (Source: Charlton-Perez *et al.*[14])**



▲ **Figure 2. The effect of training GraphCast on more data. Each coloured line represents GraphCast trained with data ending before a different year, from 2018 (blue) to 2021 (purple). The y-axis represents root mean square error (the lower, the better) on 2021 test data, for 500 hPa geopotential height (approximately 5,000 m above sea level), compared to GraphCast trained before 2018, over a 10-day lead time (x-axis). (Source: Lam *et al.*[10])**

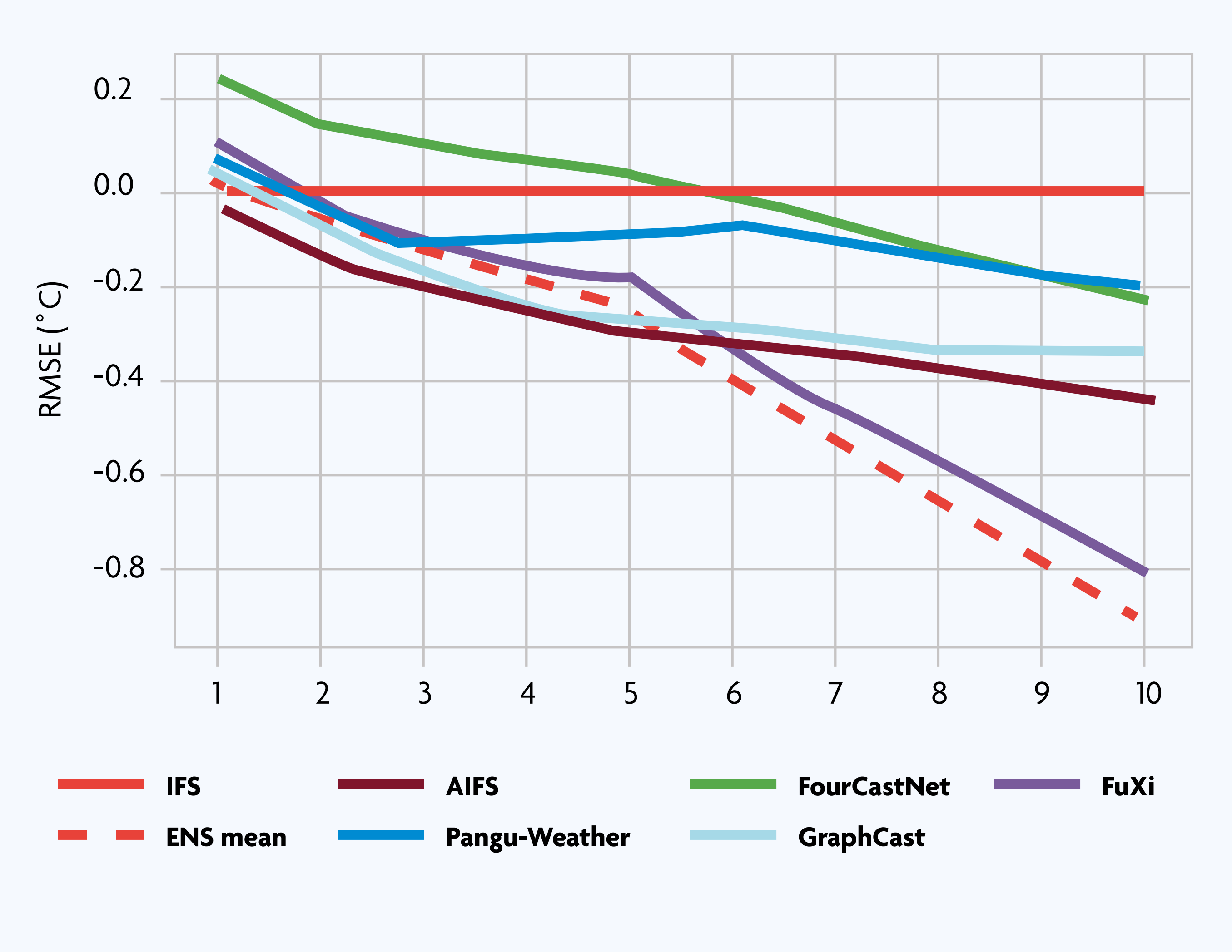
PANGU-WEATHER

The second model, Pangu-Weather, was released by a team of Huawei scientists about eight months after FourCastNet.[9] Pangu is the name of a mythological Chinese figure, said to have separated the Earth, sky and humans, who after death became clouds, rivers, lakes, land, the sun and the moon. Pangu-Weather is an impressive innovation but does not yet live up to its namesake.

Like FourCastNet, the backbone of Pangu-Weather is a stack of vision transformers (16 in total) with two special adaptations. The first, quite common in vision transformers, is shifted window attention; in other words, the patches used for embedding in each layer shift position in each subsequent layer, allowing information to pass more effectively between neighbouring regions. The second, unique to Pangu-Weather, is to include information about where on the Earth the region is directly into the embedding in what is called an Earth-specific transformer. To mitigate the accumulation of errors by running the model recursively to produce long forecasts, the developers trained the model separately for a range of lead times between one and 24 hours, meaning longer lead times need less recursion. The developers estimated that Pangu-Weather runs about 10,000 times faster than the IFS.

GRAPHCAST

GraphCast was released by scientists from Google in the summer of 2023. Unlike the other two models, GraphCast (and here the hint is in the name) relies on GNN architecture rather than on vision transformers.[10] The graphs are six icosahedral meshes (think, roughly, a standard football size or, if you are more inclined to tabletop games, a 20-sided die) of varying resolution. These meshes are allowed to interact with each other over the course of 16 layers, and so information can be passed between nodes locally (on the finest mesh) or globally (on the coarsest mesh).



▲ **Figure 3. Difference with respect to the Integrated Forecasting System statistics: root mean square error (the lower, the better) for temperature at 850 hPa (approximately 1,500 m above sea level) averaged over 1 June–31 August 2023 in the northern hemisphere. (Source: European Centre for Medium-Range Weather Forecasts[15])**

OUTLOOK

These AI models often offer forecasting skill that is comparable to the best physics-based models, even for extreme events (see **Figure 1**). So what is the advantage of this? Perhaps the biggest current advantage is speed – producing a 10-day global forecast with the IFS takes hours and uses hundreds of supercomputer nodes. The same forecast with any of the Big Three can be done on a high-spec gaming laptop in about two minutes.

This means significantly less carbon produced (about 12,000 times less, as estimated by the FourCastNet developers[8]); much larger forecasting ensembles (running the model many times helps to quantify forecasting uncertainty); potentially frees up supercomputer resources for other research projects; and opens the way for democratising weather forecasting. There are other subtle advantages as well. As more historical data become available (e.g. through projects like Weather Rescue, which seeks to digitise the millions of weather records found in old logbooks), more training data can be produced and AI models can continue to be improved (see **Figure 2**).[11] Conventional NWP models, relying on programmed physics, do not have that ability. AI models also have advantages when it comes to parameterisations and representing unknown variables or processes.

So is this the end of physical models? Well, not quite yet. Firstly, one of the great forecasting innovations of the last several decades, data assimilation – whereby observations and their measurement uncertainties are actively fed into and adjust forecasts – is still very primitive in AI models. Crucially, this means that AI models cannot yet be readily used to produce reanalyses (the datasets used to train AI forecasting models) because, among other issues, these rely heavily on data assimilation.

Secondly, any persistent errors (known as biases) in the training dataset get baked into the AI model – for example, if the reanalysis used for training underestimates temperature over the Pennines so, too, will the forecasts. Thirdly, AI models are very expensive to train – a requirement when new data become available. Even then, they immediately suffer from non-stationarity: the environment starts to deviate from the world the model was trained on. This is not, perhaps, an issue with near-term climate change, as the model should have a reasonable grasp of thermodynamics. However, increasing the amount of concrete covering the Earth's surface changes radiative feedback in a way the model cannot anticipate without new training data.

The inexorable and rapid rise of AI means that some of these issues are already being tackled in the next generation of AI forecasting models (see **Figure 3**). This includes ECMWF's own Artificial Intelligence Forecasting System (ensemble forecasting), Google's GenCast (ensemble forecasting using diffusion models) and Fudan University's FuXi (data assimilation).[12,13]

AI has effectively won the war with conventional weather models. The next frontier? Climate models. ES

Kieran Hunt is a senior research scientist in tropical meteorology and AI at the University of Reading. Throughout his career, he has focused on trying to better understand and predict extreme rainfall events in the tropics using a variety of methods, including machine learning. He has taught extensively on machine learning applications in meteorology.

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FEATURE

Lens on the wild: innovations in wildlife monitoring with machine learning

Benjamin C. Evans, Marcus Rowcliffe, Chris Carbone, Emma L. Cartledge, Nida Al-Fulaij, Henrietta Pringle, Richard Yarnell, Philip A. Stephens, Russell Hill, Kate Scott-Gatty, Chloe Hartland and **Bella Horwood** show how applying artificial intelligence techniques to study hedgehogs can be applied to animal research more widely.

Hedgehogs, one of the UK's most loved creatures, have substantially declined in number over the last 50 years.[1] The National Hedgehog Monitoring Programme (NHMP) has completed its pilot year, marking the first milestone of a three-year endeavour to better understand the causes of this decline and, ultimately, to monitor the status of other wildlife populations across the UK.

IMAGE IDENTIFICATION AND LABELLING

The NHMP uses camera traps, small units that automatically capture sequences of images akin to short video clips when a passive infrared sensor detects movement in front of the lens (see **Figure 1**). The programme works in a large and growing number of survey areas across the UK, distributing cameras

▲ **Figure 1. A camera trap set up in a forested area to monitor wildlife activity as part of the National Hedgehog Monitoring Programme. (© National Hedgehog Monitoring Programme)**

systematically within each site and deploying them at each location for around a month, providing a glimpse into the life of hedgehogs and other wildlife without the need for challenging nocturnal observations by people. To turn these glimpses into useful information on the size and distribution of wildlife populations, an analysis pipeline is being built that draws on tools from a unique combination of artificial intelligence, citizen science, photogrammetry, data science and statistics.

The NHMP expects to collect millions of images each year using camera traps, and the number will continue to grow as more survey sites are added. This creates the first challenge: to label images that contain animals and, if so, which species. For project staff to look at each image and create the labels would take an impossible amount of time. Harnessing developments in machine learning and computer vision using an ensemble of models to detect whether sequences of images contain animals, deployed alongside citizen science, makes this task easier.

Detection models aim to predict the object type and its localisation within an image, producing a box around the desired object (see **Figure 2**). The models in use consist of the MegaDetector, an open-source generalisable detection model trained to detect animals, humans and vehicles in camera trap imagery, along with Conservation AI, an ongoing endeavour to produce detection models with finer-grained classification of image regions down to species level.[2,3] It has been found that this combination can reduce the image sets requiring further

FEATURE

processing by up to 70 per cent, saving large amounts of annotation time. Both models are accessible with user-friendly packages, including CamTrap Detector and the Conservation AI web interface.[4]

APPLICATION OF CITIZEN SCIENCE

After filtering the images to those that contain animals, the imagery is made available on the MammalWeb platform, a citizen science website dedicated to tagging camera trap imagery.[5] This platform shows one sequence at a time, allowing users to flick between images and respond with the species seen. Algorithms are currently under development that prioritise the images shown to citizen scientists based on the degree of certainty in the machine classifications, allowing human spotters to correct the sequences that are most likely to be misclassified by the machine. Combining machine and citizen science techniques in this way capitalises on the strengths of each to complete the task rapidly and accurately with minimal human labour.

EXTRAPOLATING TO STUDY SPECIFIC SPECIES

Once all images are classified on the MammalWeb platform, those containing hedgehogs are exported, together with their metadata, in Camtrap DP data format. This standard for working with camera trap data has been developed over the last two years, providing portability and interoperability between platforms and tools.[6] Until now, many platforms and organisations employed their own methods and formats for storing camera trap data, hindering collaboration and data processing. The camera trap data standard allows for a collaborative ecosystem of digital technologies in wildlife monitoring projects, with the wider benefits of improved data accessibility and the reproducibility of published results.

The next step in the pipeline uses the Agouti platform to estimate the positions of animals.[7] This process uses a combination of calibration imagery created at the time of camera deployment and a pinhole camera model to create a depth map for each image (see F**igure 3**). From this, the position of each animal within the image can be translated into a real-world position in front of the camera. Furthermore, positions across sequences of images can be linked together to estimate animal speeds.

As the approach is refined, one promising area of research is incorporating direct image-to-depth models, which are deep-learning models trained to predict a depth map directly from an image.[8] In principle, it should be possible to combine these techniques with an object-detection model in a way that greatly reduces the human labour required for this task. More work is needed to develop and refine this approach so that it becomes fast and reliable, with limited human interaction; possible solutions for this are currently under evaluation.

▲ **Figure 2. Image of a hedgehog (*Erinaceus europaeus*) captured as part of the National Hedgehog Monitoring Programme, tagged using artificial intelligence. The camera trap detected and identified the hedgehog, highlighting it within a green box. (© National Hedgehog Monitoring Programme)**

Finally, the data exported from Agouti are processed to estimate animal density, which can then be used to evaluate variations across the country in response to differences in the environment or in management techniques. This is done using the random encounter model, a statistical technique for estimating the abundance of wildlife from camera trap data when individual animals from images cannot be identified.[9] The method works by using a process derived from physical gas modelling to extract a density signal from the camera trap rate while controlling for confounding factors – in this case, the size of the camera detection zone and the speed of animal movement, which was generated in the previous step. The link from Agouti to analysis is again facilitated by using the Camtrap DP data standard, making it possible to draw on emerging statistical packages that make it easy to generate abundance outputs from this form of data.

The NHMP's use of innovative technologies and public engagement is paving the way for more effective large-scale wildlife monitoring. By harnessing the power of machine learning and citizen science, we can gain deeper insights into the processes driving changes in hedgehog and other wildlife populations and implement better conservation strategies for them. Ensuring these technologies are open and accessible to all will be crucial to expanding their impact and fostering a collaborative approach to wildlife conservation.

▲ **Figure 3. Camera trap image showing the calibration process, a straight pole with markings every 20 cm for building a 3D depth map used in the random encounter model for estimating density. (© Zoological Society London)**

GET INVOLVED

If you would like to help with this crucial task, you can spot hedgehogs and many other wildlife species as part of the MammalWeb NHMP project.

Visit www.nhmp.co.uk for more information. ES

Dr Benjamin C. Evans is a postdoctoral researcher at the Institute of Zoology at the Zoological Society of London (ZSL) and specialises in developing machine-learning methods for conservation. He focuses on automating density estimation and creating data pipelines for the NHMP. His earlier research involved developing an end-to-end semi-automated camera trap pipeline with advances in multi-frame detection and generalisable species classification methods.

Benjamin.Evans@ioz.ac.uk
@bencevans
https://bencevans.io

Professor Marcus Rowcliffe is conservation scientist at the Institute of Zoology, ZSL. He specialises in biodiversity monitoring using advanced technologies such as camera traps, drones and acoustic sensors. Marcus has developed key statistical tools for estimating animal abundance. His work spans urban wildlife in the UK to endangered species conservation globally.

Marcus.Rowcliffe@ioz.ac.uk
@marcusrowcliffe

Professor Chris Carbone is a scientist at the Institute of Zoology, ZSL. His work combines theoretical and practical research in ecology, focusing on body size, diet and human–wildlife interactions. He founded the London HogWatch project and has published on a wide range of topics focusing on mammalian ecology and biodiversity.

Chris.Carbone@ioz.ac.uk
@tigerfoodman

Dr Emma L. Cartledge is a research fellow at Nottingham Trent University, and was involved in setting up the NHMP. Emma's research interests lie at the interface of conservation science and practice. Her recent work has focused on mammalian population monitoring and survey methods.

emma.cartledge@ntu.ac.uk
@EL_Cartledge

Nida Al-Fulaij is Chief Executive Officer at the People's Trust for Endangered Species (PTES), a UK-based wildlife organisation. She is a committed conservation leader with over two decades of experience funding and managing evidence-based conservation projects in the UK and abroad, supporting research and practical conservation on endangered species and threatened habitats. As Co-Chair of the International Union on the Conservation of Nature's (IUCN) National Committee UK Species Survival Working Group and a member of the IUCN Species Survival Commission Small Mammal Working Group, Nida has a particular interest in small mammal monitoring and conservation.

Nida.al-fulaij@ptes.org

Dr Henrietta Pringle is the NHMP's Project Coordinator at the PTES and the British Hedgehog Preservation Society. Experienced in using large-scale citizen science datasets to explore drivers of population change in birds and other species, Henrietta now focuses on the data collection side of the process, working with volunteers and biological recorders.

Henrietta.pringle@ptes.org
@HenPringle

Dr Richard Yarnell is Associate Professor in Ecology at Nottingham Trent University. He has research interests in conservation and ecology, with a focus on hedgehogs in the UK. He uses remote sensing cameras and movement loggers to understand variability in population size across regions and how individual animals select and use habitats.

Richard.yarnell@ntu.ac.uk

Professor Philip A. Stephens is an ecologist at the Department of Biosciences at Durham University. His research focuses on population ecology and monitoring, including the use of citizen science to inform biodiversity management and conservation.

philip.stephens@durham.ac.uk
https://orcid.org/0000-0001-5849-788X

Professor Russell Hill works at the Department of Anthropology at Durham University and is a Director of MammalWeb. Russell's research interests span predator–prey interactions, biodiversity conservation, and interdisciplinary approaches to understanding human–wildlife interactions.

r.a.hill@durham.ac.uk
https://orcid.org/0000-0002-7601-5802

Kate Scott-Gatty manages the London HogWatch project at the Institute of Zoology, ZSL, a London-based hedgehog conservation project. She specialises in urban biodiversity monitoring using camera traps, and her previous work focused on trends in global biodiversity.

Kate.Scott-Gatty@ioz.ac.uk

Chloe Hartland is a researcher at London HogWatch. Her research interests are in urban biodiversity monitoring, ecology and the use of population genomics for wildlife conservation and management.

Chloe.hartland@ioz.ac.uk

Bella Horwood is a researcher at London HogWatch. Her interests include bridging urban conservation efforts with inclusive community engagement initiatives.

Bella.horwood@ioz.ac.uk

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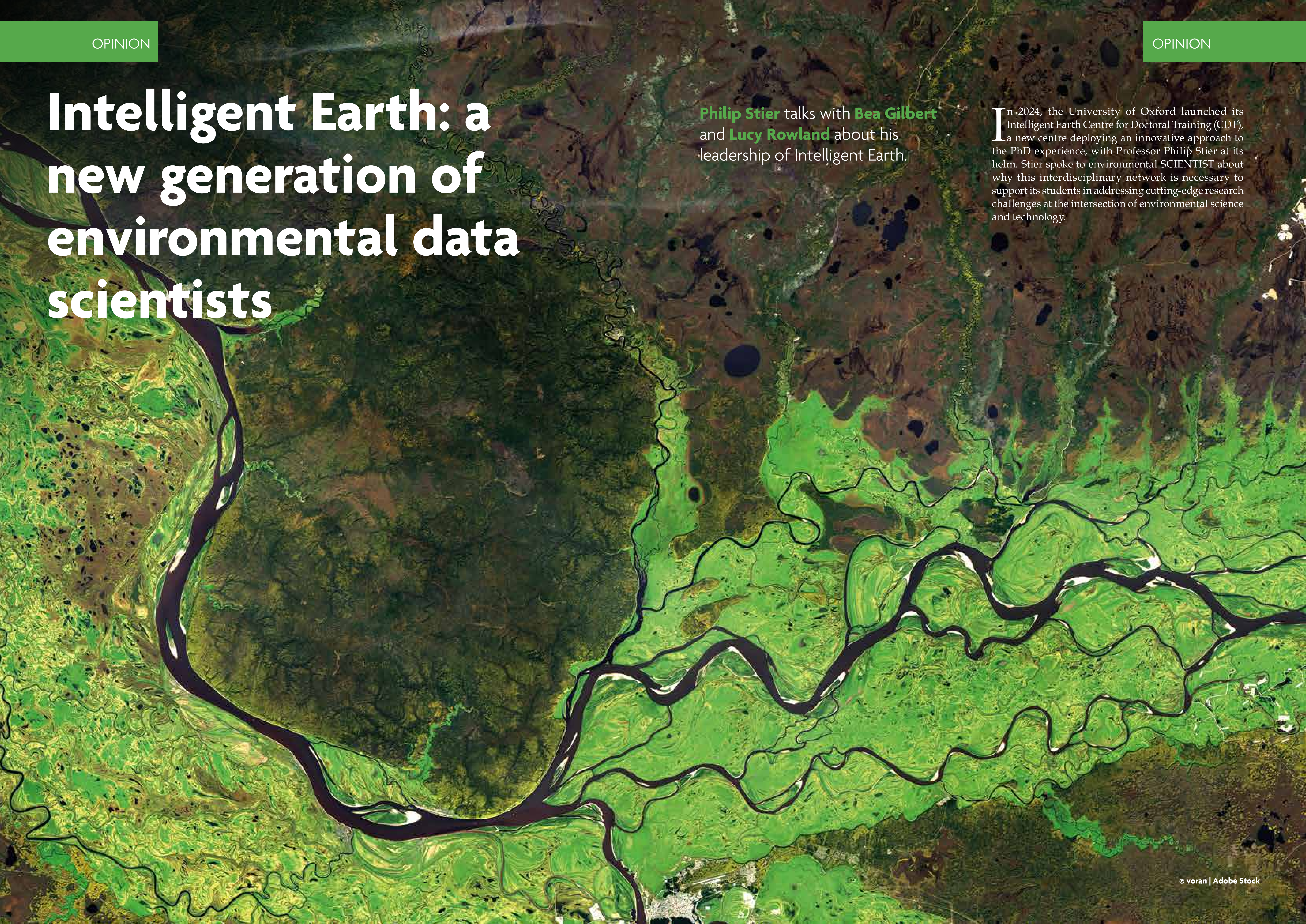
OPINION

Intelligent Earth: a new generation of environmental data scientists

Philip Stier talks with **Bea Gilbert** and **Lucy Rowland** about his leadership of Intelligent Earth.

In 2024, the University of Oxford launched its Intelligent Earth Centre for Doctoral Training (CDT), a new centre deploying an innovative approach to the PhD experience, with Professor Philip Stier at its helm. Stier spoke to environmental SCIENTIST about why this interdisciplinary network is necessary to support its students in addressing cutting-edge research challenges at the intersection of environmental science and technology.



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LUCY ROWLAND:
Could you tell us a bit about the impetus behind Intelligent Earth, how it got set up and the drivers behind its creation?

PHILIP STIER:
I'm a climate physicist myself, and we tend to work with climate models, including a lot of satellite datasets, observations from aircraft, and observations from all kinds of other modalities. As a community, we've done quite a good job in this area, but we're increasingly limited by our ability to interpret the ever-growing data. The datasets are extremely big and extremely complex, and we currently use only a tiny fraction of the information we're getting.

I've grown into the field of artificial intelligence (AI) and machine learning, which is one way to extract more information from the data; but it's also a way to understand the data better. You can use these AI and machine-learning tools to learn something about the data and its structure. That's my own perspective, but it's true for pretty much all environmental sciences, as the field has taken off exponentially. I've just come back from EGU [European Geosciences Union] recently, where our machine-learning AI sessions are exploding. We have to get bigger and bigger rooms each time, so it's a really hot topic.

It's clear that there's a training need; there's a lot of people who like the idea of using AI but they don't know how to do it, and there's people who do use it, but don't know how to use it well.[1] This is the impetus behind Intelligent Earth – we see a real need for students to be trained in depth. You see quite a few programmes or initiatives where people just take off-the-shelf tools and apply them to environmental science questions. While that's a really useful approach for some questions, and we don't criticise that at all, we think students should know more about the tools: they need to have a more in-depth understanding about the methods they use and, ultimately, they should work to improve these methods.

The reason this can be so fruitful is because the datasets that we have are so big, and they are so complex that it's a real challenge for AI and machine learning. For example, we currently have about an exabyte of Earth observations data, which is a huge amount of data to train AI models on. Conventional AI methods often work on fairly small image tiles, which can be a challenge for climate applications. Therefore, the AI-based data-analysis tools don't exist so we see this gap as a real development cycle: a way to use AI and machine learning to improve environmental sciences and speed things up. We don't have a lot of time, and we need to make a lot of progress. At the same time, we need to see this development cycle as a way to improve AI itself, because we have really interesting and complex questions to answer, which is what gets our AI colleagues engaged.

BEA GILBERT:
How do you think the CDT programme is going to help foster interdisciplinary and systems thinking, and connect its researchers to wider issues beyond their individual research projects?

PHILIP STIER:
Interdisciplinarity is really baked into the whole setup of the CDT. In the EU-funded Marie Skłodowska-Curie Innovative Training Network (ITN) iMIRACLI we've already developed some of these ideas. So we really see how it can work: the CDT is intrinsically interdisciplinary.

Every student will be supervised by two academics: one specialist in AI or machine learning, and one in environmental sciences. Aside from giving the students a fantastic training experience, this will also get the academics working together, and the best way for people to work together is through co-supervision. It's a natural way of collaborating, so each student will have an intrinsically interdisciplinary focus. Each PhD project will span the full project interface of AI in the environmental sector, but it can sit in either domain. It can be sitting in biodiversity with machine learning involved, or it could be fundamentally AI developed with environmental science applications involved. It really depends on where the student, and their project, lands.

The CDT has five core themes: climate, biodiversity, natural hazards, environmental solutions and AI. The core AI theme is one of the most important and what


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makes it interesting to AI academics. Many programmes just apply off-the-shelf tools to environmental sciences, which are typically 20 years old; that doesn't get my colleagues in AI departments excited! But working on cutting-edge, emerging technologies does.

In terms of going beyond their individual projects, in addition to the dual supervisors, students will also have an adviser from one of our non-academic partner organisations so they can experience the world outside of academia. These advisers come from industry, non-governmental organisations (NGOs), conservation and research labs. This way, students will also be exposed to a much broader set of ideas, such as responsible AI.

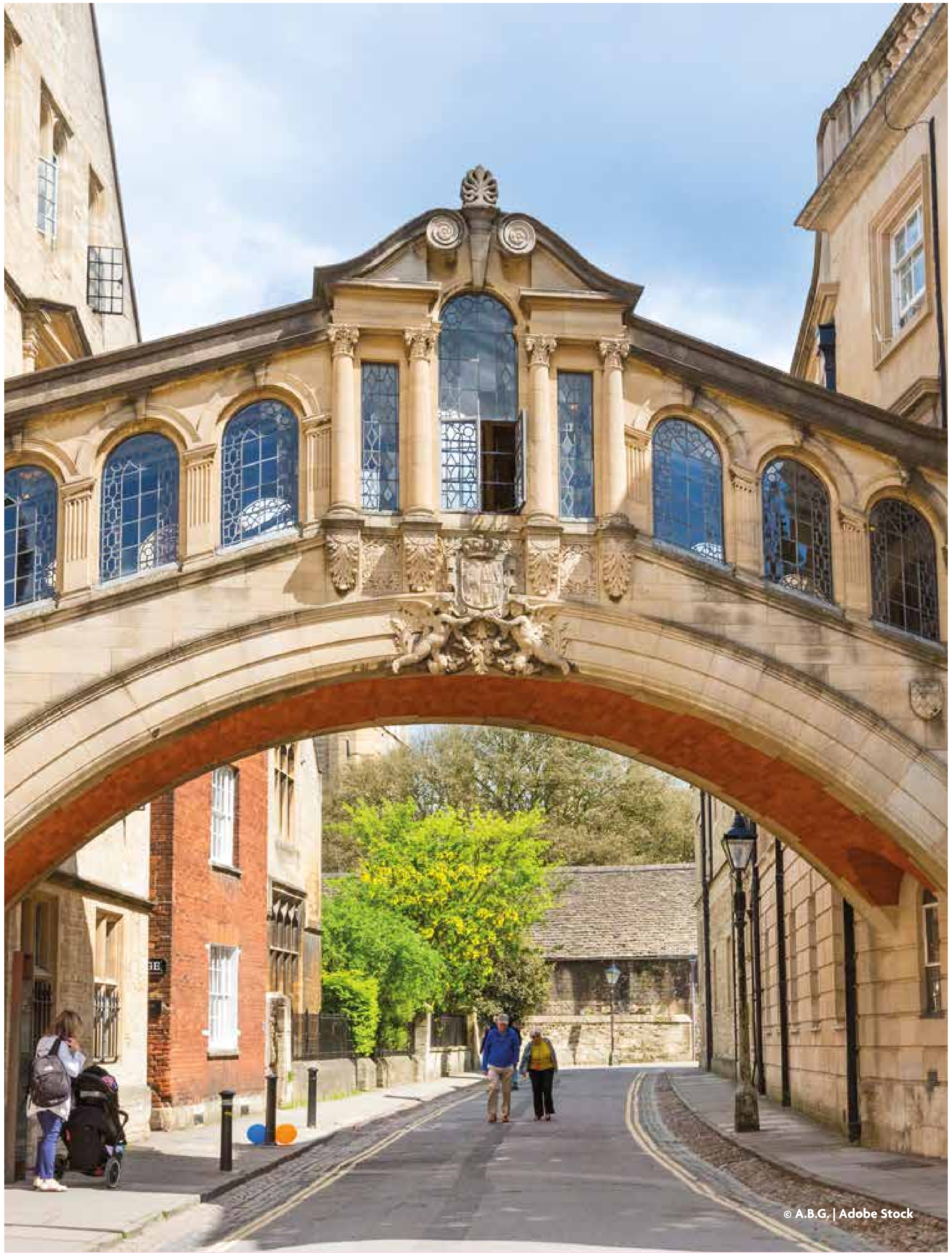
Another thing that distinguishes Intelligent Earth from other doctoral research centres is that students won't have to decide on their PhD project until the end of year one. They will get exposed to many different ideas in that first year, and they can then decide what's most interesting to them and set their project parameters at the end of that year. It's a real student-led programme.

LUCY ROWLAND:
What are you hoping to achieve with the CDT in terms of equity, diversity and inclusion?

PHILIP STIER:
AI is far too fast-moving. The CDT is really student driven, but obviously we have certain things we'd like to push. We're keen on access and equality, diversity and inclusion. We have a partnership with the African Institute of Mathematical Sciences in South Africa, and we want to get students on board from underrepresented regions. It's been challenging within the timeline of the first year, but that's something we're trying to achieve, scientifically.

BEA GILBERT:
What are the benefits for students in developing their own projects, as opposed to applying to work on a pre-defined project?

PHILIP STIER:
It's a fine line. We don't have students in a room being told to write their projects and advance the field on their own; instead it's a real interplay between students and academics. If, for example, students want to work on biodiversity and elephants, we will help them: the CDT will link them up with academics working in that space from the biology, machine-learning and satellite-detection disciplines. This allows students to shape the direction of their project and, as academics, we learn with them. Basically, the whole PhD is a conversation, where ideas evolve and where science evolves. We're just treating students as independent researchers from the start rather than as a workforce for a particular project.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OPINION

LUCY ROWLAND:
You mentioned the students will have an external adviser from outside academia. What will that relationship look like? Are there any expectations for how these relationships will develop, or opportunities for external placements with these stakeholders?

PHILIP STIER:
All students will have an external partner to advise them who will be part of the supervisory team. There will be two academics (one environmental, one AI) and a partner adviser. How it will work can take various forms. There's some who might want to hold weekly meetings online; others might not join weekly meetings but will be actively involved through less frequent meetings, consultations over email and professional development support.

For the external partners, it's a great opportunity to work with brilliant students. Then the idea is that students go on secondments to one of the partner organisations, typically for three months. The implementation of this will vary – we have partners ranging from very small NGOs up to big companies – but every student will go on secondment. If the partner is directly involved in the student's specific project, they may have some input on its direction. Other secondments will expose students to topics in the area of AI for the environment that they don't directly see in their PhD, and that way they see something different.

BEA GILBERT:
You said at the beginning that there is so much data and information now that needs processing. Do you think there are any recent technological breakthroughs or technology applications that have accelerated the way we can tackle climate research?

PHILIP STIER:
Yes, that's definitely something we're thinking about and working on. I'm currently organising a workshop at the 2024 United Nations AI for Good Summit in Geneva, addressing the future of climate prediction and asking what role AI will play. The landscape is quite complicated: AI is very different to what most people thought it would be five years ago, so it's very hard to predict. One big element that we're engaged in is ultra-high-resolution models that represent the Earth in the right scales.

At the moment, a climate model for the Earth has a resolution of around 100 km, which is a key uncertainty, in particular, for the representation of clouds that we're working in. But now we have a new generation of models where we can do kilometre-scale modelling. But these models are so big that they fill the biggest supercomputer, and we can only simulate a few decades – not what you want in a conventional climate model.

OPINION

There's a lot of thought going into how we can build very fast models for machine-learning-based surrogate climate models. These already exist for weather forecasting, but not at these resolutions. So that's a brand-new development, and the field is moving really quickly. At the same time, there's fantastic satellite observations out there at the same scale as these new models. Conventionally, satellite observations were high-resolution and the models were extremely coarse, and we used large-scale averages to evaluate the models. Now these satellite observations are both on a kilometre-scale, so we can think of entirely new ways to use the data since it can be directly compared.

BEA GILBERT:
As researchers, how can you stay on top of the field when you don't know what's around the corner and things are accelerating so quickly? Do you have to relinquish the expectation that you're able to keep up?

PHILIP STIER:
Computer science is such a big field; the area of machine learning is so big that it's virtually impossible for anyone to keep on top of anything. And even the standard literature searches are virtually impossible: things are moving so fast, for example, that the published research you might find on an AI topic at the beginning of a research project could be out of date by the time you come to use it.

I think we're still trying to figure out how AI and machine learning work for environmental applications, because it's going ridiculously fast. I think there's a lot of surprises around the corner, and there will be – not only on the pure science side, but also in our interaction with science and our interaction with models. It's totally foreseeable that you will soon be able to talk to a data-analysis platform, which will tell you the probabilities of climate change.

The most important part of this problem is how to embed the communication of uncertainty. Understanding the inherent uncertainties and calculation and parameter complexities of any model and how to communicate them, I think, is the biggest challenge. The weather community has made 30 years of progress in communicating these difficulties. Originally, people didn't want probabilistic weather forecasting, but it's very much accepted now. It's harder for the climate science community, however, because, typically, climate science communication is about global mean temperatures, not necessarily climate variability at local scales. The high resolution of these new models makes them appear very realistic at small scales. Hence, it is much harder to communicate the underlying uncertainties. ES

Professor Philip Stier is a climate researcher and Professor of Atmospheric Physics in the Department of Physics and Director of the Intelligent Earth CDT at the University of Oxford.

Philip's research focuses on clouds, aerosols and radiation, constituting the largest uncertainties in our changing climate system. His research combines atmospheric modelling with Earth observations and machine learning to learn climate physics and develop next-generation climate models.

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Andrea Hughes – Technical Director
Rengasamy Kasinathan – President
Simon Spooner – Associate Director / Fellow

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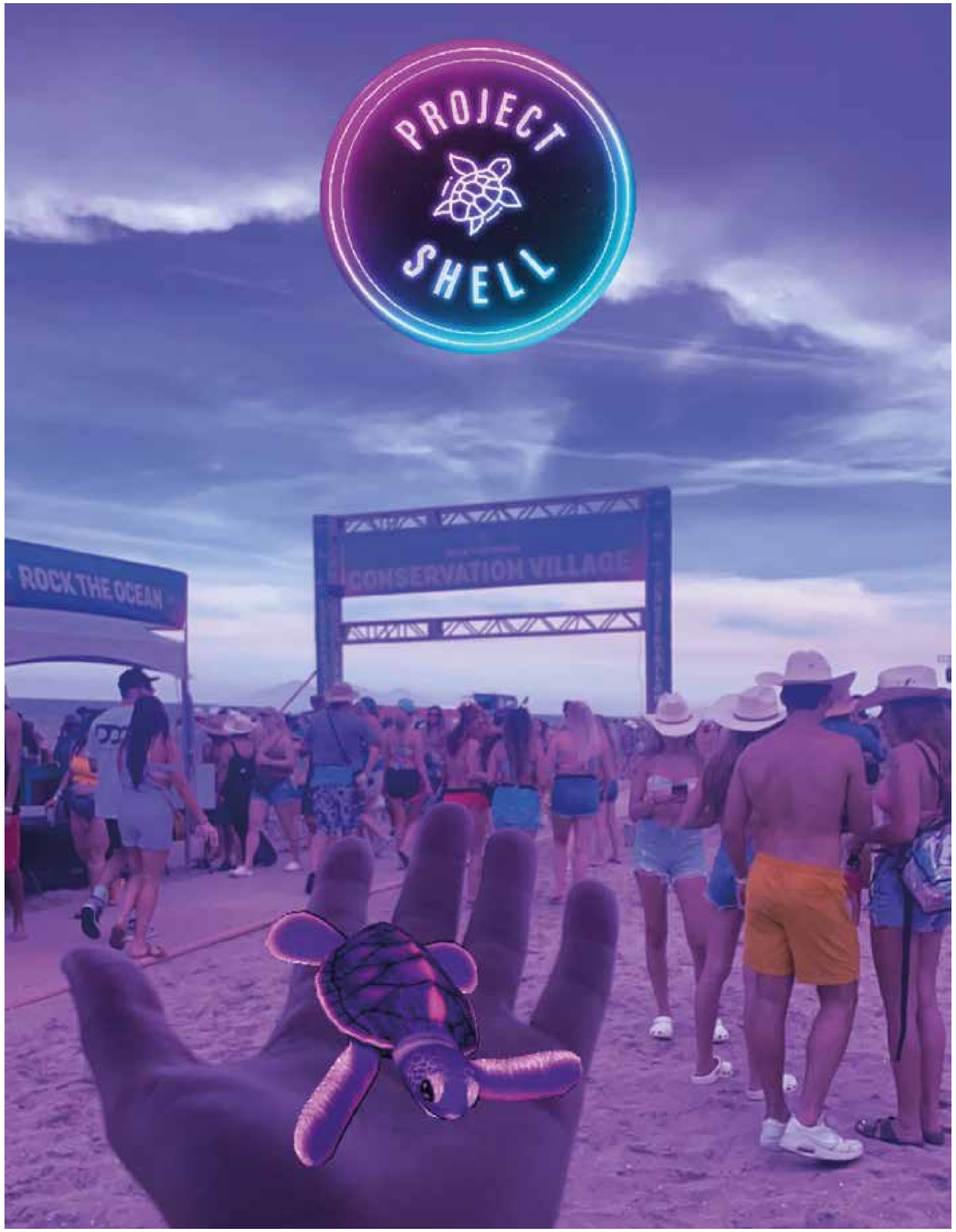
It is time to reinvent animal encounters at zoos with digital twins

Daniel Pimentel outlines the benefits and challenges of the next generation of human–wildlife encounters.

FEATURE

A year ago, a viral video of the Kiwi Encounter taken at Zoo Miami in the USA caused outrage among animal rights activists.[1] In the video, a guest was shown heavily petting and holding Pāora the kiwi inside the flightless bird's enclosure. Kiwis are nocturnal and ground-dwelling, so this daytime petting session imposed incredible stress on the animal. Zoo Miami responded by immediately terminating the experience. In the months that followed, other institutions, like Oregon Zoo, followed suit by placing similar experiences on hold indefinitely. Now, a year later, what seemed like a temporary fix and fleeting trend may be signalling the beginning of the end for a long-held practice at zoos and aquariums: animal encounters.



▲ **An augmented reality experience allowing users to interact with a sea turtle hatchling being demoed at Tortuga Music Festival (2023). © Danny Pimentel**

FEATURE

ANIMAL ENCOUNTERS

Animal encounters have been a staple at zoos and aquariums for centuries, and for good reason. Psychologically, humans have an innate desire to connect with nature and non-human life, a phenomenon known as the biophilia hypothesis.[2] Biophilia is more than a nature-seeking tendency but, rather, is an emotional need to affiliate and meaningfully engage with other living organisms. Institutions have capitalised on this by monetising our desire.

In Australia, you can touch, pat and pose for a photo with a wombat for US$15.[3] It costs even less for dingoes, kangaroos, koalas and emus, at $9 for a 10-minute petting session. This adds up and constitutes a significant chunk of a zoo's revenue, helping it pay the bills and keep operations afloat, often to the detriment of their non-human residents.

The tricky part is that zoos are not exclusively an economic enterprise built on the commodification of wildlife: they play an important role in biodiversity conservation. Revenues help fund the rehabilitation of injured animals and restore habitats affected by climate change. Such collaborative recovery programmes helped save the California condor from the brink of extinction, for example. This dichotomy between commodification and conservation is, therefore, tough to reconcile.

Experiences like the Kiwi Encounter can harm the very creatures that these institutions have pledged to protect. Not to mention the fact that animals in captivity can suffer from mental deterioration over time, a condition known as zoochosis. This can ultimately lead to detrimental behavioural responses such as self-biting and feather pulling.[4] At the same time, animal encounters can inspire ecocentric connections to wildlife, inspiring awe and contributing to conservation outcomes.[5] Indeed, scholars have long argued that zoos and aquariums, through direct interactions like feedings, can enhance nature connectedness – at the individual level as well as on a wider scale – and increase conservation activities.[6]

Yet, as someone who has participated in wildlife encounters, I recognise we cannot pet our way to de-extinction. According to the US Association of Zoos and Aquariums, there are 213 zoos and aquariums in the USA alone, housing over 800 different species that are listed on the International Union for Conservation of Nature's Red List.[7,8] That is less than 10 per cent of the total number of species accessible at our zoos, so encounters with vulnerable species are as inaccessible as they are ethically dubious.[9]

Where do conservation organisations turn to if they are unable to facilitate direct wildlife interactions but want to continue to bridge human–nature divides via the wonder of an encounter? Digital twin technology may offer an effective and ethical solution.

DIGITAL TWIN TECHNOLOGY

A digital twin is broadly defined as a computer-generated replica of any living (and non-living) entity found in the physical world, from people to entire countries.[10] Singapore, for instance, famously unveiled Virtual Singapore in 2022, a digital replica of its entire nation.[11] With recent advancements in artificial intelligence (AI) and photogrammetry, digital twins are increasingly being used to replicate living collections too. The Smithsonian Institution, in collaboration with The Hydrous – a US-based organisation focused on marine stewardship – created over 90 digital twins of coral specimens.[12] Similarly, the University of Massachusetts' digital life initiative has created digital twins of frogs, sharks and sea turtles, among others.[13]

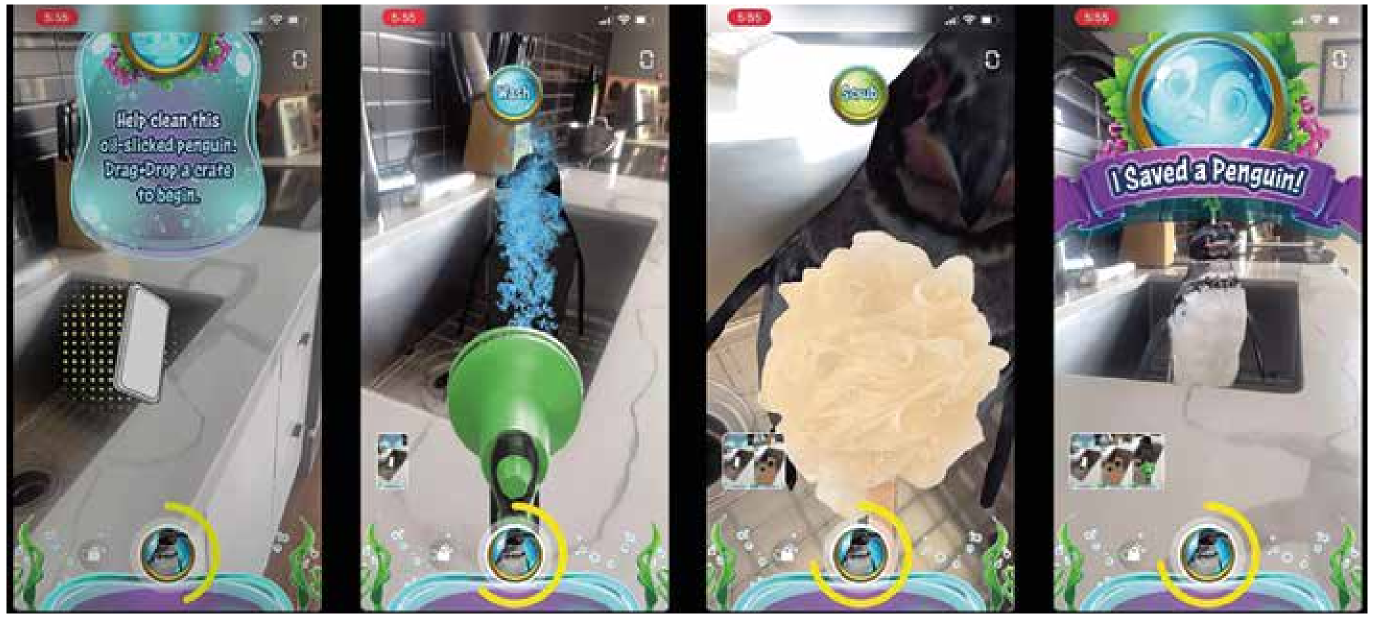
A digital twin of a kiwi presented on a screen is no different than sending a postcard of Pāora to your family. Instead, what if we could allow people to realistically interact with a digital twin of Pāora, even feed them, from the comfort of their homes? Merging digital twins with augmented reality (AR) technology, which can embed 3D models into our environments in realistic ways, can make that possible and produce an illusory sense of social presence, or 'being with' the creature.

Is it the real thing? No, but it is surprisingly close. AR's ability for social presence is a major reason why it is an effective way of dealing with animal phobias through exposure therapy.[14] Humans respond to virtual animals in AR, physiologically and psychologically, like they do in real-world encounters, for better or for worse. However, this perceptual similarity may benefit conservation efforts.

CREATING DIGITAL TWIN ANIMAL ENCOUNTERS

In 2021, an AR experience was created and tested, designed to bring audiences up close and personal with threatened wildlife – specifically, oil-slicked African penguins.[15] In the experience, users were tasked with rehabilitating a digital twin of an oil-slicked penguin in their kitchen sinks. After more than 60,000 people cleaned a (virtual) penguin, the results were promising.[16] People felt that the interaction had actually happened, which contributed to human–nature connectedness and conservation outcomes. Analysis of survey data collected after the experience demonstrated that users reported high levels of perceived plausibility (i.e. the encounter was believable), as well as social presence with the animal. Further analysis showed that these factors significantly predicted self-reported connection to nature and concern about environmental issues.

In 2023, my collaborator, Dr Sri Kalyanaraman, and I published a series of experiments examining interactions



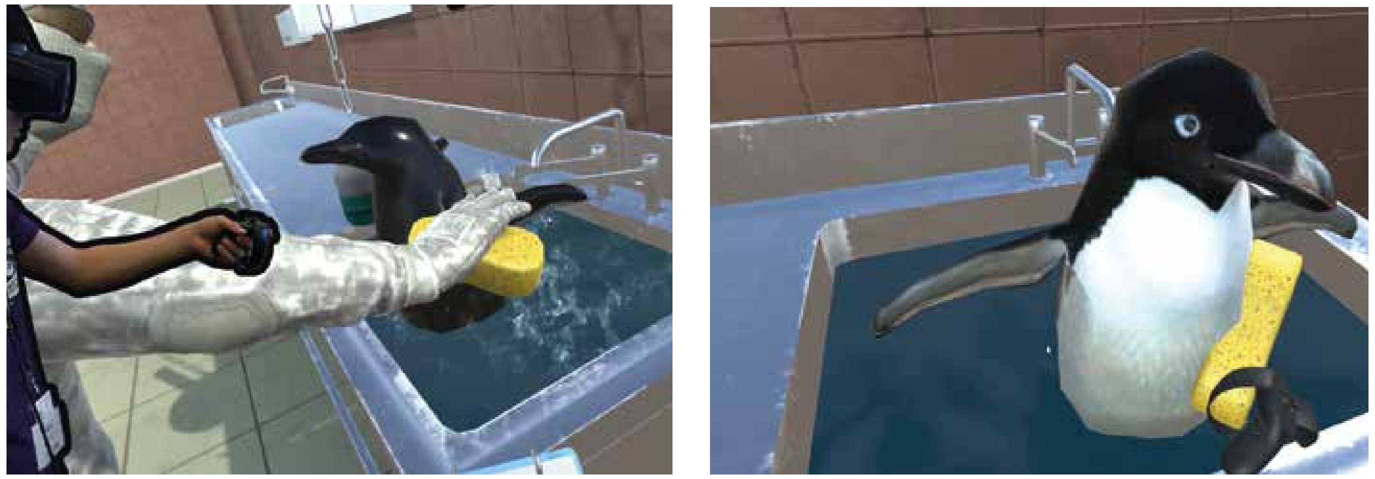
▲ **Screenshots from the Snapchat Lens "Penguin Rescue!". © Danny Pimentel**

with digital twins of sea turtles.[17] In one experiment, audiences were placed face-to-face with virtual sea turtles affected by marine debris and boat strikes. Findings demonstrated a strong correlation between how physically close participants felt to the virtual sea turtles and their intention to donate to their conservation. In other words, (virtual) wildlife encounters are not only perceptually similar, but they also affect us like real ones do.

Zoo Miami's spokesperson, Ron Magill, has argued that in a perfect world zoos would not exist. We must come to terms with the reality that modern humans see life through a prism of pixels. As such, we should adapt our approach to human–wildlife dynamics accordingly, and digital twins provide a hybrid solution to satiate our desire for such encounters.

Does this mean we do away with zoos if we can fit their collection into our pockets? Not entirely. There are clear trade-offs and barriers to the strategic use of digital twins in this capacity. For one, it is quite difficult and costly to animate animal behaviour in a realistic way. As humans, we have become adept at simulating bipedal locomotion, but accurate animation of non-human species movement remains incredibly difficult even with advances in AI and motion capture technology. Animators and artists regularly share the meticulous steps taken to render even a few seconds of animal animations.[18]

This raises the question of appearance and visual fidelity: does a digital twin need to be hyperrealistic to affect us meaningfully? The concept of the uncanny valley describes a phenomenon where virtual representations imperfectly resemble their source, creating a feeling of



▲ **A virtual reality simulation enabling travel to Antarctica to rehabilitate oil-slicked penguins. © Danny Pimentel**

© Florida Museum | Photo by Kristen Grace

discomfort and unease. The same happens when we are faced with a virtual animal that is perceptually not natural, or is imperfectly represented.[19] In this way, if a virtual animal encounter does not feel plausible, it may do more harm than good.

Another important concern relates to how interactions with digital twins may inform audiences' expectations and subsequent behaviour with wildlife in various contexts. Co-creating Project SHELL, the virtual reality simulation, required close working with sea turtle experts to review the content.[20] One scene featured the user (in this case a turtle hatchling) being picked up by a bystander and taken to shore. While this does happen, it was quickly (and correctly) pointed out that this may wrongly encourage people to do the same if presented with the opportunity. In other words, virtual actions may inform physical decision-making, which presents a slew of potential issues.

Even if we create digital twins of animals for humans to engage with, another important question must be asked: who are we to say how either would behave? Designers will also have to balance enjoyable play experiences with scientific accuracy. If we make wild (digital) animals accurately behave like wild animals, at best there will not be much of an encounter due to their tendency for human avoidance, and at worst there may be a virtual attack. Conversely, if we make them more approachable and interactive, this creates false connectedness at the expense of proper expectations and boundaries.

Despite these considerations, the promise of digital twins is evident from environmental education and wildlife conservation standpoints. It reduces the strain on animals while providing a safe and memorable interaction for audiences. But how do we initiate a culture change and motivate zoos and aquariums to embrace the

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synthetic in an otherwise wholly organic environment? Put simply, to make this a reality, zoos need to invest in digital twins. Currently, Portland's Oregon Zoo does not use digital twins, but it can be a pioneer in this space. Indeed, very few US zoos and aquariums are leveraging this technology for public engagement.

Yet it is not a matter of if, but when. With the buzz of Apple's Vision Pro AR headset still lingering, the feasibility of using AR to facilitate human–wildlife interactions at scale is growing, and institutions need to meet this opportunity head-on.[21] In many ways, the long-term preservation of Earth's biodiversity depends on it. **ES**

Dr Daniel Pimentel is an Assistant Professor of Immersive Media Psychology at the University of Oregon's School of Journalism and Communications. As co-director of the Oregon Reality Lab, he studies the pro-environmental implications of augmented/virtual reality. He is also an OpEd Project Fellow at Yale's Program on Climate Change Communication.

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ANALYSIS

The unbearable lightness of blockchain

Cathy Mulligan examines how technology can help us measure and meet environmental goals more effectively.

Blockchain is distinctive among emerging technologies due to the strong, polarised reactions it evokes in those who are aware of it. Many are only aware of blockchain in the context of cryptocurrency, as this is what receives the most news coverage, yet it has so many more applications.

Enthusiasts propose that blockchain can be a solution to everything from wealth disparity to meeting each of the 17 United Nations' sustainable development goals (SDGs). Detractors view blockchain – and cryptocurrency in particular – as a scam, as damaging to the environment and unnecessary. The reality, as with most things, is more nuanced.

A new imperative to proactively engage with environmental impacts and the resulting regulations has emerged alongside the usual technology debates. There have been numerous evolutions in the conversations around digital technologies and sustainability. If the world wishes to achieve its environmental aims, it is helpful to understand how well the technical solutions being produced match the aims of emerging policies. If they do not, such solutions are not particularly useful.

The results of our recent study, reviewing 10,800 research papers over five years, are less than encouraging but offer valuable pointers for successfully integrating blockchain to help solve the world's most complex environmental problems.[1] In the transdisciplinary space of regulation, it is worth starting with a definition.

WHAT IS BLOCKCHAIN?

Blockchain technology is a decentralised, immutable ledger system that records transactions across a network of computers in a way that ensures data are secure, transparent and tamper-proof. Each transaction is grouped into a block, and these blocks are linked together in a chronological chain. Once recorded, the data in any given block cannot be easily altered without altering all subsequent blocks, which requires consensus from the wider network. This structure ensures the integrity and reliability of the recorded information. It ensures transparency, security and trust without the need for intermediaries.

Cryptocurrency, a digital or virtual currency that utilises cryptography for security, operates on blockchain networks as a medium of exchange or 'currency'.

It enables peer-to-peer transactions and borderless financial transfers. It has often been touted as a solution for financial inclusion, revolutionising conventional banking systems and fostering innovation in industries beyond currency exchange.

Within environmental protection, some of the most common examples of blockchain's benefits include:

- Creating more transparent supply chains by enabling tracking, verifying product origins, and ensuring sustainability and ethical sourcing within agriculture, energy networks and construction;
- Carbon footprint tracking, where blockchain facilitates accurate measurement and monitoring of carbon emissions, aiding offsetting and trading; and
- Conservation funding and accountability, where blockchain-based crowdfunding platforms are used for environmental projects, ensuring transparency and accountability in fund allocation.

EMERGING REGULATION FOR SUSTAINABILITY

Governments and regulators now require disclosure around environmental, social and corporate governance (ESG) in regulated documents such as annual reports in order to inform investors of ESG risks and opportunities. This shift from voluntary to mandatory reporting aims to provide more complete and standardised information, addressing previous dissatisfaction among investors.

However, global regulators vary in their approaches to mandating ESG-specific financial reporting. Many regulations have been released, all with direct or tangential implications for solutions implanted with digital technologies. While none discuss blockchain directly, any proposed solutions need to consider these policies. The ESG regulatory environment includes a variety of regulators (see **Box 1**).

Many solutions also refer to the SDGs as an impetus for claiming environmental or social good from blockchain.

It is also relevant, therefore, to look at the SDGs in the context of solving global environmental problems. Currently, using blockchain for sustainability purposes falls into two main areas: measuring environmental impact and using blockchain as part of a solution to an environmental problem.

MEASURING THE IMPACT OF BLOCKCHAIN

There has been a lot of discussion about blockchain's environmental impact, with various claims about how much energy it consumes and how much electronic waste it produces versus how much good it can deliver. One of the main problems identified with existing attempts to measure this impact is the lack of comparable, peer-reviewed methods, as well as the disparity in the estimates produced, which vary widely. Most research methods have been funded by parts of the cryptocurrency industry or published in low-quality journals with unreliable peer reviews. As a result, none can be considered academically robust. However, it is essential to note that the same issues also occur in efforts to measure the environmental impact of the internet, cloud computing and artificial intelligence (AI) systems – including energy consumption, electronic waste generation, resource depletion, water usage, carbon emissions, pollution and biodiversity loss throughout their life cycle from production to disposal.

BOX 1. DEFINITIONS

Regulators with responsibility for environmental, social and corporate governance:

- ESMA: European Securities and Markets Authority
- ISSB: International Sustainability Standards Board
- SEC: Securities and Exchange Commission
- GRI: Global Reporting Initiative
- TCFD: Task Force on Climate-related Financial Disclosures
- ESRS: European Sustainability Reporting Standards
- IFRS S1 and S2: International Financial Reporting Standards Sustainability Disclosure Standards 1 and 2
- CSRD: Corporate Sustainability Reporting Directive

Blockchain solutions are especially prone to discussions regarding environmental impact. Unlike other digital technologies, such as AI or Internet of Things (IoT) solutions, the environmental externalities of blockchain – and cryptocurrency applications in particular – are fully available for everyone to see because the nodes are publicly available.

This network information transparency allows anyone worldwide to download and analyse the data, enabling more educated estimates of the technology's level of environmental impact. Therefore, it often receives an unfair comparison to more conventional technologies such as cloud computing. However, companies such as Microsoft, Amazon, Google and Meta refer to such data about their installations as confidential and claim that sharing it with researchers is a possible security risk. As such, there is significantly less insight into how their systems work and, subsequently, into their environmental impact.

Overall, we need a solid approach to measuring the environmental impact of digital technologies so that we can make educated decisions about which technologies to use and where. Currently, we are unable to effectively compare different technical solutions.

BLOCKCHAIN AS AN ENVIRONMENTAL SOLUTION

Many of the projects reviewed in the study investigated how to use blockchain to solve various environmental problems. Most of these projects focus on energy systems, supply chains, construction and agriculture, as well as the use of blockchain in traceability solutions, such as ensuring data from IoT sensors are not tampered with in smart city, construction or healthcare applications. Alternatively, these projects are proposed in order to create peer-to-peer trading systems in energy and agriculture. Another area is using tokens in cryptocurrencies to develop new market solutions – for example, around carbon markets. These solutions often attempt to solve a perceived market failure by creating new financial incentives for companies or individuals to do the right thing.

Blockchain's role in sustainability primarily focuses on three areas: energy systems, supply chains and IoT solutions, such as smart cities, facilitating peer-to-peer energy trading and enhancing grid efficiency.[2,3] Another significant focus is agricultural traceability, improving crop maintenance through blockchain-enabled IoT devices.[4] Similarly, literature on construction and smart cities proposes solutions for data integrity, smart buildings and smart construction.[5,6] Additionally, healthcare solutions primarily target electronic health records, while sustainable supply chains are also a key area of interest.[7,8]

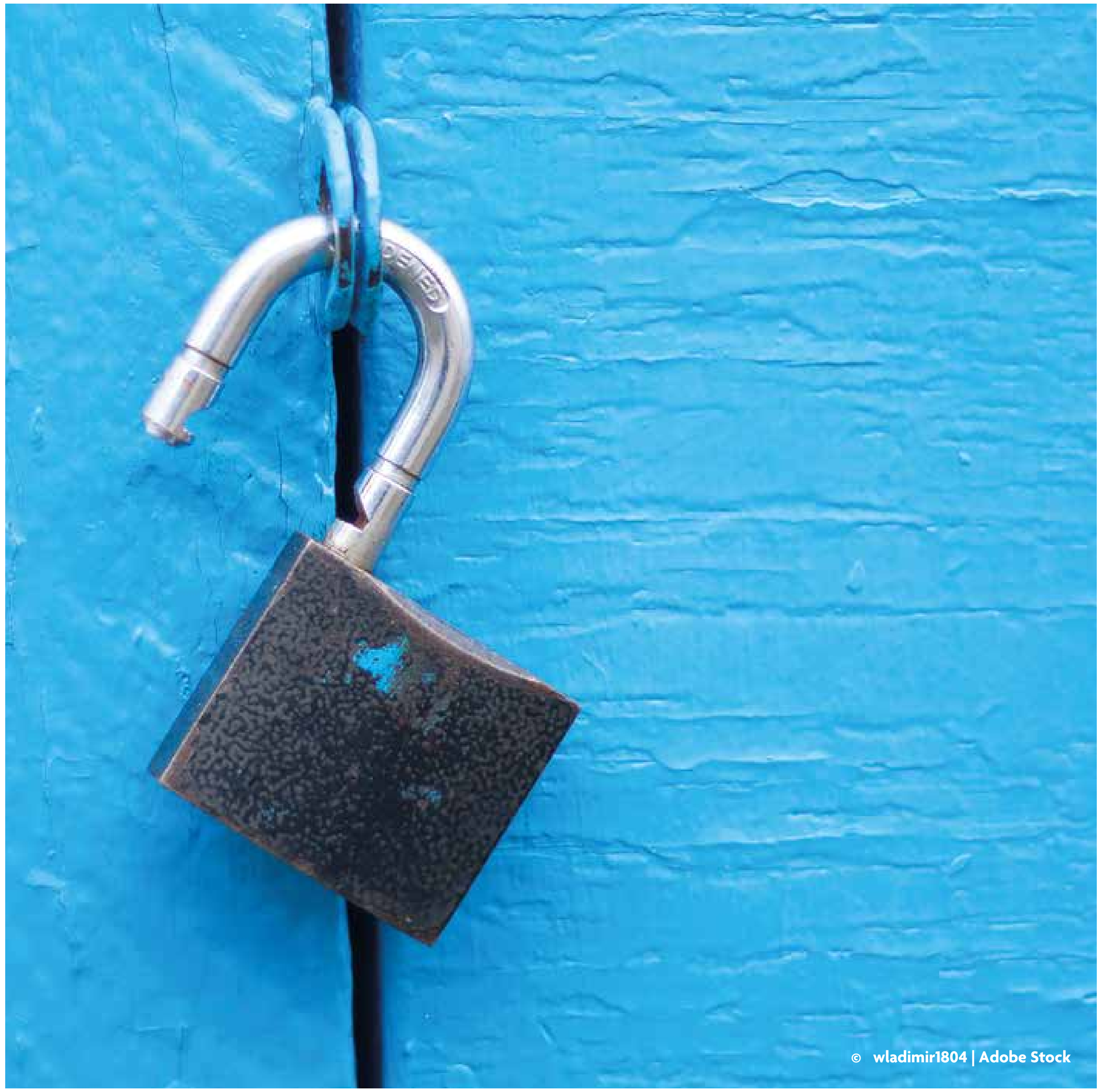
Many of these projects that formed part of the review, however, are not directly aimed at solving the problems defined by policy-makers as relevant to achieving net zero. There is a startling lack of coordination between projects – with many re-creating the same solution repeatedly, with only slight changes in implementation. As a result, the potential to solve problems at scale is lost. One area that should be improved is the connectivity between those proposed blockchain-based solutions and those who fully understand environmental impact.

For those projects proposing new incentives to solve environmental problems, a key issue seems to be understanding the nature of market failures in the first place. The use of incentives may work in some instances but, as any policy-maker will know, merely incentivising something does not mean it will work.

BOX 2. BLOCKCHAIN APPLICATIONS

The following is a list of blockchain applications in relation to the Sustainable Development Goals.

Sustainable Development Goal	Goal description	Blockchain application
1	No poverty	Financial inclusion, fair trade
2	Zero hunger	Supply chain transparency, fair trade
3	Good health and well-being	Medical records, pharmaceutical supply chain
4	Quality education	Credential verification
5	Gender equality	Financial independence, identity verification
6	Clean water and sanitation	Water management
7	Affordable and clean energy	Energy trading
8	Decent work and economic growth	Transparent labour practices
9	Industry, innovation and infrastructure	Smart contracts
10	Reduced inequality	Remittances
11	Sustainable cities and communities	Property rights
12	Responsible consumption and production	Sustainable supply chains
13	Climate action	Carbon credits
14	Life below water	Fisheries management
15	Life on land	Forest conservation
16	Peace, justice and strong institutions	Anti-corruption
17	Partnerships for the goals	Data sharing and collaboration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The reason we have taxes and public services such as the NHS is about a lot more than providing the right incentives to overcome market failure.

ARE WE USING THE RIGHT MEASURES?

Another critical question is whether the SDGs are a good tool to direct blockchain efforts. Firstly, blockchains are not implemented in isolation; they often support other technologies such as AI, IoT or 5G, making it more complex to measure the direct impact of blockchain on the different areas of an SDG. Secondly, there are 231 unique SDG indicators, and the way in which they are developed and implemented makes it difficult to measure them all effectively. Furthermore, SDGs are set at a national level, so a small-scale solution using blockchain is unlikely to deliver against the SDG indicators.

Lastly, with the focus of SDGs being on developing nations, there is a risk that the work required to mitigate climate change in the developed world is missed. Since most of the adverse environmental impacts originate in the developed world, the SDGs risk misplacing the focus necessary to solve these problems. As a result, many blockchain solutions that claim to address the SDGs are not directly doing so but often use them as advertising. To solve these issues, there should be greater focus and direction from policy-makers so that blockchain-solution innovators understand where they can make the greatest impact.

ANALYSIS

However, one of the most common aspects that is excluded from the discussions around blockchain is the environmental impact of the churn of computing equipment. Blockchain installations (and, indeed, cloud computing) rely heavily on high-speed chipsets. These components are often replaced far quicker than the suggested lifespan due to the constant hunt for higher speeds. Older chips are discarded when a new one is released, leading to large amounts of unnecessary electronic waste. One of the critical things we must focus on is how to effectively recycle and reuse chipsets and other core components of technical solutions. Precious metals from this waste are often considered to be in such small quantities that they are not worth recycling properly, and this perspective needs to change rapidly. This is an area that is as yet wholly unaddressed by the technology industry – and by blockchain solutions in particular.

THE WAY FORWARD

Blockchain does have a role to play in delivering sustainability, and it can deliver useful aspects of a solution related to trust in data sources and possibly even new methods of coordination in the economy. However, any claim that blockchain alone can meet the SDGs or enable ESG goals needs to illustrate how the proposed solution meets the policy requirements it claims to address. Moreover, blockchain cannot be implemented independently and understanding its connection to other technologies is critical when proposing solutions. Therefore, the focus should be on creating frameworks and tools that enable measurement of the entire life cycle of solutions, not just individual technologies such as blockchain or AI. **ES**

Dr Cathy Mulligan is a researcher and expert in digital innovation, blockchain and smart cities. She has extensive experience in academia and industry and contributes significantly to advancing sustainable development through technology. Cathy has been working with blockchain since 2009 and has been an expert member of the World Economic Forum.

Further Reading

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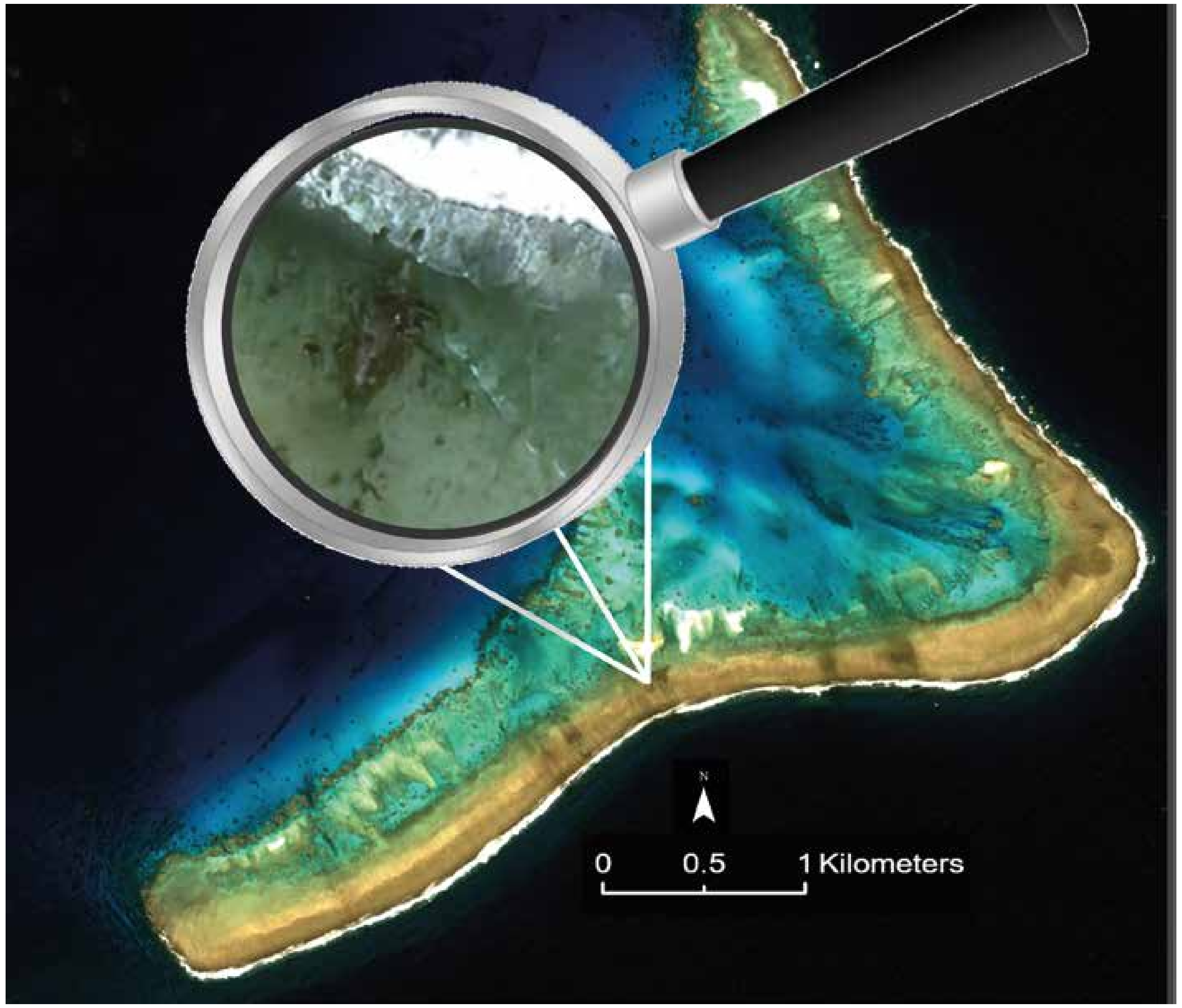
CASE STUDY

Unlocking the secrets of shipwrecks: artificial intelligence's role in coral reef conservation

Alexandra Karamitrou looks at how this technology can be used to better understand and protect heritage sites and their marine environment.

Shipwrecks can be both beneficial and harmful to marine ecosystems. While they create habitats for marine life, they can also lead to pollution and disrupt the balance of the underwater environment. In remote coral reef areas where iron levels are naturally low, these shipwreck remnants disrupt the normal life of the reef, changing the biology and the chemistry of the area, making it easier for invasive species such as turf algae, cyanobacterial mats, macroalgae, corallimorphs and other benthic bacterial communities to take over. As a result, the surrounding water might change colour, leading to what are known as black reefs – so called because of the noticeable discoloration caused by the shipwreck's impact on the underwater environment (see **Figure 1**).[1,2]



▲ **Figure 1. Kenn Reef, nestled within the Coral Sea Islands of the Australian Commonwealth Territories, boasts 11 documented shipwreck sites along its shores. The magnifying glass zooms in to illustrate a shipwreck and the black reef surrounding it within this region. (Source: Karamitrou *et al.*[3])**

By using artificial intelligence (AI) and high-resolution satellite images, such as those from Google Earth, these wrecks can be monitored more effectively to understand their impact on the surrounding area, even if they are not easily visible. This research offers new insights into how we can use technology to safeguard our underwater heritage while preserving marine ecosystems.

A LIMITED NUMBER OF BLACK REEFS

Since there are only a few known black reefs in coral areas and not all of them are visible in satellite imagery (due to low spatial resolution or high cloud coverage), and free imagery is not available for all reefs, eight sites were selected from existing research that comprised a total of 19 shipwrecks. Seven of those shipwrecks were used to label and train the algorithm and 12 were used to evaluate its performance (see **Figure 2**).

The dataset included four Vision-1 multispectral images (red, green, and blue channels) with a resolution of 3.5 m, provided free of charge by Jisc.[4] Additionally, the dataset comprised seven Google Earth images (red, green, and blue channels) of varying resolutions depending on the sensor type and the year of acquisition.

WORKING WITH ARTIFICIAL INTELLIGENCE

Deep learning is an AI technique that uses artificial neural networks, modelled after the human brain's structure and function. Over the past decade, deep learning has revolutionised research in computer vision, leading to its widespread adoption.

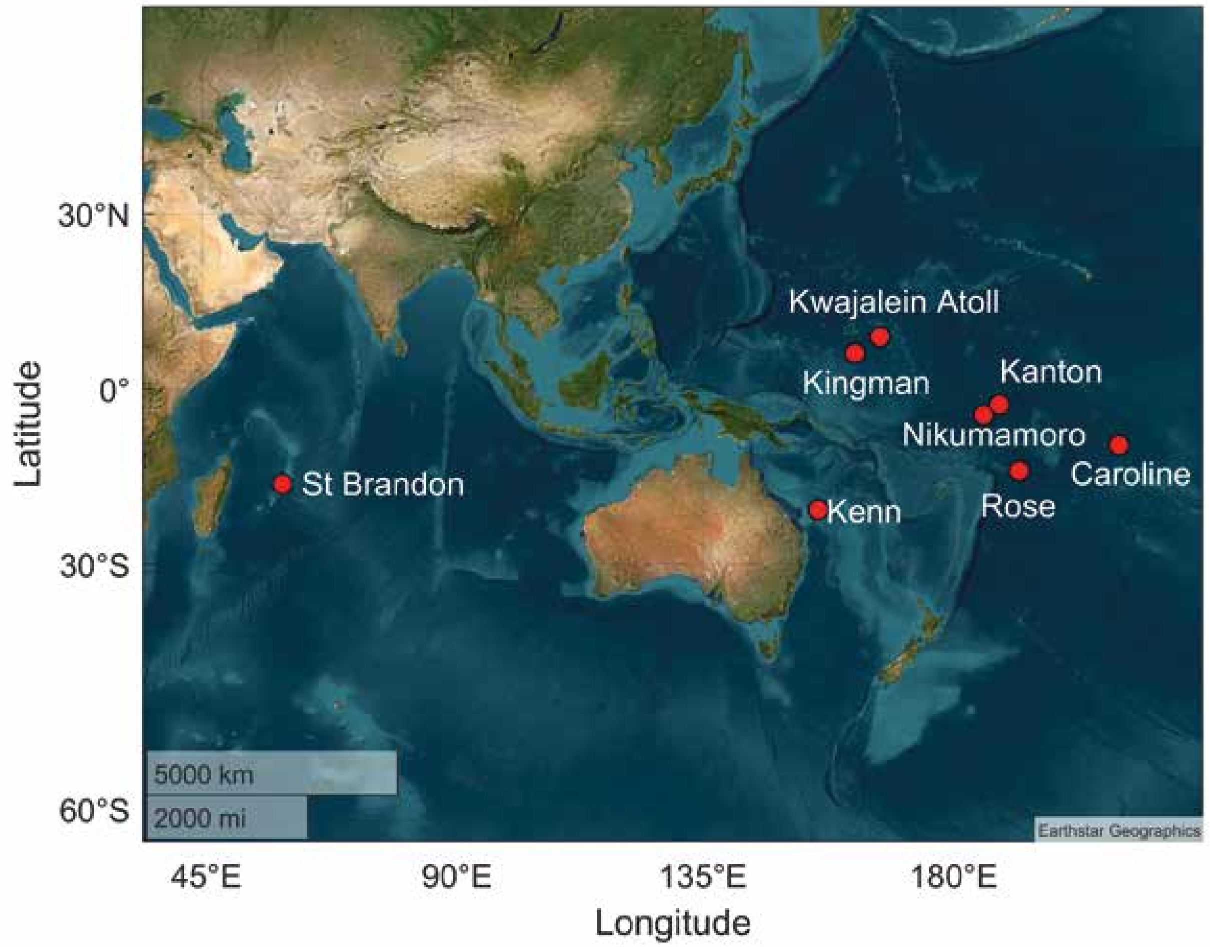
Convolutional neural networks (or space-invariant artificial neural networks) typically require large amounts of data to perform well during the training process. Currently, there is a shortage of publicly available labelled data for shipwrecks, making it challenging to train neural networks effectively. To overcome this, a supervised neural network called SimpleNet was used, which is based on the architecture of semantic segmentation.[5,6] Semantic segmentation algorithms divide images into meaningful segments and then classify each segment into one of several predetermined classes. For example, these classes could include archaeological sites, regions of vegetation, modern structures and other interpretable image regions. This model is well suited for situations with limited labelled data because it avoids using complex layers that require a lot of memory and computing power. This approach makes it easier to work with smaller datasets and still achieve accurate results.

To train the algorithm, five reefs were used – Kenn, Nikumamoro, Kanton, Rose and Kingman – resulting in about 1,600 images. These images were classified into three categories: black reefs (areas with known shipwrecks that caused discoloration); non-black reefs (other reef areas without discoloration); and water (areas with water but no reef). To save time and computational memory when training the algorithm, the Iridis supercomputer at the University of Southampton was used, providing access to high-performance computing. These computers use clusters of powerful processors that work in parallel to process vast amounts of data, providing results at high speeds. The entire process took approximately two hours to complete.

DETECTING SHIPWRECKS

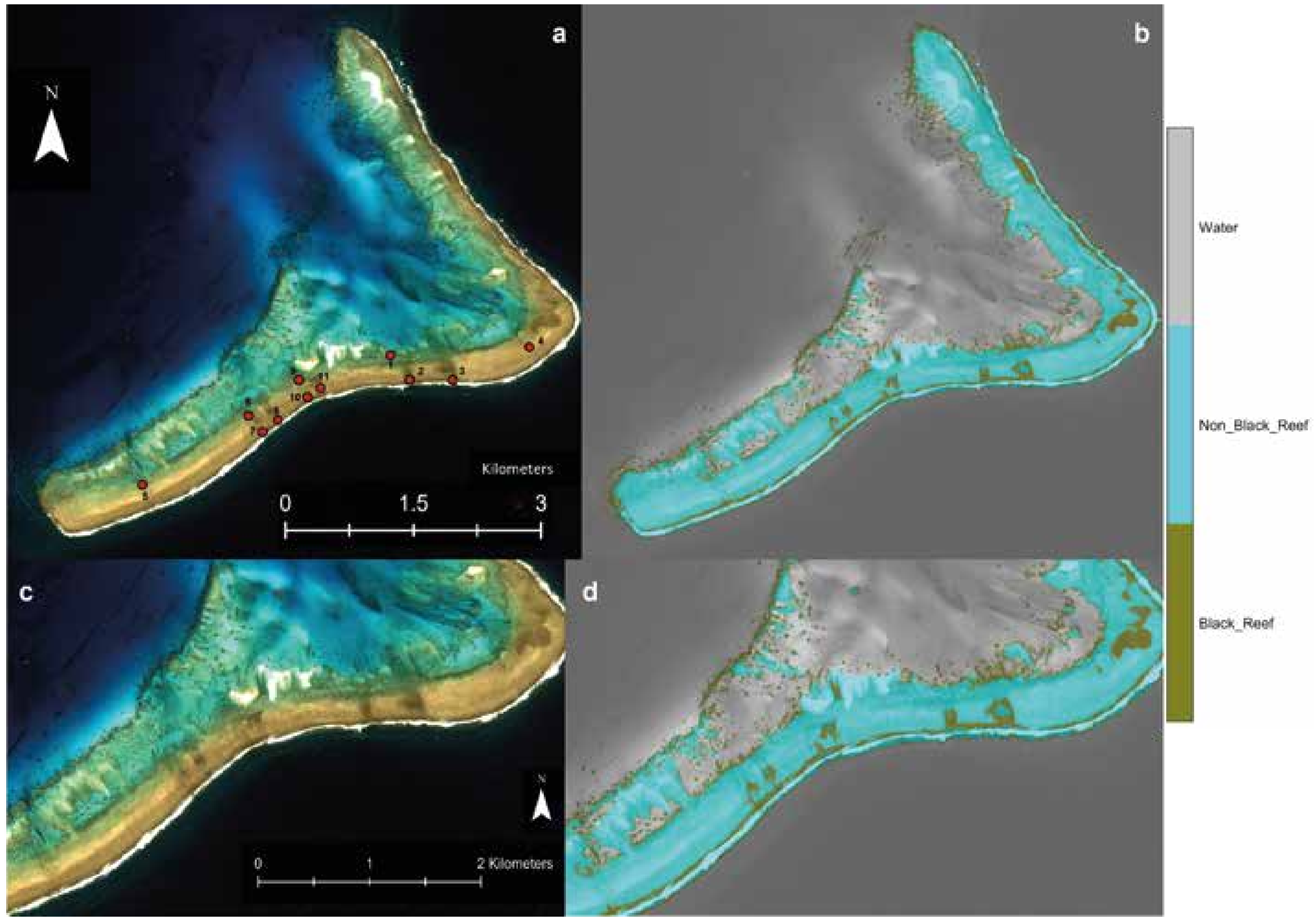
In all the cases studied, the trained algorithm was able to clearly distinguish between water and land, even in areas where the seabed was visible. The algorithm accurately identified all known black reef locations and, consequently, all known shipwreck locations.

Kenn Reef. Notably, the algorithm identified a black reef area several hundred metres to the north of this known reef, which could either indicate previously unknown shipwrecks or a misidentification (see **Figure 3**).



▲ **Figure 2. Locations of the black reefs investigated in this study. (Source: Karamitrou *et al.*[3])**

CASE STUDY



▲ **Figure 3. a) Vision-1 satellite image capturing Kenn Reef, using red dots to indicate the location of the 11 known shipwrecks; b) the segmented image after the trained algorithm has been applied; c) zoomed-in part of the Google Earth image providing a closer look at the reef; and d) the corresponding zoomed-in portion of the segmented image. The khaki colour represents areas classified as black reef by the algorithm, the light-blue colour indicates the remaining reef and the grey colour represents water. (Source: Karamitrou *et al.*[3])**

Additionally, the discovery of discoloration along the coastal area suggests that wind, ocean currents and waves can carry debris from shipwrecks to nearby parts of the reef. This emphasises the importance of considering temporal information when monitoring and evaluating environmental impacts, particularly due to the rapid changes in coastal and marine environments.

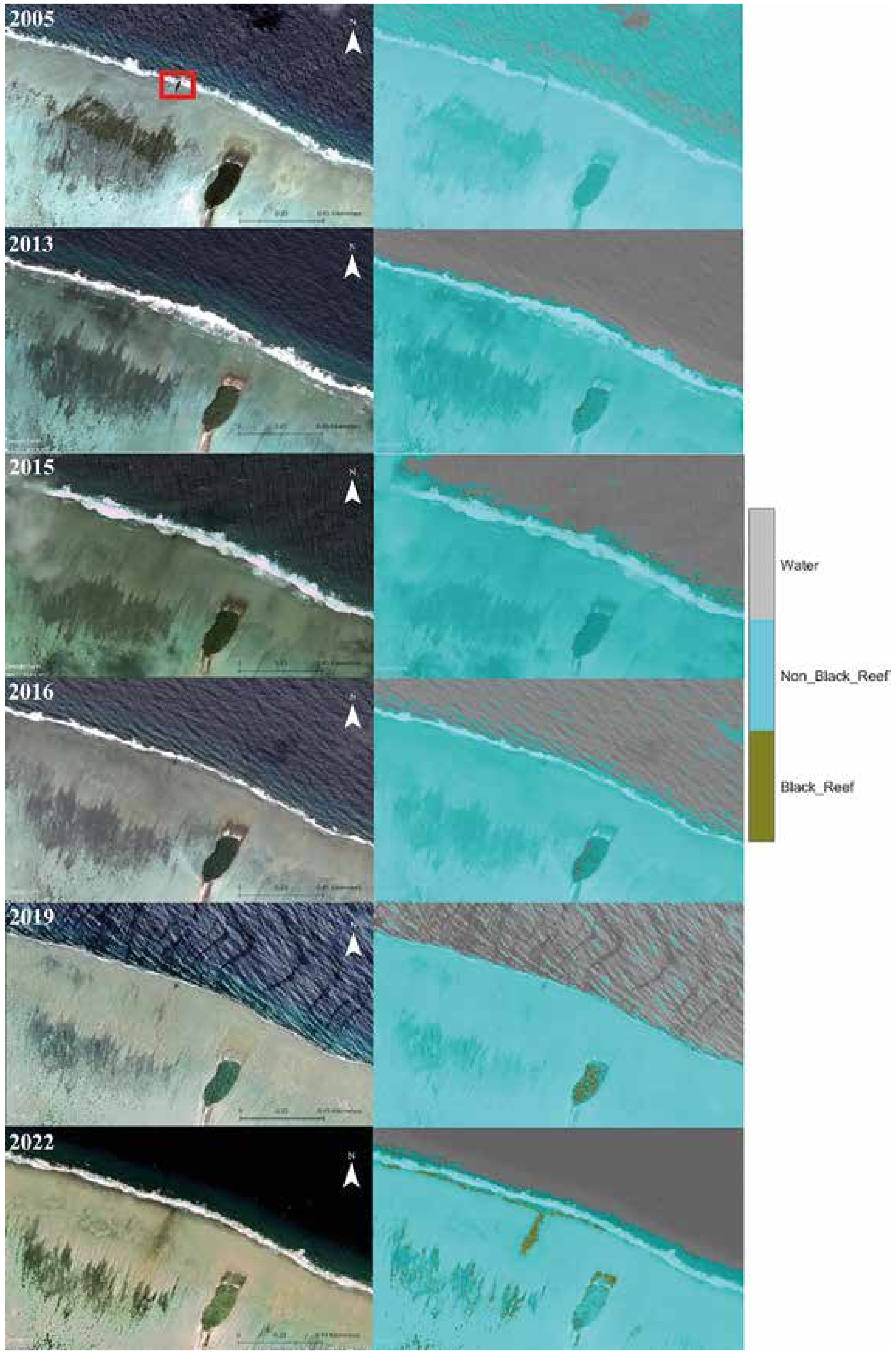
Kwajalein Atoll. Initially, the presence of a Second World War shipwreck on the atoll shore did not automatically confirm the development of a black reef, as there was no existing research indicating its presence. However, upon examining temporal information, the trained algorithm confirmed the formation of a black reef (see **Figure 4**). This highlights that as a shipwreck deteriorates over time, it accelerates the black reef formation process.

By comparing the state of the shipwreck in 2005 to that in 2019, it becomes evident that the vessel has broken into smaller pieces. Some of these fragments have visibly spread several hundred metres further inland (see **Figure 5**).

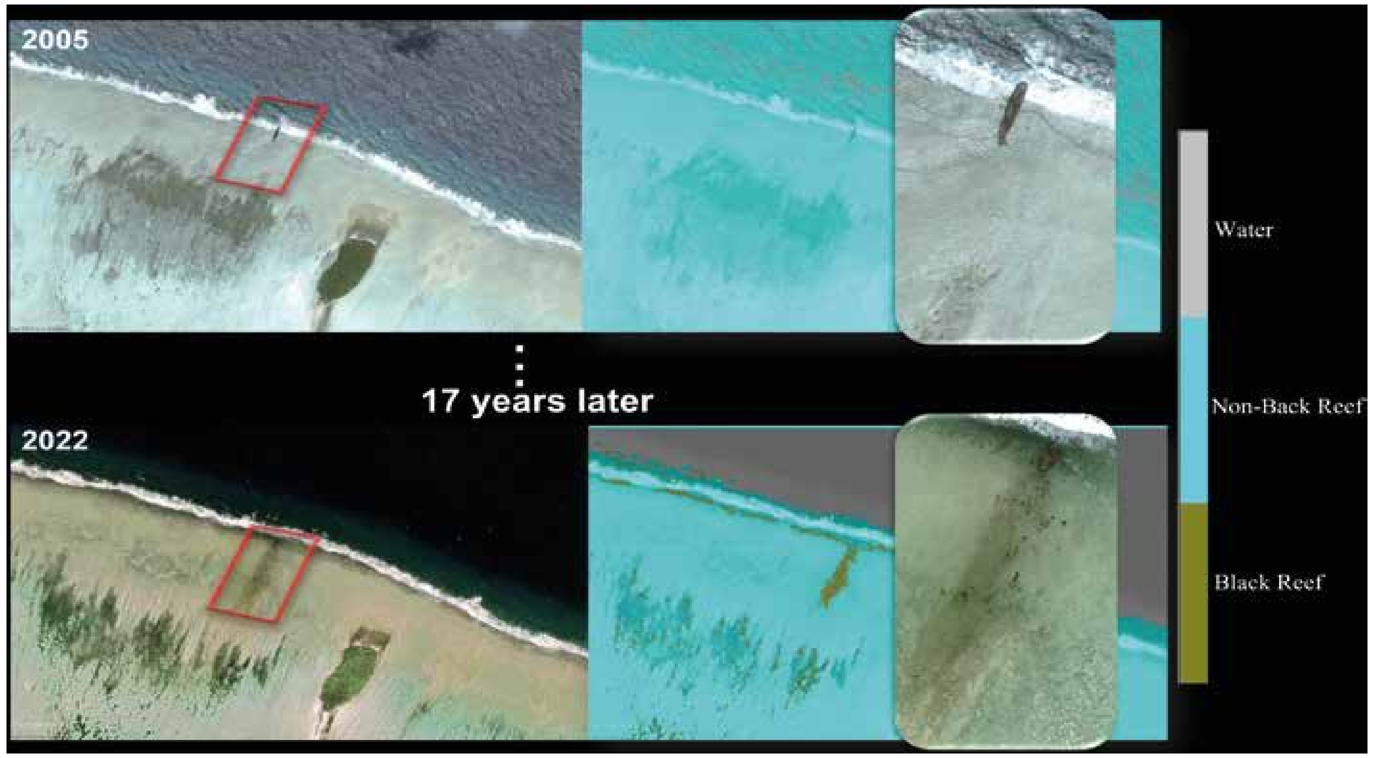
RESEARCH FINDINGS IMPLICATIONS

This research highlights the effectiveness of combining remote sensing, AI and ground-based surveys to identify and monitor the environmental effects of shipwrecks on coral reefs. The results demonstrate that AI algorithms can reliably detect black reefs, signalling the presence of shipwrecks, even when they are not visible. By analysing temporal data, it is observed that the formation of black reefs may initially be delayed but which accelerates as the shipwreck degrades over time. Additionally, environmental elements such as wind, ocean currents and waves play a role in dispersing debris, which gradually widens the affected area.

Detecting shipwrecks is crucial not only for their archaeological significance but also because they can pose substantial risks to marine environments.



▲ **Figure 4. Left column: All the accessible Google Earth images of the Kwajalein Atoll from 2005, 2013, 2015, 2016, 2019 and 2022, with the shipwreck's location marked by the red rectangle. Right column: The respective segmented images where the khaki colour represents areas classified as black reef by the algorithm, the light-blue colour indicates the remaining reef and the grey colour represents water. (Source: Karamitrou *et al.*[3])**



▲ **Figure 5. Left column: Google Earth images of Kwajalein Atoll from 2005 and 2022, with the shipwreck location marked by the red rectangle. Right column: Corresponding segmented images, which include zoomed-in parts of the shipwreck where the khaki colour represents areas classified as black reef by the algorithm, the light-blue colour indicates the remaining reef and the grey colour represents water. The presence of the black reef in the 2022 segmented image clearly suggests that over 17 years the vessel has fragmented, with some parts being dispersed in the direction of the discoloration. (Source: Karamitrou *et al.*[1])**

Toxic or hazardous materials leaking from shipwrecks can be catastrophic for marine ecosystems, human life, and local economies and societies. Even in cases where such materials are absent, the contamination of coral reefs with high amounts of iron from the vessels can significantly threaten them by forming black reefs.

ES

Alexandra Karamitrou, PhD, MSc, is a geophysicist with a background in geology and environmental science. Her research is focused on the application of AI to solve complex social and cultural problems. She is currently using multiple datasets, such as remotely sensed and geophysical data, as well as environmental information to detect submerged shipwrecks. She is applying computer vision and image processing techniques combined with deep-learning, convolutional neural networks to automatically identify and classify human-made islets, also known as crannogs. Alexandra is also studying global decommissioning practices of offshore structures including vessels, oil rigs and wind turbines, funded by the Royal Academy of Engineering.

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FEATURE


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Drone technology for monitoring in the water sector

Mónica Rivas Casado provides an overview of a range of applications of unoccupied aerial vehicles in the industry.

ASSET INSPECTION IN THE WATER SECTOR

In the last few decades there has been a significant uptake of emerging and disruptive technologies for environmental surveying tasks. Unoccupied aerial vehicles (UAVs), commonly known as drones, are an example of such technologies.

The water sector, and wastewater treatment in particular, has embraced such technologies by maximising their use in a wide range of applications – from inspection tasks to greenhouse gas emissions quantification and reporting. In wastewater treatment plants, drones have enabled operators to better understand the management needs of their assets.

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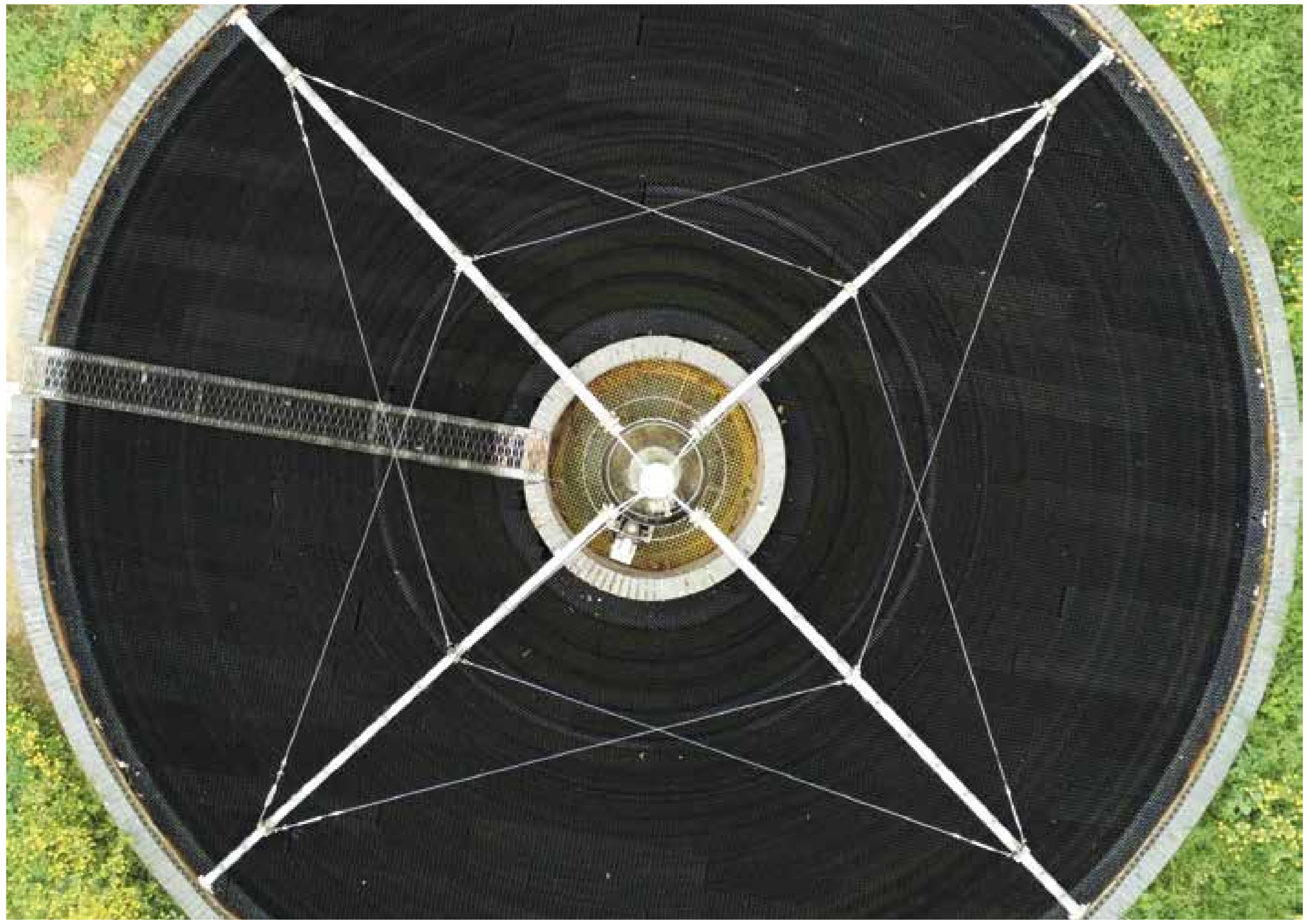
For example, UAVs autonomously deployed from a remote platform and coupled with image analysis techniques could be used to identify failures in trickling filters (see **Figure 1**) and activated sludge facilities (see **Figure 2**), where the biological processes of secondary treatment take place.[1]

Inspection and maintenance of such assets using conventional techniques (e.g. visiting each plant and visually assessing each asset) is time consuming and costly, with failures usually associated with a lack of uniform irrigation of wastewater from trickling filter rotor arms. Solids separation, bulking, foaming and aeration malfunctions are common failure points for activated sludge facilities. Such facilities inject air into tanks to promote microbial growth, and suspended solids are then separated through sedimentation.

UAVs equipped with off-the-shelf RGB (red, green, blue light channels) cameras enable the collection of high-resolution imagery. The colour of the pixels of each individual frame provides substantial detail about the operational performance of the asset (see **Figure 3**). Briefly, water coming out of the trickling filter, as well as the air bubbles in the activated sludge facilities, presents as a different (lighter) colour to that observed in the background. Image classification algorithms can detect this colour difference by comparing the colorimetric characteristics of each pixel to a predetermined range of colours established as reference values for water. Anything outside those established reference values is considered not to be water. The ratio of water over no-water pixels is then calculated. Variations of this ratio with respect to the optimal performance ratio highlights possible failure or a change in asset performance.[1] This technological advancement, when combined with the autonomous deployment of UAVs, enables the remote inspection of assets and minimises the frequency with which operators carry out plant visits and visual inspections.

Others have used UAVs to quantify methane emissions from anaerobic digesters, secondary storage tanks and cake pads.[2] In this instance, the UAV platform was equipped with a low-weight (520 g) tuneable diode laser absorption spectroscopy sensor (TDLAS) with a detection limit of 5 parts-per-million-metre (ppm.m), a measuring range of 0–50,000 ppm.m and a maximum detection



▲ **Figure 1. High-resolution imagery of a trickling filter collected using an unoccupied aerial vehicle. Trickling filters are common assets found in wastewater treatment plants. (© Severn Trent Water)**

distance of 100 m.[3] TDLASs collect path-integrated concentrations (i.e. the concentration of methane present along a column of gas), which can then be used to calculate methane flux (i.e. the rate of methane flowing across a given area) using mass balance algorithms.[4] The mass balance approach relies on the principle that the net flux can be estimated by quantifying the difference in the mass of methane entering and leaving a predetermined atmospheric volume.

SUCCESSFUL DRONE USE IN THE WATER SECTOR

The uptake of UAVs within the water sector is the result of a combination of factors – including on-demand and in-situ deployment capability, increased spatial coverage, reduced operational costs, de-risked operations and higher data resolution – compared to more conventional surveying methods that rely on visual assessments. The technology has enabled a shift in management practices from wastewater plant level to asset-specific interventions.

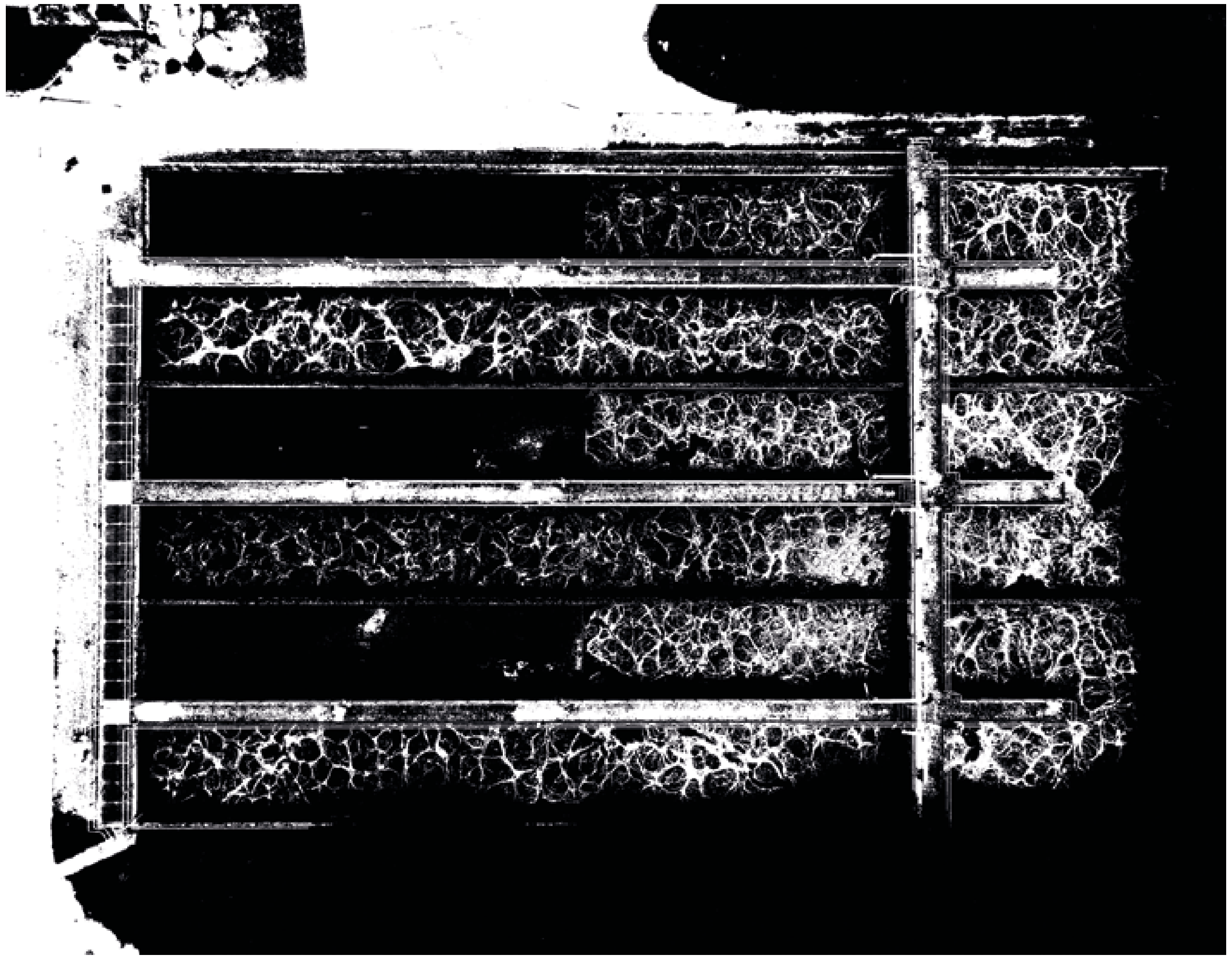
Perhaps this is most noticeable within the context of methane emissions quantification and management, where reporting practices to date have relied on plant-level estimates. Wastewater treatment plant operators follow the methodology described in the Carbon Accounting Workbook to report greenhouse gas emissions.[5] The method relies on default emissions factors, a coefficient describing the rate at which greenhouse gases are released to atmosphere, to estimate overall methane fluxes at plant level. These estimations are based on the volumes of sludge treated as well as on the type of treatment employed and provide a general overview of the magnitude of the observed emissions.

It is well understood that emissions factors are asset-specific. For example, assets such as the anaerobic digesters or pipes within a wastewater treatment plant – which are enclosed – will be characterised by fugitive emissions, which occur at discrete points. Digestate storage tanks will present a completely different pattern, as they are open and will directly release methane to the atmosphere.

Emissions factors depend on multiple parameters, such as environmental temperature, atmospheric pressure and relative humidity, in addition to the operational and technical characteristics of the assets.[6] There is also a

▲ **Figure 2. High-resolution imagery of an activated sludge facility using an unoccupied aerial vehicle. (© Severn Trent Water)**

FEATURE



▲ **Figure 3. Results of an activated sludge facility high-resolution image processed using the algorithms developed by Sancho *et al.*[1]**

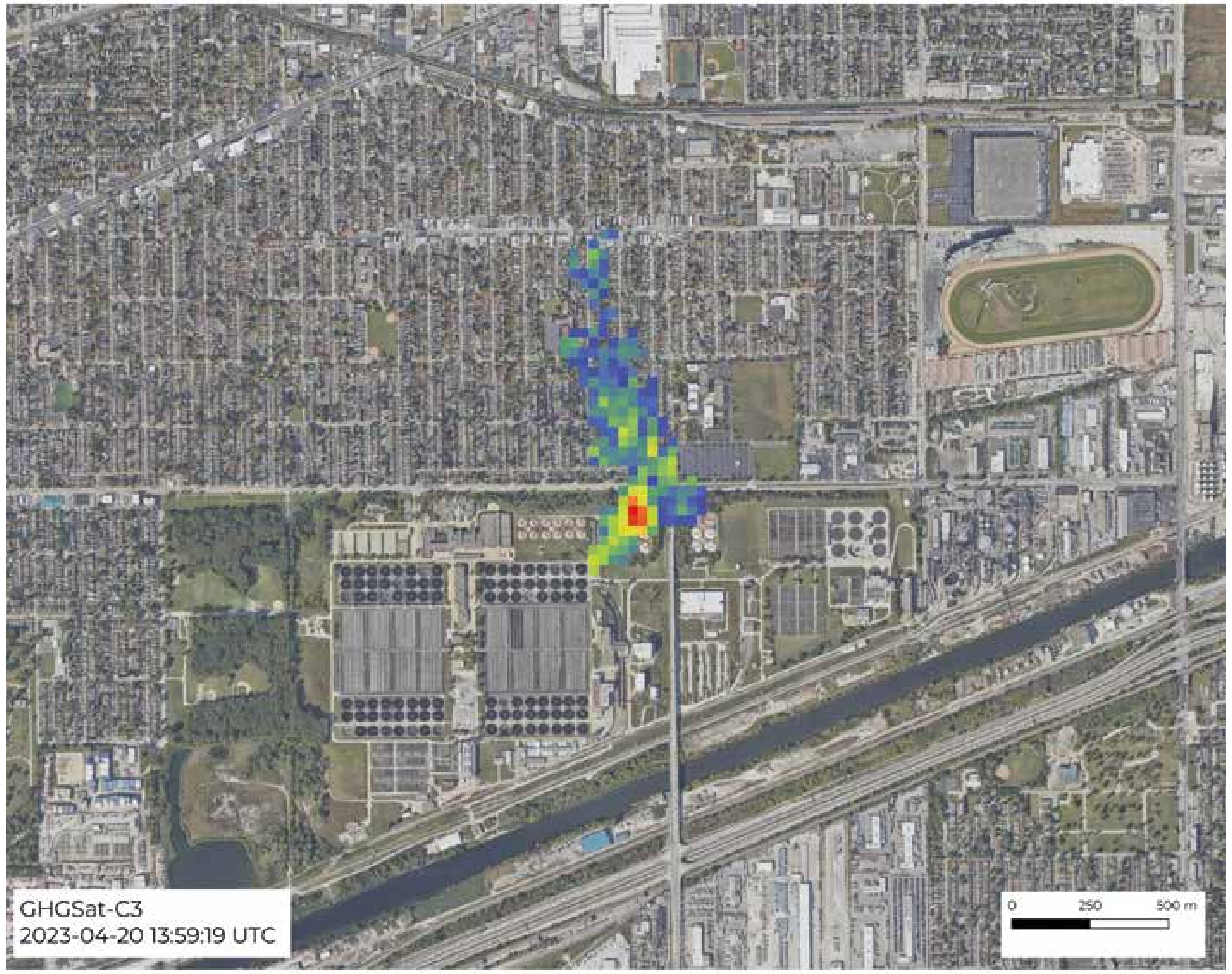
need to differentiate between emissions from open and fugitive sources, as described above. High-resolution methane concentration data collected with TDLASs embedded in UAV platforms enable the estimation of asset-specific emissions factors and, therefore, offer a pathway to enhancing current greenhouse gas emissions reporting practices.

There is evidence that state-of-the-art technologies for methane concentration measurement provide different but more accurate readings than conventional methods.[2] The high-resolution wide-area coverage offered by UAVs provides incredibly detailed concentration readings and derived flux estimations. However, the extent to which UAVs can improve reporting practices has not yet been assessed quantitatively. There is an urgent need to better understand how differences in surveying technologies translate into greenhouse gas emissions estimations. There is a risk of underestimating emissions from wastewater treatment processes if the effectiveness of current surveying approaches is not revised.

ACCOMMODATING NEW TECHNOLOGIES

The uptake of emerging and disruptive technologies needs to be thoughtfully aligned with surveying solutions already adopted by the water sector, such as ground-based sensors, thermal imaging cameras and GHGSat (a constellation of satellites measuring methane and carbon dioxide emissions from point sources) high-resolution satellite imagery (see **Figure 4**).[7] Other emerging technologies recognised as significant by governments (e.g. the Internet of Things, satellites, big data, and robotics and autonomous systems) will play a crucial role in future developments.[8]

This in turn requires the adoption of data collection and data processing practices that facilitate the fusion of information from a varied range of sources, as well as the development of algorithms for the rapid detection of patterns in data. Where comparison of outcomes across wastewater treatment plants is sought, more strict protocols or standards explicitly describing the precision and accuracy of the thresholds of tolerance will also



▲ **Figure 4. GHGSat satellite imagery reporting greenhouse gas emissions from a wastewater treatment plant. (© GHGSat)**

be required. Early-warning systems that report peaks of emissions as well as frameworks to better inform management decisions can be devised when all these distinct factors converge into a single solution.

THE SKILLS DEFICIT CHALLENGE

The use of UAVs in the water sector, and more widely in the environmental sector, could be significantly curtailed by the availability of skilled engineers required to operate the UAV platforms. The logistics around operating UAVs require specific licences and permissions that ensure all missions are conducted in compliance with airspace regulations. Similarly, data science knowledge is needed to process and interpret the data collected, which are usually provided in a wide range of formats.

The water sector will have to sustain a constant stream of investment to develop and train multidisciplinary teams of operators to use the technology for its intended purpose. How successful the uptake of emerging technologies is within the environmental and water sectors depends on the ability of governments and organisations to devise strategies that promote social acceptance and adaptation. The development of such approaches will also require dedicated resources on their successful implementation through mechanisms such as policy and regulatory frameworks, guidelines and standards.[9] ES

Dr Mónica Rivas Casado is a Reader in Environmental Systems Engineering at Cranfield University. Her academic career has been built around the development of systems engineering solutions for the design of robust environmental monitoring strategies. Mónica's research has been funded by the Engineering and Physical Sciences Research Council, the Natural Environment Research Council, the Department for Business, Energy and Industrial Strategy, the Environment Agency and a wide range of industrial sponsors.

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Digital environmental impact assessment: from evolution to revolution

Mark Elton reflects on how far practitioners have come and why developments in artificial intelligence will bring about rapid progress.

ENVIRONMENTAL IMPACT ASSESSMENT HISTORY

An environmental impact assessment (EIA) is a process through which the environmental impacts of a proposed development are assessed. EIA is undertaken in more than a hundred countries and has been a legal requirement in the UK since 1988 through the EIA Directive (85/337/EC).[1] In the past 36 years of UK EIA practice, survey techniques, impact assessment methodologies and software tools have been digitised, standardised and updated.

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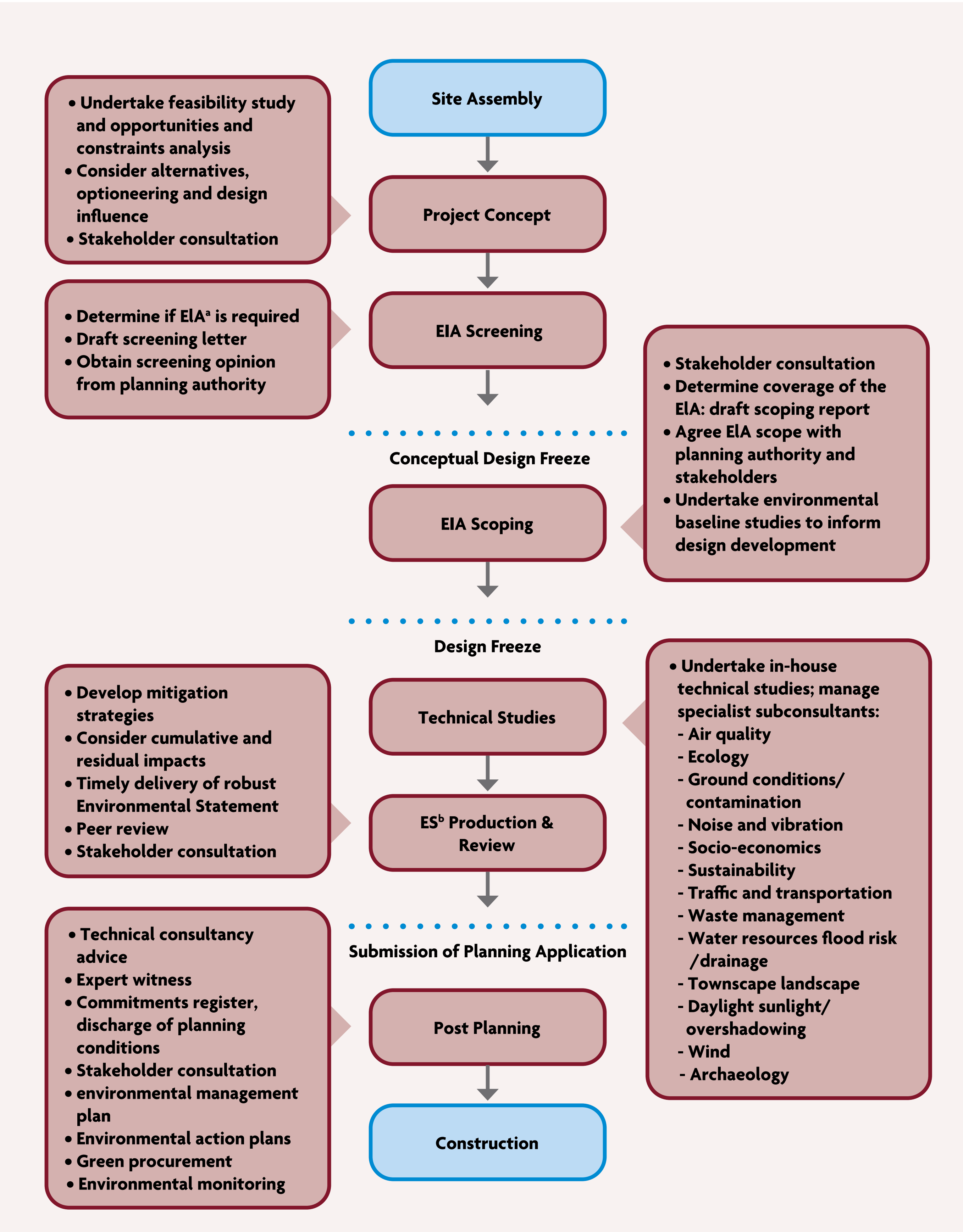


▲ **Figure 1. Environmental impact assessment process diagram. Note: [a] EIA: environmental impact assessment [b] ES: environmental statement**

Environmental statements – the reports setting out the findings of an EIA – have expanded from the narrow, focused, short documents they started out as in the early 1990s to become multivolume, lengthy (some may say impenetrable) series of documents in the first decade of the 2000s. Today, they are modern online reports and maps, with a narrower focus. However, the environmental statement format and structure remains recognisable, with the main stages of the EIA process being fundamentally unchanged (see **Figure 1**).

Advances have been made since, adding hyperlinks to figures within Word documents and using geographic information system (GIS) tools for data surveys and mapping. The EIA practitioner community has come together and undertaken some excellent research exploring the benefits of a truly digital EIA process – for developers, consultants and the public. For example, an Innovate UK-funded report highlighted several key priorities, including a national environmental data hub, digital EIA workspace, and interactive and accessible environmental statements.[2]

BOX 1. DIGITAL ENVIRONMENTAL IMPACT ASSESSMENTS

The benefits of digital environmental impact assessments include:

- More efficient decision-making in the planning and design process;
- Transparency in the visualisation of and access to project-specific spatial data;
- Enabling standardisation of data collection and potential for artificial intelligence application and machine learning;
- Effective integration of project phasing and multiple data sources;
- Ability to assess impacts (positive and negative) earlier and to consider multiple scenarios in the EIA process;
- Streamlining and driving efficiencies through multi-stakeholder collaboration;
- Maximising stakeholder communication and public engagement; and
- Use of digital platforms to train and manage the project team resources in line with best practice in the industry and in other sectors and countries.

However, there has been some frustration with the pace of change and implementation – especially when the benefits appear so obvious and attractive (see **Box 1**). So why has progress been limited?

Should developers pay for digital innovation when a standard PDF version of an environmental statement meets regulations and satisfies the information needs of planning authorities? Tools and software innovation have led to some progress, individual environmental consultancies have developed and promoted their own digital EIA platforms, web versions of non-technical summaries are more common but, in reality, more than 90 per cent of all environmental statements remain in PDF format.

WHY IS PROGRESS SO SLOW?

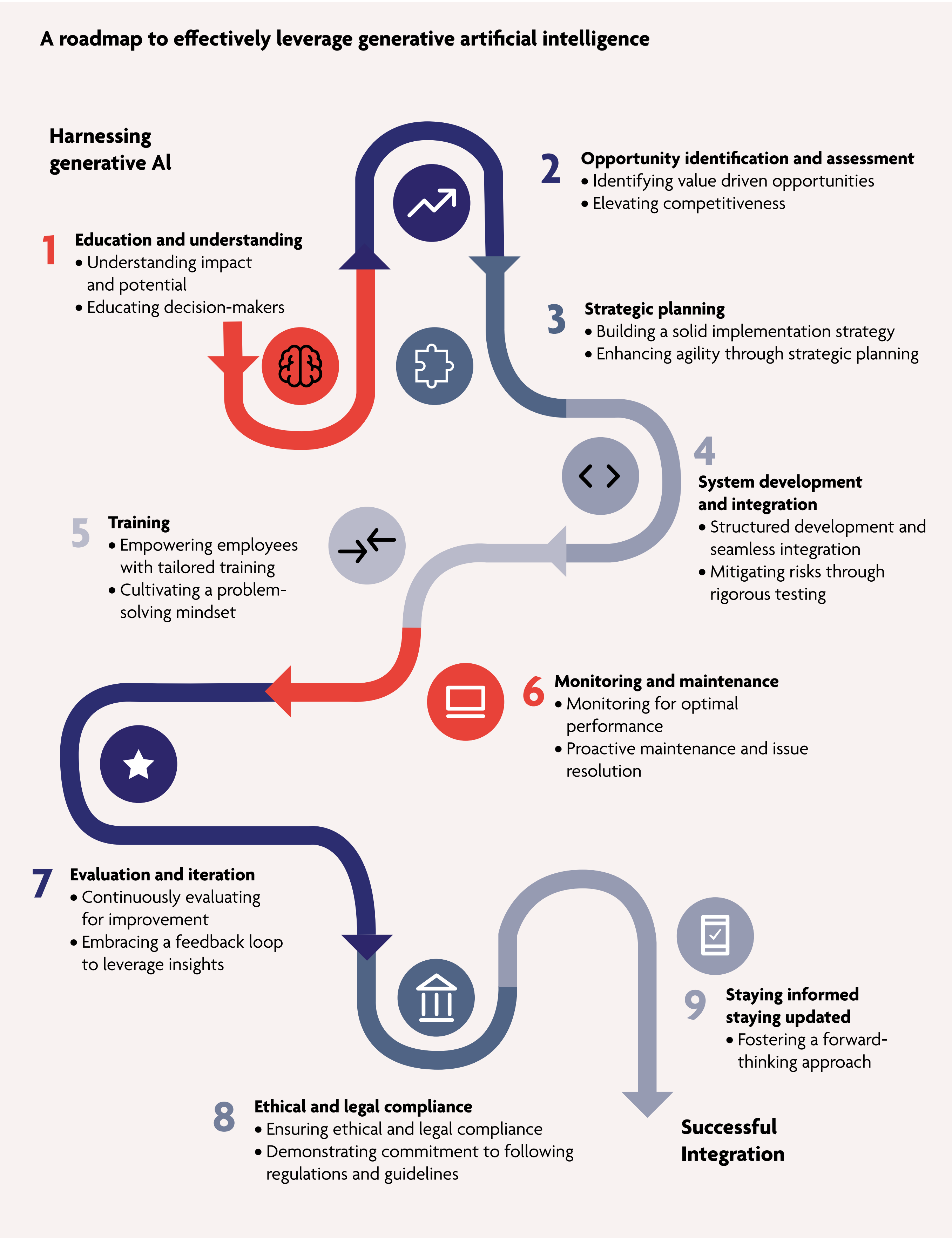
The 'if it is not broken why fix it' mentality has led to a generic approach to EIA, despite the continuous best efforts of industry leaders, the IES, the Institute of Environmental Management and Assessment, focus groups and environmental consultancies to drive change. However, the consensus is that artificial intelligence (AI) will dramatically transform the way we manage, analyse and present environmental data (see **Figure 2**). With or without changes to the EIA regime – in light of the potential move towards Environmental Outcomes Reports or a new UK Government approach to streamlining the planning process – are we about to see a revolution in digital EIA?

For EIA consultants, AI already has the potential to automate routine tasks, analyse massive datasets, detect patterns and trends, and make predictions at a speed and scale beyond human capability. A revolution in digital EIA embracing generative AI could be imminent, and with it comes the ability to drive change in both environmental protection and strategic planning decision-making (see **Figure 2**).

COLLECTING THE DATA

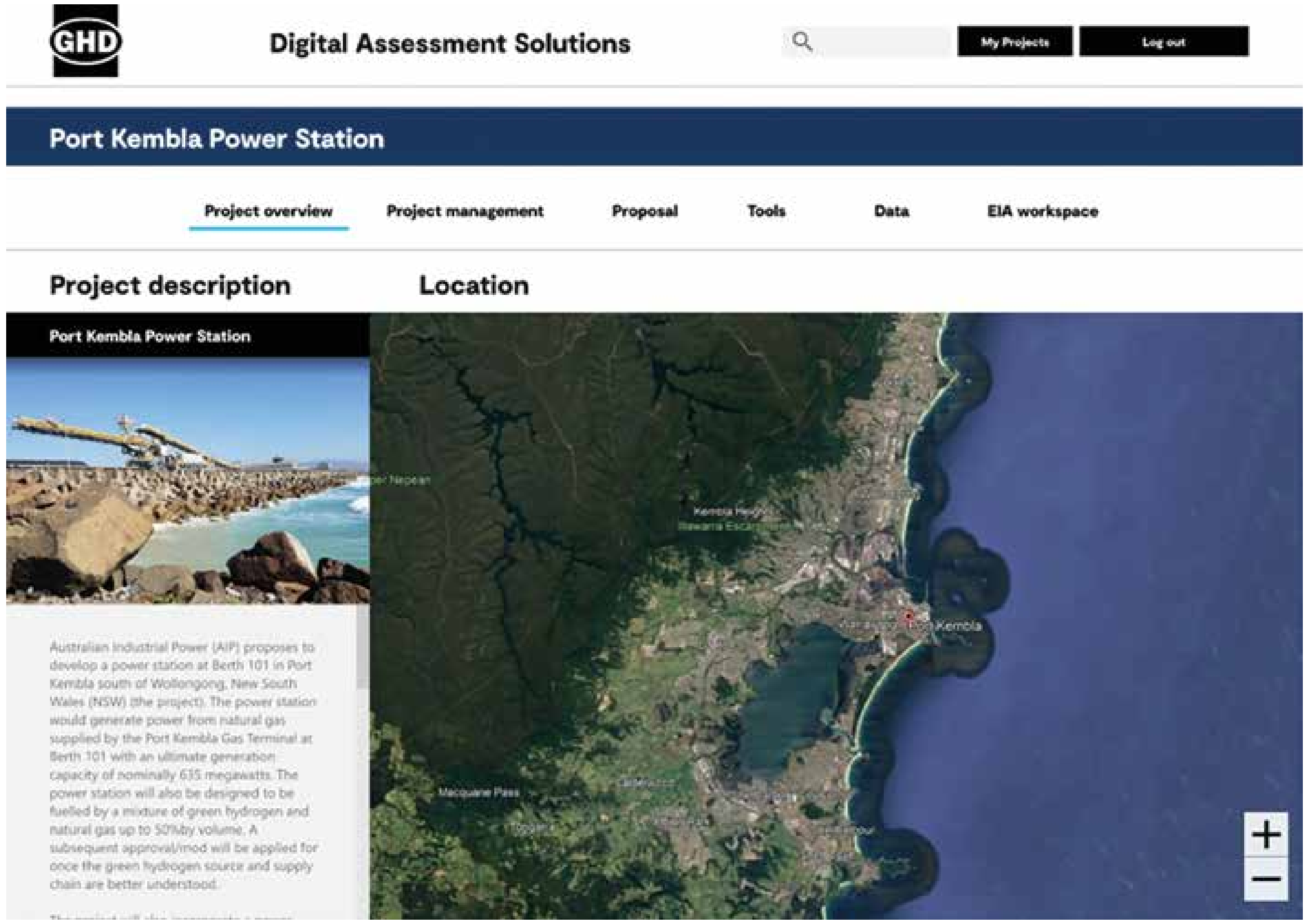
Baseline environmental planning data are key to an effective digital EIA process. There needs to be a level of transparency, collaboration and standardisation across the industry to ensure data are both accessible to all involved in the planning process and up to date. Defra's MAGIC website, launched in 2002, pioneered this approach and currently has over 400 datasets from partners including the Environment Agency and Historic England.[3] At present, it is the closest thing to a national environmental data hub.

The digital planning programme from the Department for Levelling Up, Housing and Communities has been supporting local planning authorities through funding and partnering with technology providers to develop innovative digital planning tools focused on efficiency and accessibility of planning data.[4]



▲ **Figure 2. Transformative artificial intelligence. (© GHD)**

ANALYSIS



▲ **Figure 3. GHD Digital Assessment Solutions platform. (© GHD)**

To facilitate this, users have access to live planning datasets, either at national (e.g. map of planning data for England) or city scales, such as London's Planning London Datamap.[5,6] Both have information on when the data were last updated to maintain data quality.

What is still missing is the collation of all the environmental survey and assessment data collected during the EIA process for new proposed developments. For ecology, some data are saved and reported back via local environmental records centres. For example, ecology survey data in London can be submitted to the Greenspace Information for Greater London Community Interest Company, London's environmental records centre, and accessed by other consultants or the public. But this is not automated; it relies on ecological consultants submitting project data, combined with casual and ad hoc wildlife sightings and reporting from the public.[7]

Environmental consultants working on digital EIAs have a responsibility to collate information from across the industry, to agree on standards for data collection and templates, and to take a shared approach to formats that ensure environmental statements are machine readable and that the survey data are not locked away in PDF chapters and appendices. AI has the potential to transform the current approach to data collection and management. Tools like ChatGPT and Microsoft Copilot already enable users to instantly summarise any report or document. The next step would be the ability to collate specific datasets from environmental statements and to provide the information in a far more accessible form. However, this still requires human review and editing to ensure consistency of methodologies and that the datasets are comparable.

The use of drone and AI sensors, remote sensing technologies for habitat mapping and monitoring together with automated report summaries, and the collation of data from multiple sources are expected to be standard practice in the consultancy sector in the next 12 months. There are already examples of 'sensors incorporating artificial intelligence algorithms to analyse and interpret data in real time, providing valuable insights into complex environmental systems'.[8] If all mitigation measures outlined in published environmental statements for a specific area or type of project could be collated, combined with 'live' baseline data and monitoring, and reviewed in the context of initial plans for other new development proposals, in theory, AI could provide instant indicative EIA Screening and Scoping reports for any new proposal. While these would still need to be reviewed by consultants, it would be a useful starting point.

DIGITAL WORKSPACE

GIS is and has always been central to a successful digital EIA process. It plays a part in all aspects of the process and is built into most digital EIA platforms already in use. GIS is at the heart of GHD's Digital Assessment Solution (see **Figure 3**). This example of a digital EIA workspace has been developed to enable a project team to collaborate efficiently, all accessing the same spatial project data – the 'single source of truth' for a development. It is currently being trialled on projects in the UK and internationally. Other digital EIA platforms include those by other consultancies such as Arcadis, Jacobs, WSP (Wood) and AECOM.

Overall, digital EIA platforms are primarily of interest to EIA coordinators and the technical and project teams involved in a specific proposed development. They provide the potential to cover all stages of the EIA process – from screening and scoping through to monitoring mitigation measures (see **Figure 1**). External access to the platform enables collaboration with multiple technical teams and allows planners, clients and other stakeholders to review spatial data and modelling results during the assessment process. The impacts of any scheme design or red line boundary changes are instantly reflected on the platform and relevant technical teams are notified to review and update their assessment as required.

Many consultants utilise a SharePoint-style platform approach, which also allows for the incorporation of links to other software programs and tools. In this way, the EIA can be effectively project managed and coordinated with full access by the project team to all project data, GIS mapping and technical reports.

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Ultimately the information can be published on a website for stakeholders and the public to access the EIA findings and non-technical summary.

DIGITAL ENVIRONMENTAL STATEMENTS

More effective stakeholder engagement is often cited as the main benefit of digital EIA. It can be argued that, on the one hand, we are still constrained by the planning process and need for PDF documents to be issued to a local planning authority; whereas, on the other hand, we already have the tools and techniques in place to present environmental statements digitally – online and in a much more accessible and interactive way.

An environmental statement, once submitted as part of a planning application, is a public document and, in theory, available online. A local authority's planning portal provides online access to any submitted environmental statement; however, these portals are often difficult to navigate, especially those without mapping or effective topic-specific search functions. Even when you do find the planning application of interest, you still have to search through a long list of PDF chapters, which for the general public still makes the environmental statement inaccessible.

Where a proposed development has a project website, there is an opportunity to present the environmental statement, its technical assessment chapters (e.g. noise, air quality, ecology) and the EIA conclusions in an interactive and accessible format. This enables the EIA findings to be directed to various readers, from regulatory bodies and statutory consultees to community groups and the public. Most EIA consultants are already utilising the accessible Environmental Systems Research Institute's ArcGIS StoryMaps tools to present this information – including maps, 3D scenes and multimedia content.[9] Even if it is only done for the non-technical summary, it is a definite improvement on a PDF report.

The A303 Stonehenge Scheme – proposing to tunnel a section of the A303 as it passes by Stonehenge – was one of the first examples of a digital EIA website using ArcGIS StoryMaps to present the assessment findings in 2019. The Crossrail 2 project, before being paused in 2020, was intended to be the first fully digital EIA.[10,11]

The EIA process could benefit from recent innovations in the virtual reality presentation of data and 3D modelling. Virtual reality headsets are increasingly used to present project design in an immersive way at consultation events. Tools such as Mission Room, which supplies whole-room-based interactive and immersive displays to reach a wider audience, can assist in increasing engagement with the EIA process, especially when combined with more conventional tools such as public events and community newsletters.[12]

3D ENVIRONMENTAL IMPACT ASSESSMENT

Visualising the environmental baseline and assessment data in a 3D model or digital twin would allow the project team, planners and public to review the potential impacts through a fully interactive and timeline-based tool. For example, a resident may want to know how peak air quality and noise impacts during construction would affect them. Meanwhile, the nearby school would like to see the cumulative impact of traffic levels for a proposed development, combined with projected noise and air quality levels.

▲ **Figure 4. VU.CITY 3D model of Birmingham. (© VU.CITY)**

VU.CITY has been at the forefront of creating accurate and interactive 3D models of UK cities for architects, planners and developers to visualise and assess potential new developments (see **Figure 4**).[13] The value of such 3D city models was demonstrated with an interactive virtual reality digital twin of London's Square Mile, launched in 2020.[14] This model enabled planning pre-application discussions and stakeholder engagement to be undertaken using virtual reality to walk around and view the proposals for a new development in the City of London.

3D models have been used to assess and present potential impacts of new developments on, for instance, daylight and sunlight levels, wind conditions, townscape and visual effects, and noise levels. Presenting in 3D gives users the ability to view the potential effects from above and at street level. The technology also has the potential to combine data layers for multiple planning applications and to present cumulative environmental impacts in a transformational way.

THE FUTURE

Digital EIA techniques and tools have been slowly evolving over the past decade and practitioners have embraced ways to make the process more interactive and collaborative. However, AI provides an opportunity to truly transform the EIA process. What is considered a complex interaction of environmental, economic and social factors that many find inaccessible will be unrecognisable in the next five years. AI will enhance our ability to manage and process environmental data and once integrated into EIA assessment and presentation it will revolutionise the whole process. ES

Mark Elton, BSc MSc FRGS CEnv MIEnvSc, is the Technical Director for EIA at GHD, a global, multidisciplinary professional consultancy providing integrated solutions across digital, engineering, environmental, design and construction disciplines. He has been providing EIA strategy, assessment and project management for over 28 years in the UK and internationally. Mark is passionate about finding solutions to both developer and technical problems and has been working on digital EIA innovation and platform development in the UK.

mark.elton@ghd.com
www.linkedin.com/in/eltonmark/
www.ghd.com/en-gb

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Editors	Bea Gilbert and Lucy Rowland
Guest editor	ChatGPT
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Designer	Kate Saker katesaker.com
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Email	info@the-ies.org
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