Met Office

Embedding machine learning and artificial intelligence in weather and climate science and services

A framework for data science in the Met Office | 2022-2027

The purpose of this document is to set the framework for the Met Office to achieve its goal of 'to harness the power of data science to push the frontiers of weather and climate science and services'. In doing so, it builds upon the 'fusing simulations with data science' theme within its Research and Innovation Strategy (Met Office, 2022).

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Contents

Foreword

Over the last few decades, we have seen advances in technology increase the power and sophistication of computer models that underpin weather and climate science and services. Recent progress in these areas has brought the world to the cusp of potentially game-changing breakthroughs in weather and climate modelling. Data science and artificial intelligence have huge potential to drive forward new advances in weather and climate science to help make society better able to survive and thrive in a changing climate. Therefore, the Met Office is committed to making the most of this opportunity.

Capability in data science within the Met Office has been growing over the last few years, with recent efforts focusing on consolidating and developing this work further. This process has developed a vibrant community of practice, building critical infrastructure and delivering demonstrator pilot projects that have really brought to life what can be achieved in this important area of research. I am delighted to launch the framework in this document, which sets out how we can now take the next step forward to help realise the potential of a new frontier in machine learning and artificial intelligence for weather and climate science and services.

This work will all form a key part of the Met Office Research and Innovation Strategy, cutting across the entire value chain from fusing simulations with data science, right through to hazard to decision-making. This work is timely, and also aligns well with key government priorities to help us on our journey to a resilient Net Zero future. I am excited to see what the future will hold for this work and I look forward to seeing the Met Office develop further thought leadership in this arena.

Professor Stephen Belcher
Chief of Science and Technology

Executive Summary

We are in the midst of 'a revolution in Artificial Intelligence' (Clark *et al.*, 2019; UKRI, 2021) where the world's fastest-growing deep technology has the potential to rewrite the rules of entire industries (HM Government, 2021b) fundamentally changing the way we work and live. Advances in data science, including machine learning and artificial intelligence, mean that computers can now analyse, and learn from, vast volumes of information at high levels of accuracy and speed, offering significant gains in efficiency and performance to most sectors. To take full advantage of these technological breakthroughs, many scientific disciplines, including weather and climate science and prediction, are revising their operating plans (Dueben *et al.*, 2021b). Here we present a framework for how the Met Office will respond to this opportunity and achieve its goal 'to harness the power of data science to push the frontiers of weather and climate science and services'.

Data science is not new: the Met Office has always been a 'data science' organisation in that it produces, stores, analyses, visualises, and extracts meaning and value from vast quantities of data. Likewise, machine learning activities have been ongoing in the Met Office for many years though perhaps not acknowledged under that label, for example the use of regression, clustering, Gaussian processes, Bayesian modelling, principal component analysis and shallow neural networks. The impact of data science can be seen across the value chain[1] for weather and climate science and services, from observations (including data thinning, quality control, gap filling), through simulation (including data assimilation and model simulation), analysis (including post-processing) to products and services (including risk forecasts, warnings and dissemination). The Met Office has taken steps to accelerate the adoption of data science across its weather and climate science and service activities with a range of pilot projects, training and development activities, and focused partnerships with organisations applying data science to the domain. This framework builds on these successes and the progress that has been made in embedding data science in weather and climate science and services.

To ensure that the Met Office is well positioned to respond to opportunities, a research theme on 'fusing simulations with data science' is embedded within its Research and Innovation Strategy (Met Office, 2022).

The purpose of this framework is to supplement that theme by describing how we will organise activities to develop, support and maintain an enabling environment wherein data science can thrive. Using this framework, data science resources and capabilities can be configured and deployed to maximize opportunities and address challenges as they arise (Barney, 1991). This approach ensures that the Met Office remains resilient, agile and able to respond to the demands and opportunities associated with a fast-moving technology.

The framework comprises three pillars:

- **Capabilities.** This first pillar identifies the Met Office's priority data science capabilities within science and production. These can be combined with other Met Office capabilities, and those of partners, to ensure we are able to respond to the opportunities and threats of a dynamic and fast-evolving environment and technology.
- **People.** People are the engine of any strategy. This second pillar describes how an enabling environment will be created that attracts, retains and develops the skilled and diverse workforce needed to realize the potential value of data science in the weather and climate science and services.
- **Partners.** The Met Office on its own cannot realize the value of data science to the weather and climate endeavour, nor can it keep abreast of all the developments and opportunities associated with this fast-evolving technology: this can only be with partners across the national and international community. This pillar describes how we will work with partners to deliver more than the sum of our parts.

Together these pillars will support the Met Office in delivery of its goal for data science 'to harness the power of data science to push the frontiers of weather and climate science and services'.

[1] Competitive advantage stems from the many discrete activities that a firm performs in designing, producing, marketing, delivering and supporting its product. A value chain is the simple tool for examining all of the activities a firm performs which provide competitive advantage (Porter, 2011).

1. Context

We are in the midst of ‘a revolution in Artificial Intelligence (AI)’ (Clark *et al.*, 2019; UKRI, 2021) and the ‘Fourth Industrial Revolution’ (Schwab, 2016) is well underway. Three factors have combined to bring us to this point:

- volumes of data an order of magnitude greater than we have previously experienced;
- the development of data science and analytical tools with which we can interrogate and extract value from data, and an increasing pool of expert scientists who know how to use these tools;
- a greater availability of increasingly powerful computing capacity and infrastructure (Hall and Pesenti, 2017).

With advances in data science, including machine learning and AI, computers can now analyse, and learn from, vast volumes of information at high levels of accuracy and speed, offering significant gains in efficiency and performance to most sectors. To take full advantage of these technological breakthroughs, many scientific disciplines, including weather and climate science, are revising their operating plans (Dueben *et al.*, 2021b). This is a vital, and timely, opportunity since breakthroughs in data science may help tackle one of the gravest threats facing society today: our vulnerability to extreme weather events in a changing climate.

Extreme weather events, such as in 2021 — a record heatwave on the west coast of Canada, catastrophic floods in Belgium, Germany and the Netherlands, or wildfires in several countries of southern Europe — all highlight our vulnerability to natural climate variability in the present-day and are a forewarning of the increasing risks associated with climate change. ‘The need for action on climate change is urgent’ (Vallance and Belcher, 2021); science and technology have a vital role to play in ensuring we can better understand and manage the key hazards in order to become climate resilient[2] through both mitigation and adaption.

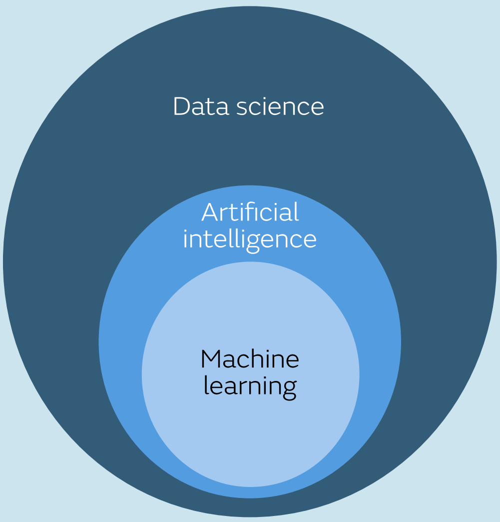
The global weather and climate science community is embracing the opportunity presented by data science to deliver benefits (see next section). For example, in 2020 the National Oceanic and Atmospheric Administration (NOAA) published its AI Strategy, dramatically expanding ‘the application of artificial intelligence in every NOAA mission area by improving the efficiency, effectiveness, and coordination of AI development and usage across the agency’ to deliver ‘transformative advancements in the quality and timeliness of NOAA science, products, and services’ (NOAA, 2020) and in 2021 the European Centre for Medium-Range Weather Forecasts (ECWMF) published a roadmap for deployment of machine learning for weather and climate prediction in a coordinated effort across Member and Cooperating States (Dueben *et al.*, 2021b). Increasingly, national meteorological, hydrometeorological and hydrological services around the world are using data science approaches (including AI and machine learning capabilities) alongside physics-based techniques to extract patterns and insight from ‘the ever-increasing stream of geospatial data’ (Reichstein *et al.*, 2019).

BOX A

What is data science?

Data science encompasses all activities to do with the curation, processing, analysis and visualisation of data to extract knowledge and provide insights.

Machine learning comprises a large range of techniques and algorithms that allow ‘machines’ to ‘learn’ patterns autonomously from data. The sub-field of deep learning focuses mainly on many layered, complex neural networks.



Artificial intelligence is concerned with techniques that learn to mimic human behavior or intelligence. These techniques can come from machine learning (including deep learning) as well as traditional logic and if-then-else programming disciplines.

[2] Resilience: ‘the capacity of social, economic, and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity, and structure, while also maintaining the capacity for adaptation, learning, and transformation (Arctic Council, 2013).’ (Allwood *et al.*, 2014)

The use of data science is not a new development in the Met Office: it has always been a 'data science' organisation in that it produces, stores, analyses, visualises, extracts meaning and value from vast quantities of data. Likewise, machine learning activities have been ongoing in the Met Office for many years though perhaps not acknowledged under that label. For example, clustering has been used for cloud classification (Tsushima *et al.*, 2016) and identifying weather patterns in the operational DECIDER system (Neal *et al.*, 2016); Gaussian processes have been used for downscaling UK climate projections; and the Havemann-Taylor fast radiative transfer code uses principal component analysis and kernel regression (Havemann *et al.*, 2018). The newer machine learning techniques of the last ten years or so, particularly deep learning, have shown impressive success in many domains such as computer vision and natural language processing and consequently are beginning to be deployed in weather and climate science (Reichstein *et al.*, 2019). This is true across the value chain[1] for weather and climate science and services: from observations (including data thinning, quality control, gap filling), through simulation (including data assimilation and model simulation), analysis (including post-processing) to products and services (including risk forecasts and dissemination). The Met Office has taken steps to accelerate the adoption of data science across the weather and climate science and service endeavour with a range of pilot projects, training and development activities, and focused partnerships with organisations applying data science to the domain. This framework builds on these successes and the progress that has been made in embedding data science in weather and climate science, some of which are highlighted in the next section.

What is new about data science is the rate of change — the rapid expansion in what is possible brought about by an explosion of data[3], acceleration in development and adoption of data science approaches, and enhanced availability of world-leading high-performance computing and cloud infrastructure. To ensure that the Met Office is well positioned to respond to this opportunity, a research theme on 'fusing simulations with data science' is embedded within its Research and Innovation Strategy (Met Office, 2022). This framework supplements this theme by setting overarching objectives that support the development of an enabling environment wherein the use of data science in the weather and climate science and services thrives.

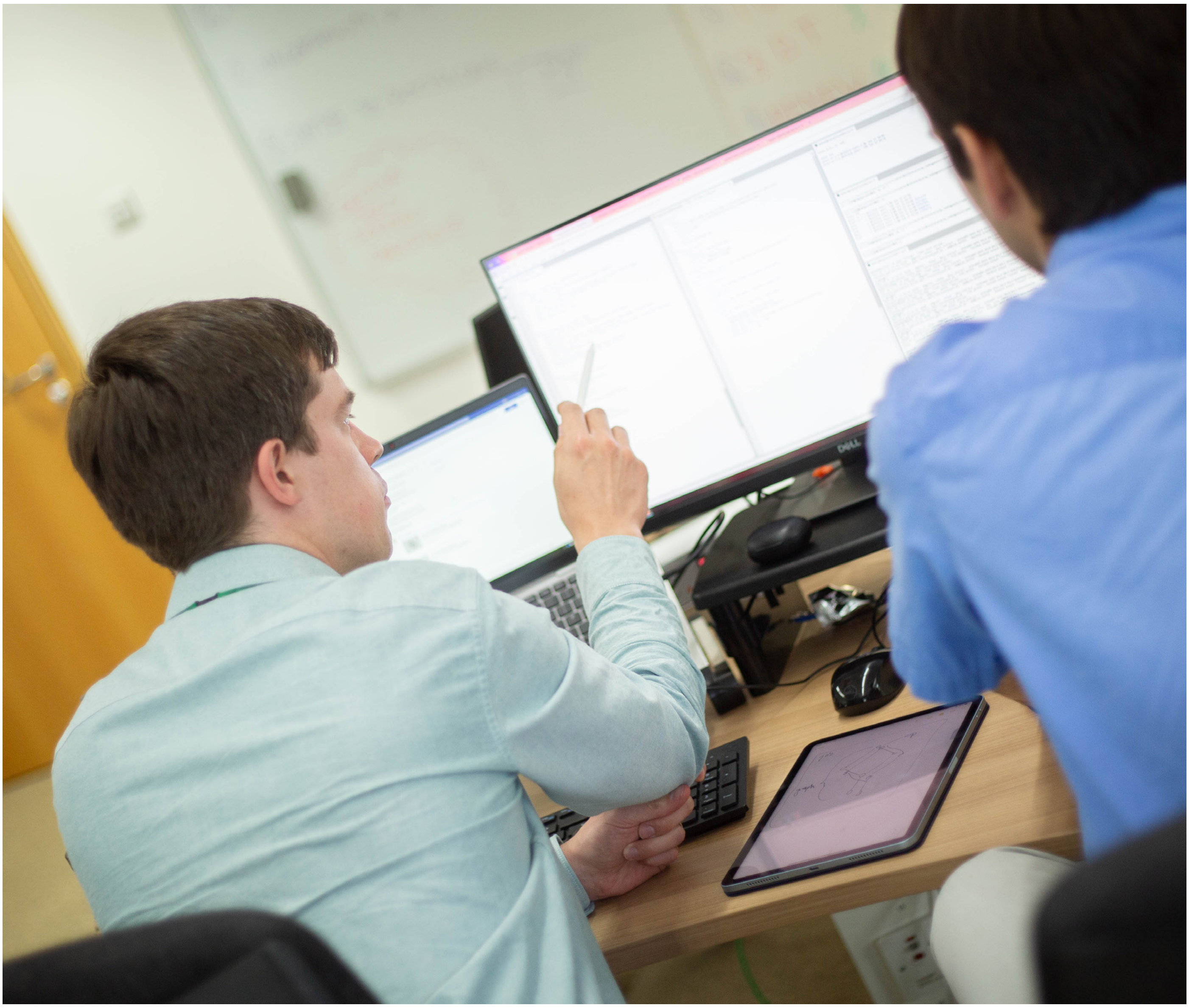
In doing so, the framework supports the domain-specific implementation of UK strategies such as the UK Innovation Strategy (BEIS, 2021), the Integrated Review (HM Government, 2021a), UK Artificial Intelligence Strategy (HM Government, 2021b), and the National Digital Strategy (DCMS, 2020). A concerted, coordinated effort is needed if we are to accelerate successfully the use and realization of the value of deploying data science. For this reason, the framework purposefully seeks to complement the existing strategies and plans of partners across the environmental science research community, both within the UK and internationally. Critically, it also builds on the gains already made in the adoption of data science within the Met Office and harnesses complementary plans that exist within the Met Office and with our partners; leveraging these commitments will ensure we can rapidly accelerate.

[3] Note: as of 2021 the operational and parallel suites for numerical weather prediction in the Met Office produce 18 terabytes of data per day.

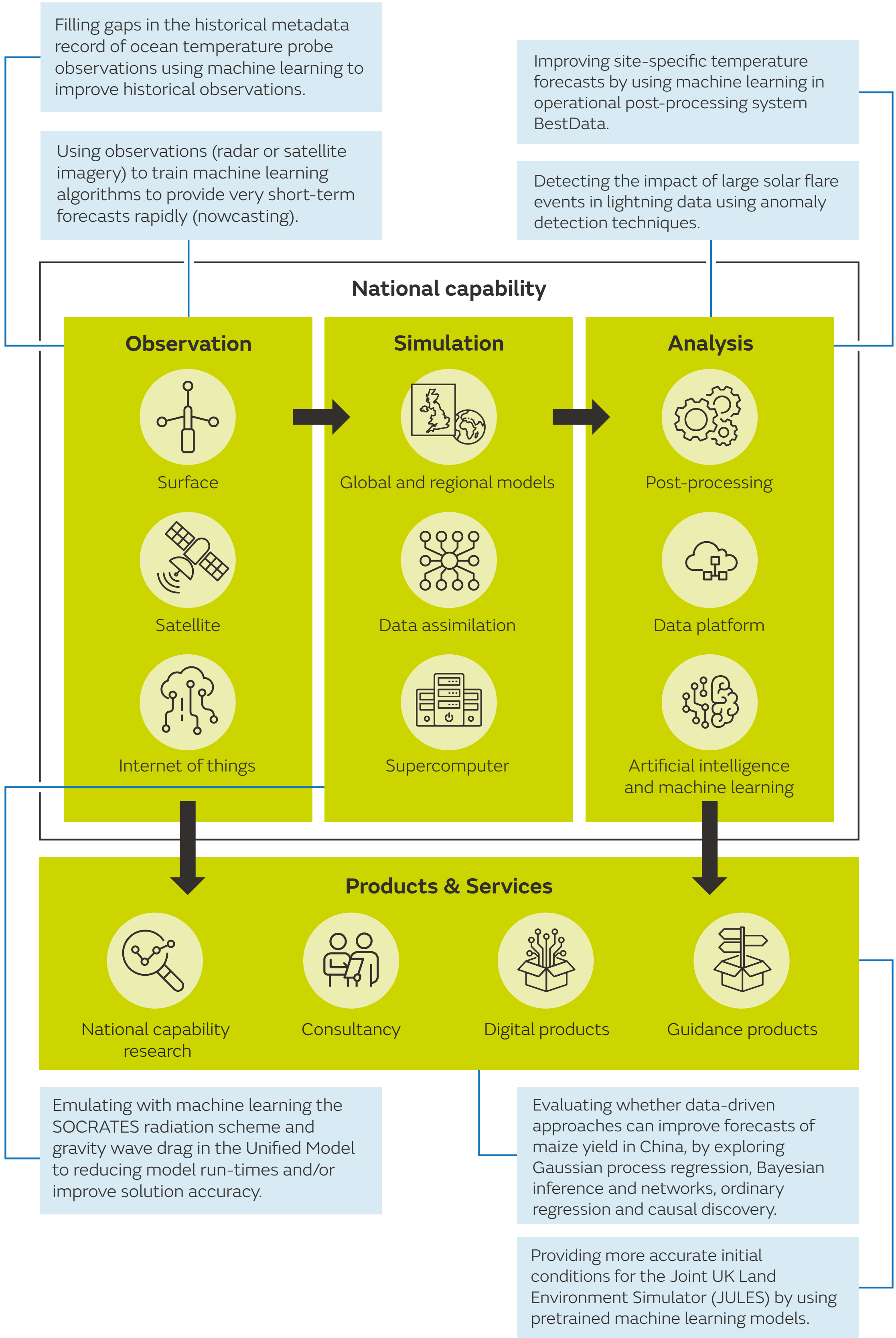
2. Overview of data science in weather and climate science and services

Forecasting the weather and changes in our climate is innately difficult. It requires a vast amount of observational data, advanced understanding of complex physics-based models and their outputs, and access to significant computational power (Dueben *et al.*, 2021a). Complex workflows are needed with a value chain stretching from observations through simulation (including data assimilation and model simulation), analysis and interpretation (including post-processing) of model outputs, and translation into products and services (including risk forecasts and dissemination). There is an opportunity to deploy data science across the whole of the Met Office national capability (see figure), fusing data science with conventional physical modelling approaches and expert knowledge, leading to potential improvements to computational efficiency, information quality (e.g. completeness, accuracy, etc.) and interpretation (Maskey *et al.*, 2020; Dueben *et al.*, 2021b). The opportunities associated with applying data science to the workflow of weather and climate science and services are well recognised (Dueben *et al.*, 2021a) and research efforts are starting to bear fruit across many weather and climate centres and academic institutions.

The remainder of this section discusses some examples across the value chain, including areas where the Met Office has already made progress.



Examples of data science applications to the national capability



The national capability encompasses the science, technology and other key competencies required to deliver the data which underpins all weather and climate services. It includes the observations, numerical weather prediction modelling and analysis (post-processing and data production) required to make weather forecasts and climate projections, as well as the technology required to perform the forecasts and projections, and to process, manipulate, store and serve the data. The weather and climate national capability enables the UK to deliver world-leading weather and climate science and services, to support national strategic needs, and to respond to emergencies. It includes the research and development activities which keeps this capability at the cutting edge (Met Office, 2022). Examples of data science applications to the national capability are added.

Observations

Machine learning applied to 'nowcasting'[4] applications (especially for rainfall) has been an active area of research for at least the last five years (Shi *et al.*, 2015; Lebedev *et al.*, 2019; Sønderby *et al.*, 2020). Here, observations (radar or satellite imagery) are used to train machine learning algorithms to provide very short-term forecasts rapidly. Such applications often use deep learning techniques originally designed for spatio-temporal prediction tasks (e.g. video sequence generation). The Met Office, in partnership with DeepMind, developed such a system using generative models and evaluated it in comparison to standard nowcasting methods (Ravuri *et al.*, 2021). In addition, research is ongoing on precipitation nowcasting for aviation (funded by the Civil Aviation Authority) also using generative techniques (variational auto-encoders).

Another application area is using machine learning to improve historical observations: in 2020, the Met Office ran a pilot project to investigate the use of machine learning for filling gaps in the historical metadata record of ocean temperature probe observations (Haddad *et al.*, accepted). The Met Office also uses a neural network method to detect clutter in radar data to improve the accuracy of quantitative precipitation estimation (Husnoo *et al.*, 2021).

Simulation

The possibility of using machine learning techniques to emulate components of numerical weather prediction and climate prediction models has received considerable attention over the last ten years. The primary aim for such work is often to reduce model run times, but the potential to improve simultaneously the accuracy of the solution (e.g. by training the machine learning emulator on much higher resolution data than could be used in the physics-based model) also exists. Research at several modelling centres has shown the potential of the approach for radiation, convection, cloud physics, atmospheric chemistry and gravity wave drag parametrisations (Krasnopolsky *et al.*, 2010; Rasp *et al.*, 2018; Brenowitz and Bretherton, 2019; Keller and Evans, 2019; Chantry *et al.*, 2021). More recently, entire land-surface models have been emulated (Baker *et al.*, 2021). Over the last few years, the Met Office has actively pursued machine learning emulation of the SOCRATES radiation scheme and also gravity wave drag in the Unified Model.

[4] Nowcasting is a technique used for very short-ranged forecasting (e.g. over the next 0-2 hours).
[5] 'Big data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision-making, and process automation.' (Source: https://www.gartner.com/en/information-technology/glossary/big-data.)

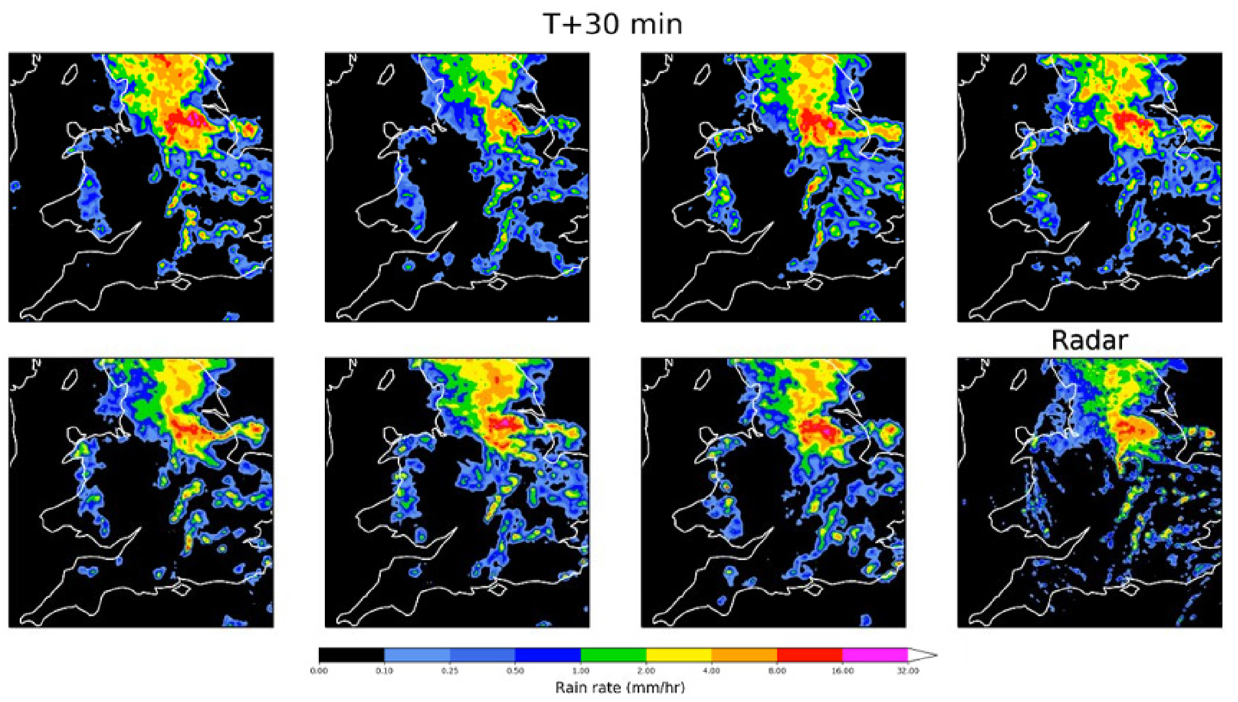
BOX B

Nowcasting

Nowcasting uses the most recently available observations to provide frequently updated short-term forecasts that support users making operational decisions in real time. Machine learning offers new ways to capitalise on the value that lies in high volumes of observation data. Models can be trained with multiple data sources allowing simple trialling of new combinations of data types. Once trained, models can be run extremely quickly and allow for frequent rapid updates and the possibility of multiple runs to quantify uncertainty through ensemble forecasting.

The Met Office has been exploring the use of deep learning techniques for nowcasting in two projects that have used different ensemble-based approaches to predict where it will rain in the next few hours from RADAR precipitation observations:

- A collaboration with Google DeepMind (Ravuri *et al.*, 2021) drew on world-leading expertise from both organisations to demonstrate that a generative adversarial network can produce realistic forecasts and ensembles. The output verified positively using both standard measures and when assessed by operational meteorologists in a blind study.
- A project funded by the Civil Aviation Authority has also produced realistic forecasts (Bartholomew *et al.*, 2020) using a variational auto-encoder. However, in this case, the rainfall nowcast is being used as a proxy for convection and the project is now looking at how additional data sources can be added to forecast better the activity of convective storms which significantly impact air traffic management and safety.



Rain rate from seven ensemble members generated 30 minutes ahead using a variational auto-encoder accompanied by the corresponding observed radar image.

Analysis

Data science techniques, and in particular machine learning techniques, have many applications for dealing with the large volume of data produced by weather and climate models – for example traditional post-processing activities such as bias correction of systematic errors to improve forecasts and downscaling model output to provide site-specific forecasts or climate projections (for a recent review of the field, see Haupt *et al.*, 2021). There is also a significant opportunity to use unsupervised or semi-supervised machine learning techniques for understanding, summarising, and detecting patterns in 'big data'[5]. Examples of applications are anomaly detection, feature extraction, dimension reduction, clustering, learning dynamical equations, and visualisation. The Met Office currently uses machine learning to improve site-specific temperature forecasts in its operational post-processing system (BestData) and in 2020 ran a pilot project looking at applying machine learning to its new post-processing system, IMPROVER. Other Met Office projects of note include using anomaly detection techniques to detect the impacts of large solar flare events in lightning data (the LEELA ML project), automatic clustering and classification of biomes from climate data (a project that ran as part of the AWS Embark programme) (Sidoumou *et al.*, 2022), and causal analysis techniques for quantifying pathways of teleconnections (Kretschmer *et al.*, 2021).

Products and services

Developing and using scientific knowledge, people, partnerships, and infrastructure to improve risk-based decision-making could greatly benefit from data science. Whether on weather or climate timescales, traditional statistical techniques have been in use for many years to translate science into impacts that inform products and services which unlock greater value for users from Met Office data. More recently, within the Met Office, machine learning techniques have been applied across many sectors, ranging from impact forecasting to risk modelling, on all timescales. Despite it being early days, results from such initiatives are promising and span both supervised and unsupervised techniques (with an emphasis for the former), illustrating the broad applicability of machine learning to products and services. In the weather domain, to cite a few, natural language processing is being used to build a database of impacts for validation of impact forecasts, artificial neural networks and long short-term memory networks to forecast solar power in South Africa, pretrained machine learning models to provide more accurate initial conditions for the Met Office land-surface model JULES, or even extreme gradient boosting to forecast lee waves and rotors at Mount Pleasant Airport in the Falklands. On the climate front, convolutional neural network and fully connected neural networks are being investigated to obtain future projections of wave parameters along South African coasts from atmospheric climate data, and Gaussian process regression, Bayesian inference and networks, ordinary regression and causal discovery are being explored to evaluate whether data-driven approaches can improve forecasts of maize yield in China. Other potential applications are being explored with partners and highlight common barriers and technical challenges when adopting machine learning as a standard technique for products and services.

Challenges

Applying data science to the weather and climate domain is not without its challenges. Existing problems are emphasized, and new ones emerge.

For example, the advancement of data science for weather and climate science and services depends upon reliable access to compute infrastructure, either on premises or in the cloud, alongside appropriate data science infrastructures, workflows and tooling, here collectively referred to as the 'data science environment'. Dependencies on hardware and software should be addressed for the impact of data science to be realized.

Other challenges include the limitations associated with training data: despite the promise of accelerating simulation models using machine learning emulators or of using machine learning to capture relationships between data, one caveat is that machine learning approaches are not well suited to extrapolation outside the data distribution on which they have been trained and thus cannot deal well with non-stationary processes (for example, the effects of a changing climate). This is known in the machine learning community as 'out-of-sample error', and methods do already exist to identify and deal with it.

Vast amounts of data are produced that are not generally in a format directly consumable by machine learning algorithms. Researchers working on weather and climate science and services lack a common approach to structuring data in formats that can be easily consumed by machine learning algorithms, meaning that data sharing (interoperability) is difficult.

Work is also needed to establish a domain-specific set of benchmark datasets, as part of a wider drive to develop robust, flexible, and transferable frameworks for best implementing new approaches. There are further challenges regarding the 'explainability' and physical interpretability of data science and machine learning models, something that can only be overcome by ensuring domain scientists and data scientists work closely together on projects, incorporating expert knowledge and system/process understanding.

To realize the full value of data science, these challenges and others must be overcome and a path forged that delivers physically-consistent machine learning solutions which exploit the full potential of advances in data science while complementing and enhancing existing physics- and process-based solutions. The full benefits from applying data science to the weather and climate science and services require collaboration and pooling of knowledge and expertise between data science experts and domain experts.

3. Data science vision and goal

The Met Office's overarching goal for data science is 'to harness the power of data science to push the frontiers of weather and climate science and services'. This is contained within the 'fusing simulations with data science' theme within the Met Office Research and Innovation Strategy (Met Office, 2022). The purpose of this framework is to supplement the Research and Innovation Strategy by describing how we will arrange our activities under three pillars to develop, support and maintain an enabling environment wherein the use of data science in the weather and climate science and services can thrive.

Using this framework, data science resources and capabilities can be configured and deployed to maximize opportunities and to address challenges as they arise (Barney, 1991). This approach will ensure the Met Office remains resilient, agile and able to respond to the demands and opportunities, associated with a fast-moving technology. The framework comprises three pillars that together will enable the Met Office to deliver its goal for data science: **Capabilities**, **People** and **Partners**.

The three pillars of the data science framework

Capabilities

This first pillar identifies the Met Office's priority data science capabilities within science and production. These can be combined with other Met Office capabilities, and those of partners, to ensure it is able to respond to the opportunities and threats of a dynamic and fast-evolving environment and technology.

People

People are the engine of any strategy. This second pillar describes how an enabling environment will be created that attracts, retains and develops the skilled and diverse workforce needed to realize the potential value of data science in the weather and climate science and services.

Partners

The Met Office on its own cannot realize the value of data science to the weather and climate endeavour, nor can it keep abreast of all the developments and opportunities associated with this fast-evolving technology: this can only be with partners across the national and international community. This third pillar describes how we will work with partners to deliver more than the sum of our parts.

The framework will be used to set objectives and priorities and inform the golden thread between the top-level goal and operational activities. A key principle of this approach is that resources and capabilities are developed and nurtured, so that they can be rapidly configured and deployed to respond to opportunities and challenges as they arise. This agility and flexibility will allow the Met Office to respond as data science develops within its research domain.

The framework should be considered alongside Met Office strategies, in particular the Met Office Strategy 2019-2024[6], Open Data Policy[7] and its approach to Data[8], High Performance Compute[9] and within the context of the Met Office's Corporate Plan[10].

[6] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/library-and-archive/library/publications/corporate/our-strategy-2019-2024.pdf
[7] https://www.metoffice.gov.uk/about-us/legal/open-data-policy
[8] https://www.metoffice.gov.uk/services/data
[9] https://www.metoffice.gov.uk/about-us/what/technology/supercomputer
[10] https://www.metoffice.gov.uk/research/library-and-archive/publications/corporate

4. Three pillars of the data science framework

The three pillars of this framework will enable the Met Office to deliver its goal for data science. They align with the cross-cutting themes of the Research and Innovation Strategy (People, Partnership and Practices) while adding detail specific to data science. The three pillars have been configured to complement progress achieved in embedding data science within the Met Office and the strategic approach of our partners. This complementarity should enable the Met Office and partners to work together to achieve their shared aims and be greater than the sum of their parts.

By developing, nurturing and protecting resources and capabilities within these three pillars, an enabling and agile environment will flourish. This operating environment will enable the Met Office to respond rapidly to the changes, opportunities and threats, associated with a rapidly evolving and dynamic technology.

Pillar 1: Capabilities

This pillar identifies the Met Office's **four core data science capabilities** (the building blocks):

- **Capability 1: Discovery and attribution**
- **Capability 2: Fusing simulation with data science**
- **Capability 3: Uncertainty and trust**
- **Capability 4: Data to decisions**

These capabilities are areas in which the Met Office can excel so that it both delivers its goal and offers advantage to its partners. They can be harnessed to ensure that the Met Office remains at the forefront of weather and climate science and services. All four capabilities are at differing stages of maturity: some are areas in which the Met Office already excels, others are areas being developed. Together they will enable the Met Office to respond to changes in a dynamic operating environment so that all four will be nurtured. These capabilities are listed below with a brief description and examples of their application to the weather and climate science endeavour.

Capability 1: Discovery and attribution

Data science, including machine learning, contains an abundance of tools that can help the Met Office improve and make better use of the vast quantities of weather and climate data that it produces. Data mining encompasses various unsupervised or semi-supervised techniques that allow us to understand, summarise and extract information or detect patterns in 'big data'. Examples include anomaly detection, feature extraction, dimension reduction, clustering, and visualisation of high-dimensional data. A commonly used statistical analysis technique to find patterns and relationships between features in data is correlation; most popular data-driven machine learning methods are correlation-based. However, it is well known in statistical science that correlation does not imply causation and there is now an emerging trend for causal machine learning. Causal analysis and discovery are disciplines in their own right and increasingly used in environmental sciences for testing and quantifying hypothesised causal relationships and data-driven discovery of new relationships.

Examples where causal methods could be useful include discovering previously unknown relationships, increased understanding of causal pathways for climate mechanisms and downstream impacts. Finally, supervised techniques as well as estimation of uncertainties also offer opportunities to improve the quality of existing data, for example gap filling of data and metadata.

In 2020 the Met Office ran several pilot projects forming a foundation for this capability. Firstly, the use of machine learning was explored for filling gaps in the historical metadata record of ocean temperature probe observations (Haddad *et al.*, accepted). Secondly, a collaboration between the Met Office and the University of Reading led to a paper highlighting the importance of a causal approach to quantifying teleconnection pathways (Kretschmer *et al.*, 2021). Lastly, a project looked at automatic clustering and classification of biomes from climate data (Sidoumou *et al.*, 2022).

BOX C

Ocean temperature probe classification project (XBT)

There is a significant amount of missing metadata (e.g. instrument type, manufacturer) in the historical record for deployed ocean temperature probes (Expendable Bathythermograph – XBT). This compromises our ability to correct bias in the data leading to uncertainty in the historical ocean temperature dataset, a dataset which is important in understanding climate change. In 2020 the Met Office led a project applying supervised machine learning techniques to predict values for the missing data and deliver improved accuracy in classifications of instrument type for XBT temperature profiles. The project delivered a 25% increase in data accuracy and a new approach for scientists developing ocean heat content reconstructions. As a result of the project, uncertainty in the datasets of historic ocean temperature has been reduced, strengthening our understanding of how the climate has changed.

Capability 2: Fusing simulation with data science

Data science has the potential to transform our approach to weather and climate modelling. By exploiting advances in fields such as machine learning and taking advantage of modern graphics processing units, there is an opportunity to rethink fundamentally the approach to building operational forecasting models. The focus of this capability is to evaluate systematically components of our numerical weather prediction and climate models and, where an opportunity for improvement exists, to reconstruct them with an optimal blend of data science and traditional physics-based techniques.

Computationally intensive components of weather and climate models may be substituted with machine-learning-based alternatives. In weather and climate science, this is traditionally referred to as emulation; in other sectors, such as engineering, this takes the name of 'surrogate modelling', recognising that machine learning approaches can be used as a substitute when beneficial.

Embedding emulators of physics schemes within numerical weather prediction is an active area of research as they may be faster, computationally cheaper and, in some cases, more accurate than traditional modelling approaches (Chantry *et al.*, 2021). This may be particularly beneficial for computationally intense and costly parametrizations such as schemes for convection, microphysics and aerosols, although it is noted that the non-linearity of these present some challenges (Hatfield *et al.*, 2021). Use of computationally cheaper and thus faster emulators within numerical weather prediction can ultimately improve the quality of the forecasts by freeing up computing resources to run models at higher resolution, with increased ensemble size or with more sophisticated (expensive) physics schemes. Furthermore, it may also be possible to learn the effects of unresolved processes from higher-resolution models such as cloud-resolving models or large eddy simulations with the prospect of improving the representation of some physical relationships.

The Met Office has embraced the opportunity to fuse simulations with data science. For example, in 2018 the Met Office led a project emulating the radiative transfer scheme (SOCRATES) and is currently collaborating on an international project emulating gravity wave drag parameterization. Both projects aim to fuse simulation with data science to deliver a more accurate forecast.

Looking to the future, lessons on the use of surrogate models (emulators) can be drawn from engineering. Here the use of surrogates can be optimised once their performance characteristics are known. For example, workflows may be designed such that the surrogate model steps in when advantageous (for example when delivering cost savings) and falls back when operating outside of its target operating regime. It may also eventually be possible to produce end-to-end machine-learning-based forecast models which, while they will not completely replace traditional physics-based forecast models, could be important decision-making tools. Examples include the use of emulators as components of digital twins (e.g. for exploring scenarios and triaging case studies before running an expensive traditional model) or as a computationally inexpensive forecasting capability for users who lack the computational capacity to run traditional (non-machine-learning) models.

The successful integration and orchestration between simulation models (potentially from multiple different domains in the case of digital twins) and emulated components is a practical challenge and will remain a key requirement.

BOX D

Emulation of the SOCRATES radiation scheme using machine learning

Profiling of the Met Office global forecast model shows that ~35% of the execution time is spent on sub-grid parametrizations with radiation being among the most costly.

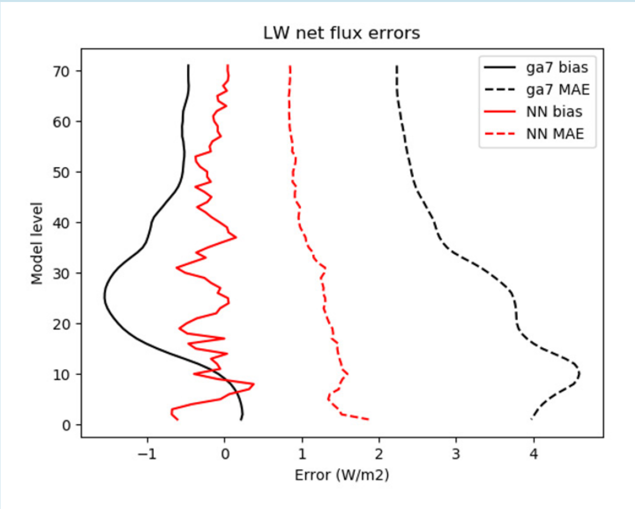
The aim of this project was two-fold:

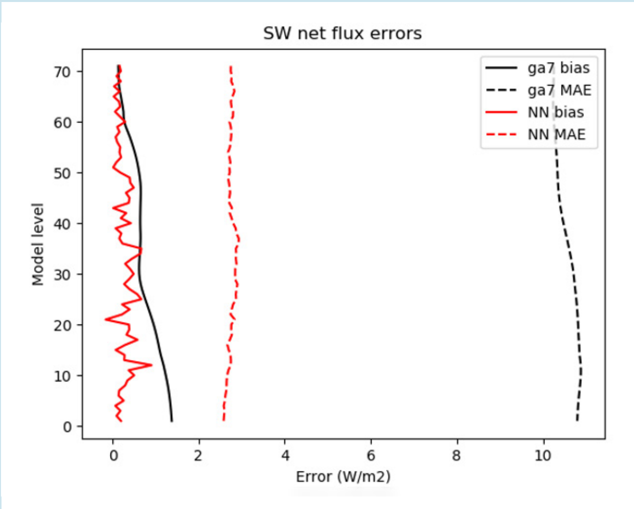
- Can we emulate existing operational parametrization schemes cheaply and with sufficient accuracy to replace the existing schemes?
- Can we emulate more complex and accurate sub-grid models to improve accuracy in an operational setting, but at a fraction of the cost?

The best results in terms of accuracy and model size were achieved using a convolutional neural network (NN) for the emulator. The SOCRATES radiation code was run offline in two configurations:

- GA7 – the broad-band operational configuration used in the Global Atmosphere 7 configuration of the Unified Model (six bands in shortwave and nine in long-wave).
- NB – a narrow-band configuration (260 bands in shortwave, 300 bands in long-wave) used to produce training data for the emulator. In addition, the number of sub-column samples used in the McICA cloud scheme was increased.

An independent set of data was used for validation. The figures below show examples of mean error (bias) and mean absolute error (MAE) profiles with respect to the narrow-band SOCRATES output. The NN trained on the narrow-band dataset outperforms the broad-band operational configuration in these offline tests. The next step will be to conduct online tests with the trained NN called from within the Unified Model.





Integrating a Python-built machine learning component with the Unified Model is not a trivial task: although many machine learning frameworks offer different language bindings, there are no off-the-shelf solutions to integrate these with Fortran codes. As part of a pilot project, a solution was developed, which uses the C or C++ APIs available in a number of machine learning packages to link directly with the Unified Model, thereby avoiding problems associated with using Python during run-time.

Capability 3: Uncertainty and trust

A significant challenge when using data-driven machine learning methods is the need to understand and explain the logic underpinning their predictions and to quantify the confidence in the outputs and associated level of uncertainty. In contrast to physics-based models (and standard statistical models), there often is no easy way to understand how machine learning models arrive at their predictions or to trace the cause of inaccurate predictions.

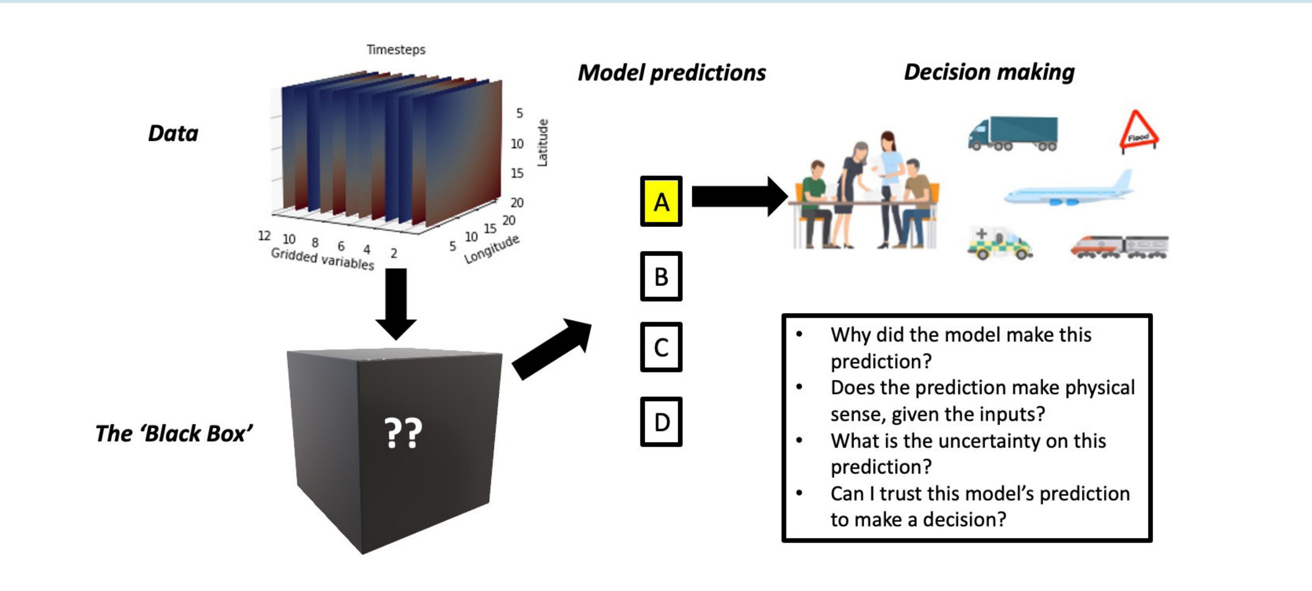
Explainable, interpretable and trustworthy AI is a research hot topic and has already attracted the notice of the weather and climate community — recent examples include McGovern *et al.* (2019, 2022). As well as ethical concerns (e.g. understanding the rationale for decisions made by an algorithm that significantly affect an individual or group of individuals), interpretable machine learning processes are needed to ensure the scientific integrity of machine learning models that should obey physical laws and constraints. To ensure machine learning models are trustworthy, the representation of underlying physical processes needs to remain realistic (based on applying fundamental principles), transparent, understandable, and interpretable. There are many existing explainability and interpretability techniques available that can range from very specific local analysis (e.g. at the level of a particular neuron or layer of neurons in a neural network) to more global analysis (e.g. how the combination of model inputs affects the output prediction) and these should be used as part of best practice for all of future data science projects.

Understanding the limits on and level of confidence in predictions (known as uncertainty quantification) is a fundamental principle of scientific research and is already a core component of much of the Met Office's scientific research — for example, the use of ensemble methods to generate multiple predictions arising from simulations run with different initial conditions. When planning future data science projects, where possible, probabilistic machine learning techniques should be considered in preference to deterministic ones so that uncertainty quantification can be built in at the outset.

BOX E

Beyond the Black Box

The 'Black Box' nature of most popular machine learning models (in contrast to physics-based simulation models and standard statistical models) means it is often difficult to understand the process by which they arrive at their predictions. They also generally do not produce estimates of confidence (or uncertainty) in their predictions. The ability to explain decisions is a key feature of human intelligence and if we are to consider seriously using AI and machine learning for decision-making tools then it is reasonable to expect some level of explanation. The wider machine learning field is already researching techniques for 'explainable' and 'interpretable' AI and machine learning which we intend to explore and adopt as appropriate. We also intend to focus on using techniques to ensure our machine learning models produce confidence estimates alongside their predictions.



The Met Office is already involved in data science projects that touch on these topics. Firstly, the 2021 Biomes project used explainability methods to understand which data features contributed most strongly to biome classification (Sidoumou *et al.*, 2022). In terms of uncertainty quantification using probabilistic machine learning methods, several projects are ongoing. The Strategic Priorities Fund EnvSensors project — a collaboration between the Met Office, the Alan Turing Institute, STFC and the University of Cambridge[11] — applies existing Bayesian machine learning models to intelligent sensor placement (Kirkwood *et al.*, 2022; Vaughan *et al.*, 2022), and a project within the 'Climate Science for Service Partnership – China' explores methods to improve maize yield prediction over China using Bayesian machine learning methods for nonlinear modelling incorporating uncertainty quantification.

BOX F

Ethics

Data science undeniably presents significant opportunities for innovative solutions that address major challenges, such as climate change. However, as with most rapidly evolving technologies, risks and mistakes are inevitable. There is an opportunity to draw lessons from other domains where, despite the best of intentions, the introduction of AI led to unintended societal consequences, such as hard coding racial bias in the criminal justice system or increasing economic inequality through the financial system (McGovern *et al.*, 2022). There is a common misconception that environmental sciences are immune to such unintended consequences, as most data come from observations and AI algorithms are based on mathematical formulas which are often seen as objective. However, recent research suggests the converse may be true (McGovern *et al.*, 2022) and the environmental scientists community should consider ethical implications and unintended consequences early when designing research programmes. For example, one important ethical issue is to ensure that (as far as possible) the data used to train algorithms are not biased and are representative of all relevant areas and populations that could be affected by decisions made by that algorithm. A figure in McGovern *et al.* (2022) highlights that areas of highest Black American population in the US appear to be underserved by the national Doppler weather radar network.

To help guide development of this technology the Office for Artificial Intelligence and the Government Digital Service[12] partnered with The Alan Turing Institute's public policy programme[13] to produce guidance on the responsible design and implementation of AI systems in the public sector. The guide 'Understanding Artificial Intelligence Ethics and Safety' (Leslie, 2019) identifies the potential harms caused by AI systems and proposes concrete, operationalizable measures to counteract them. Using this guide, the Met Office will take steps to anticipate and prevent potential harms by embedding a culture of responsible innovation and governance processes that support the design and implementation of ethical, fair, and safe AI systems.

[11] https://www.turing.ac.uk/research/research-projects/environmental-monitoring-blending-satellite-and-surface-data
[12] https://www.gov.uk/government/organisations/office-for-artificial-intelligence
[13] https://www.turing.ac.uk/research/research-programmes/public-policy

Capability 4: Data to decisions

Data science techniques play an important role in unlocking the power of data, translating data into knowledge and understanding, and helping people make better decisions to stay safe and thrive. This capability will focus on applications which move from traditional hazard-based forecasting into impact- and risk-based decision-making.

To support users making informed decisions, relationships between weather and climate data and the users' data or metrics that ultimately guide their decisions need to be identified. Machine learning allows relationships between inputs and outputs to be determined where an upfront specification (e.g. a physical law) may be intractable (e.g. the relationships are emergent). This opens a broad range of possibilities, from improving model outputs (e.g. ensemble calibration, forecast blending, downscaling), to linking with other data sources and domain experts to predict metrics and outputs important to the end-user, to the communication and interpretation of complex information.

Numerical weather prediction forecasts are imperfect, from limitations in the observations that feed them, to the spatial and temporal resolutions constraints necessary to make them practical. Data-driven processing of the model output has long been used in the Met Office to improve significantly these outputs. For example, the Met Office uses machine learning to improve the accuracy of user-driven site-specific forecasts (BestData).

Relating an environmental quantity to a user decision and predicting that quantity with adequate accuracy are often non-trivial tasks. Beyond the environment there will be myriad of other factors with complex interactions that need modelling to enable predictions and inform better decisions. Data science approaches, such as agent-based modelling, can make this a more tractable problem, being a powerful tool for sampling deterministic scenarios from complex systems such as those involving human behaviour. Most decisions influenced by the environment involve managing risk. Risk can be defined as the statistical combination of hazard, exposure and vulnerability (such as defined by the IPCC in Lavell *et al.*, 2012; Reisinger *et al.*, 2020). Data science can improve the modelling of each of these components such as by utilising 'big data' or modelling complex relationships.

Regardless of the approach taken to move from data to decision-ready information, the effective communication of this information is critical but also challenging, given the complex and probabilistic nature of much of it. It is crucial to ensure the information that supports a decision is well understood, easy to visualise and accessible — this may include information on a range of plausible or potential outcomes. Tooling that enables the user to interact with the information and to ask 'what if' questions supports communication of complicated information and aids users in understanding computer-aided decisions. New interactive technologies, such as digital twinning provide a means to support accessible, interactive and question-led approaches and will be an important component of this capability.

BOX G

Digital twins

Digital twins are virtual representations of assets, which through the fusing of data, simulations and rich interactive environments can help to facilitate improved decision-making. Digital twins are a new approach which brings together data and cutting-edge data science capabilities. By directly answering asset-centred, user-focussed questions, digital twins represent a transition from hazard-based forecasting into risk-based decision-making. In contrast to more traditional modelling approaches, digital twins have two features which set them apart.

1. A golden thread between the real-world and digital representation

The virtual representation may be updated in near real-time, based on observed properties in the real world. This opens the possibility for the digital twin to update the operating characteristics of a physical asset based on its predictive capabilities (e.g. closing the windows of a building based on an increase in observed external air pollution).

2. A rich user interface that enables non-expert users to interrogate the digital twin

User interaction is key to inform the design of the twin and determines which components of a model are run. Digital twins support a risk assessment by providing the ability to run 'what if' analyses, allowing improved understanding of low-probability but high-impact scenarios, without endangering the real-world asset.

BOX H

Post-processing (IMPROVER)

Post-processing describes the additional processing that is applied to weather forecasts to improve their accuracy and usefulness for decision-making. There are two main aims: firstly, to improve the skill of the forecasts by adjusting for errors or deficiencies, resulting in consistent and well calibrated forecasts; secondly, to cover the synthesis of data sources to present forecast information in a way that aids decision-makers, this includes the production of novel outputs targeted at specific use cases. In both cases, data science techniques play a natural role.

The Met Office is currently developing a new probabilistic post-processing system, IMPROVER, for its operational numerical weather prediction (NWP). IMPROVER is designed to exploit fully the rich information contained in modern convective-scale NWP ensembles, and will produce seamless probabilistic forecasts from nowcasting out to the medium range (three to ten days ahead). The design of IMPROVER provides consistency between gridded and site-specific forecasts, and allows for integrated verification at each stage of the post-processing pipeline, which provides a useful environment to exploit data science techniques. To date, IMPROVER has trialled the use of statistical calibration and machine learning techniques, and there is potential for data science to continue to play a key role in the future.

Enabling the capabilities

These four core capabilities will be our priorities for development. They can be, and are, deployed across the whole of the Met Office national capability, stretching from observations through simulation, analysis to products and services (see figure on page 9), therefore encompassing numerical weather prediction and climate science to services. As the technology develops, and there are changes in the data and compute available, new opportunities will emerge to apply these core capabilities to various points within the value chain. By focusing on developing these four capabilities we will ensure that the Met Office is ready and able to respond to opportunities and changes in the operating environment as they arise. They will be areas in which the Met Office excels in offering advantage to partners and in accelerating delivery of the Met Office's data science goal.

To support the development and integration of these capabilities, consistent data science infrastructure, workflow and tooling are needed. A consistent, scalable and reproducible approach to this 'data science environment' (see Challenges on page 13) is needed to support capability development. For example, tooling needs to provide access to software via a standard experience across on-premises and cloud infrastructure and to support seamless collaboration across organisational boundaries. Infrastructure will need to meet the compute requirements for data science, including access to accelerators such as GPUs (graphics processing units) or TPUs (tensor processing units). In this way, data science and the capabilities contained within this framework offer an additional route to realise the benefits and value of the Met Office's supercomputer facilities.

A standard workflow, built on best practice, for data science capabilities will ensure we avoid the accumulation of technical debt often associated with the quick wins of implementing data science without appropriate frameworks (Sculley *et al.*, 2015). This standard workflow will ensure data science activities are well designed, coordinated, repeatable, and critically that they are explainable and transparent. This will ensure the core capabilities are able to be readied for rapid deployment and redeployment, and ensure approaches are sustainable and maintainable.

This standard workflow will be particularly important when collaborating across disciplines and with partners when a common approach is needed to ensure interoperability and maximize progress. Alongside standardised workflows, the data science environment will include approaches that foster collaboration and support innovation both within and outside the weather and climate science and service sectors.

Pillar 2: People

We will lead and invest in our people and culture to ensure the Met Office is a great place to work for all. Strength comes from who we are, our expertise, experience, diversity, passion and commitment. We know that with great leadership and management comes the ability to embrace the skills of our people, retain our talent, recruit effectively and enable people to develop their skills[6]. Fundamentally, the Met Office will only be able to achieve its overarching vision of being 'recognised as global leaders in weather and climate science and services in our changing world' if it can attract, retain, inspire and develop the best people. We must foster a vibrant, interesting, challenging and empowering workplace in order to attract and retain the brightest workforce. In line with the National AI Strategy (HM Government, 2021b), we acknowledge that this means a diverse workforce.

In common with many of our partners, the Met Office has embedded a 'hub and spokes' model for data science: the Informatics Lab is a dedicated team providing a centralised source of expertise to guide and support data science activities across the Met Office. This approach creates a critical mass of dedicated expertise who champion the use of data science and provide a focal point for engagement with partners. As data science is embedded across the Met Office, this expert team will provide leadership for a distributed capability coordinating activities and capability development. This team will have overall responsibility for implementing this framework. They will achieve this by remaining at the forefront of data science and working with domain experts (within and outside the Met Office) to provide expert support for data science projects.

Activities in this pillar will accelerate progress in the following three areas.

Attracting, retaining and developing talent

The nature of work, the workplace and the workforce are changing. Ensuring the Met Office has the capabilities it needs to deliver its purpose and achieve its goal for data science will depend on being prepared for these changes. Those now entering the workforce have different expectations of work where impactful, socially valuable, flexible working and variety are important. Requirements to innovate alongside existing delivery bring challenges to balance traditional hierarchical structures and processes with greater innovation and agility. There is growing competition for STEM[14] skills, in particular data science skills, which are fundamental to the success of the Met Office. The 'People vision' laid out in the Met Office Research and Innovation Strategy (Met Office, 2022), is to lead and invest in our people and culture to make the Met Office a great place to a work. This will enable us to attract and retain the brightest data scientists. To keep our scientists at the top of their game we will continue to provide opportunities for development and training through both in-house courses and those provided by partners.

Fostering a diverse and representative workforce

Equality, Diversity and Inclusion (EDI) is a journey, and while we have made significant gains, there is more that can be done[15]. The Met Office's EDI Strategy (Met Office, 2021) states a firm commitment to make 'the Met Office a great place to work for all'. It should be noted that this presents a challenge for some protected characteristics. For instance, there is a 'troubling and persistent absence of women employed in the Artificial Intelligence (AI) and data science fields' (Young *et al.*, 2021). Globally women represent just 22% of professionals in these fields and within the UK this drops to 20%. There are examples across other dimensions of demographic/identity diversity, i.e. race, age, gender and religion and protected characteristics. As the Fourth Industrial Revolution progresses, and data science becomes ever more ubiquitous in our daily lives, mobilizing a diverse data science workforce will become increasingly important. The bottom line is that "if it's not diverse then it's unethical" (Dame Wendy Hall, Ethics Dialogues, 2019) and data scientists should reflect the society they represent.

Engaging the next generation of data scientist to create a skills pipeline

We want to inspire the next generation to study STEM[14,16] subjects, attract a diverse and inclusive workforce and enable our staff to develop their professional skills during their careers. This is essential for data science where there is an ongoing and widening gap between the demand and supply of AI skills (Dabhi *et al.*, 2021; HM Government, 2021b). There is 'exponential growth in the demand for advanced applications of data science and machine learning across all sectors' (DCMS, 2020), including environmental sciences.

[14] Science, Technology, Engineering and Mathematics.
[15] https://www.metoffice.gov.uk/about-us/careers/equality-diversity-and-inclusion
[16] https://www.metoffice.gov.uk/about-us/who/sustainability/community/schools-and-colleges

The Met Office participates in and coordinates a wide range of education and outreach activities as part of its sustainability commitments. The aim of these activities is to increase interest in Met Office science and technology (and STEM more generally) and encourage interest in STEM careers at the Met Office and further afield. To remain flexible to our future skills requirements, we will endeavour to ensure that data science is represented in Met Office STEM activities. Engagement with early career scientists is already bearing fruit for data science with a number of active placement schemes and a vibrant graduate recruitment programme. As the requirement for data scientists grows, so will this activity.

Pillar 3: Partners

As stated in the Met Office Research and Innovation Strategy (Met Office, 2022), 'the ambition and vision contained within this strategy can only be realised by working in partnership'. We will collaborate widely and continue to strengthen and expand our network of partnerships with exceptional organisations both nationally and internationally. Partnerships will be developed and nurtured to complement our own expertise with that of others to support delivery of our data science ambitions. This is particularly pertinent when considering the capabilities laid out in this framework: the four core capabilities identified for development may not enable us to respond to every opportunity. In this situation we will seek partners with complementary expertise — the value of data science to the weather and climate science and services will not be realised by a single organisation, a concerted effort is required, nor can any organisation remain at the forefront of every aspect of this emerging technology. The Met Office will seek to maximise resilience and bolster expertise through partnership to advance the application of data science in our sector. By working across organisations, we will be greater than the sum of our parts and accelerate the application of emerging data science technologies.

Activities in this pillar will accelerate progress in the following three areas.

Strengthening and expanding our network of partnerships

There are a number of existing multilateral relationships that can be called upon to support the acceleration and adoption of data science, for example the Unified Model Partnership[17] with leading international operational weather forecasting centres; the Met Office Academic Partnership[18] that brings together the Met Office and institutions which are among the leading UK Universities in weather, climate and AI; and the Joint Weather and Climate Research Partnership[19] with the Natural Environment Research Council (NERC) centres that drives forward national capability and research in predicting weather and climate. The Met Office has longstanding programmes of collaborative work with a number of world-leading organisations such as the ECMWF and the UKRI Councils such as the Engineering and Physical Sciences Research Council and a well-established partnership with NERC that covers both research and the use of shared infrastructures.

There are also relationships specifically on data science such as the Joint Centre for Excellence in Environmental Intelligence[20], launched in 2020 to bring together world-leading researchers from the University of Exeter and the Met Office to pioneer the development of environmental intelligence research, innovative solutions and interdisciplinary training, and a formal partnership with the Alan Turing Institute, the UK's national institute for data science and AI. These relationships leverage science and technical effort beyond that possible from a single organisation. They will be nurtured, developed and expanded to support the acceleration and adoption of data science in our field.

Growing our community

Data science has the potential to change fundamentally the weather and climate science and services endeavour. These opportunities exist across the whole of the Met Office value chain. To capitalise on these opportunities, we will need to work as an environmental science community combining our strengths and pooling our expertise and resources, as appropriate. There is a significant opportunity for us to learn from one another and advance towards our shared goals together. In 2019 a data science 'Community of Practice' (CoP) was launched for staff within the Met Office. This group has developed into a vibrant and flourishing community. The two mainstays of this CoP are regular meetings where participants enjoy a programme of thought-provoking talks by subject matter experts and have the opportunity to share experience; and a set of co-developed training materials designed to raise gradually understanding, knowledge and confidence. By purposefully developing materials that demystify data science this CoP has provided a nurturing environment in which staff can experiment with machine learning approaches before introducing more complex topics and approaches. Over the last year this CoP has expanded to include links to other data science CoPs within the UK and internationally a 'Network of CoPs' (NCoPs) is forming with members of the Unified Model Partnership. The purpose of these networking activities is to develop the relationships needed to accelerate the use of data science and realise the benefits and value for weather and climate science and services. These interventions will continue to form a key strand within the pillar.

[17] https://www.metoffice.gov.uk/research/approach/collaboration/unified-model/partnership
[18] https://www.metoffice.gov.uk/research/approach/collaboration/partnership
[19] https://www.metoffice.gov.uk/research/approach/collaboration/jwcrp/index
[20] https://jceei.org

Working with other communities

The full value and impact of data science will be realised by interdisciplinary working where there is an opportunity to look across sectors, identify common challenges and learn from one another's experience. In addition to pooling knowledge and expertise, interdisciplinary working can catalyse innovation — 'recombinant innovation' (Brynjolfsson and McAfee, 2014) — as new applications of existing technologies are discovered in a process of technology brokering between sectors. We will actively seek opportunities to work across disciplines to share what we have learned, learn from others, and combine effort to maximise opportunities for innovation.

The Fourth Industrial Revolution is bringing together new communities and forging new relationships. For example, in 2021 the Met Office and Microsoft joined forces to build world's most advanced supercomputer dedicated to weather and climate. This facility will be in the top 25 supercomputers in the world and be twice as powerful as any other in the UK. Our relationship with one of the world's leading hyperscalers presents considerable opportunity to advance data science.

BOX I

Joint Centre for Excellence in Environmental Intelligence

Environmental intelligence harnesses rapid advances in AI and computing capacity to extract meaning and value from vast amounts of environmental data to transform our understanding of the complex interactions between the environment, climate, natural ecosystems and human social and economic systems.

The Joint Centre for Excellence in Environmental Intelligence (JCEEI) pioneers the use of environmental intelligence to provide the meaningful insight needed to inform decision-making and improve risk management, leading us towards a sustainable interaction with the natural environment and delivery of Net Zero.

The JCEEI is a collaboration between the Met Office and the University of Exeter providing the expertise, skills and capability to utilise fully AI in order to address the escalating threats of climate and biodiversity change.

Joint Centre for Excellence in
Environmental Intelligence
Met Office
University of Exeter

5. First steps towards implementing the three pillars

The three pillars outlined in this framework will be used to guide activities and inform objectives, with Pillars 2 and 3 being also further developed in other Met Office strategies and plans. A small subset of example activities is provided below for each pillar; these illustrate the types of activities that will be needed to implement the framework. Such activities will be developed and reviewed annually to ensure momentum and progress are maintained.

	Example activity	Objective
Pillar 1 – Core capabilities	1. Enabling the capabilities	By end 2023 deliver a project which develops a standard workflow for building, deploying and monitoring machine learning systems.
	2. Initiating projects for core capabilities	By end 2023 instigate projects within each of the four capabilities, for example: Capability 1: Discovery and attribution ▪ Project investigating data-driven approaches using globally-important patterns of sea surface temperature variations to predict seasonal forecast of weather variables over Northeast China, feeding into a maize yield prediction model. Capability 2: Fusing simulation with data science ▪ Project to prototype the integration of machine learning emulators for two specific parametrisations in the Unified Model (radiation and gravity wave drag). ▪ Project investigating the use of machine learning approaches for forecasting the UK weather. ▪ Project delivering a systematic evaluation of components of numerical weather prediction and climate models and plan for implementing the optimal blend of data science and traditional physics-based techniques. Capability 3: Uncertainty and trust ▪ Implement the 'Beyond the Black Box' research. theme that aligns data science projects exploring uncertainty quantification, explainability, interpretability and trustworthy AI. Capability 4: Data to decisions ▪ Project developing a prototype digital twin to demonstrate value for improving decision-making across different timescales (e.g. from weather to multi-decadal timescales, or for operational, tactical and strategic decisions). ▪ Project(s) developing climate and weather services using machine learning approaches to add value through identifying relevant hazards, quantifying how hazards translate into risks and cascade through complex systems, and understanding/learning the utility of this information for managing risks across timescales.

	Example activity	Objective
Pillar 2 – People	1. Engaging the next generation of data scientists to create a skills pipeline	By end 2022 appoint STEM ambassadors within the core Met Office data science team.
	2. Fostering a diverse and representative workforce	By end 2022 provide a baseline analysis of diversity amongst the core data scientist team within the Met Office and wider data science community. Develop a plan for engaging a more representative community in data science activities.
	3. Attracting, retaining and developing talent	By end 2023 have reviewed and refined the Met Office's learning pathway for data science. Ensure data science skills are considered and embedded within wider corporate initiatives and plans.
Pillar 3 – Partners	1. Strengthening and expanding our network of partnerships	By mid-2023 ensure that data science is addressed in plans to develop Met Office science partnerships.
		By mid-2024 create a programme of data science opportunities for early-career scientists across targeted partnerships (for example the Met Office Academic Partnerships and the Unified Model Partnership) to support enhanced collaboration and technical skills development.
	2. Growing our community	By end 2023 appoint a Data Science Communities of Practice coordinator within the core Met Office data science team.
	3. Working with other communities	By end 2023 have co-developed and embedded a plan to collaborate with partners from other domains in data science.

6. Closing remarks

Advances in data science mean that computers can now analyse, and learn from, vast volumes of information at high levels of accuracy and speed, offering significant gains in efficiency and performance. The data science framework builds on the 'fusing simulations with data science' research theme of the Research and Innovation Strategy (Met Office, 2022), and identifies the three pillars that will enable the Met Office to achieve its goal 'to harness the power of data science to push the frontiers of weather and climate science and services'. In doing so, the framework lays the foundation upon which objectives and priorities can be agreed, resources allocated, and capabilities nurtured, informing the golden thread between the top-level data science goal and operational activities. The three pillars of Capabilities, People and Partnership have been configured to complement progress achieved in embedding data science within the Met Office and the strategic approach of our partners both nationally and internationally. These are exciting times for organisations working with data science and we look forward to working with partners to realize the full potential of data science to push forward the frontiers of weather and climate science and services.

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