WMO Concept Note on Data Handling and the Application of Artificial Intelligence in Environmental Modelling

WMO Research Board – Task Team on Exascale Computing, Data Handling and Artificial Intelligence

Contents

Acknowledgements

The Task Team on Exascale Computing, Data Handling and Artificial Intelligence was formed in July 2020. The Task Team was split into two sub-teams in March 2021 (the Exascale Computing sub-team and the Data Handling and Artificial Intelligence sub-team) to focus the writing teams and discussions.

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Preface

The environmental modelling community faces new opportunities, through a combination of increased computing power and the potential for the application of artificial intelligence (AI) to open up new areas for progress. However, these opportunities come with the associated challenges of ever-increasing data volumes and the need to navigate rapid development in the application of AI. In the context of the provision of products and services by WMO Members, these areas of increased computing power and the application of AI have the potential to enhance outputs, but may lead to disruption and transformational change to workflows and production chains. It is therefore imperative for the WMO community to understand the opportunities and challenges, and to share insight and experience to support the WMO community in responding. The present concept note provides an overview of the status, opportunities and challenges of data handling and application of AI in the environmental modelling field, with recommendations for actions for WMO to support the community in its response.

Summary of recommendations

The rapid expansion of research into the application of artificial intelligence (AI) methods, combined with the changing nature of hardware platforms, has created an imperative for WMO Members running end-to-end modelling systems to develop strategies and plans for adoption of AI methods[1] in operational and production systems. There is a need to share experience in the environmental modelling community to develop good practice guidance for the adoption of AI methods.

- **Proposed short-term action 1:** WMO Research Board to promote exchange of insight between centres running end-to-end modelling systems, to support development of plans and strategies for adoption of AI methods into operational/production workflows (in the present recommendations, the term “centres” is used to refer to WMO Global Producing Centres (GPCs) and National Meteorological and Hydrological Services (NMHSs), and the term "modelling centres" is used to distinguish the subset of these centres that run end-to-end modelling systems).
- **Proposed long-term action 1:** WMO to develop and promote adherence to good practice guidance for the adoption of AI methods into operational/production workflows.

While the combination of the use of AI methods and the expansion of the range of available data sets creates an opportunity for centres to provide new services, considerable practical barriers remain.

- **Proposed short-term action 2:** WMO to explore the potential to improve delivery to customers for centres looking to incorporate data produced elsewhere into their processing chains, including through use of AI methods. This should include elicitation of the requirements for support covering areas such as access to data, computational platforms, selection and validation of methods, and training of staff. Recommendations for how the WMO community can meet these requirements should be made.
- **Proposed long-term action 2:** WMO to develop a roadmap for coordinated provision of support in response to the recommendations identified in short-term action 2.

The ability to share data and methods effectively and efficiently is dependent upon common standards and practice; it is important to note that other communities and groups are also engaged in similar endeavours

- **Proposed short-term action 3:** WMO to collate and develop guidance and standards for: (a) sharing data and tool sets, including for use in AI methods; and (b) objective evaluation of the performance of AI methods. Adherence to the resulting guidance and standards should be promoted across the WMO community.
- **Proposed long-term action 3:** WMO to identify a suitable body for long-term ownership and promotion of guidance and standards for: (a) sharing data and tool sets, including for use in AI methods; and (b) objective evaluation of the performance of AI methods.

There is particular potential for public–private partnerships to deliver benefits through access to a combination of data, platforms and methods.

[1] In the context of the present concept note “AI” is used to refer to the “field of science … that focuses on attempting to mimic human intelligence in a computer or machine” (https://csuglobal.edu/blog/whats-the-difference-between-artificial-intelligence-and-machine-learning), whereas “machine learning” is defined as the “the process of using mathematical models of data to help a computer learn without direct instruction” (https://azure.microsoft.com/en-gb/overview/artificial-intelligence-ai-vs-machine-learning/#introduction). The term “AI methods” is used interchangeably with “machine learning”.

- **Proposed short-term action 4:** WMO public–private partnership development efforts to specifically include efforts focused on the application of AI methods to weather, water, oceans, climate and environment data, delivered through sustainable partnerships, in particular in support of improving product delivery for developing countries.

Data-handling challenges are placing conventional workflows under increasing strain, creating an imperative for changes in workflow design and methodologies.

- **Proposed short-term action 5:** WMO Research Board to promote collaboration between centres running end-to-end modelling systems on approaches to adapting workflows to handle increasing data volumes.

1. Background

The *WMO Strategic Plan 2020–2023* (WMO-No. 1225) outlines a set of long-term goals and strategic objectives up to 2030, and identifies shorter-term high-priority areas of focus until 2023. The third long-term goal, “Advance targeted research: Leveraging leadership in science to improve understanding of the Earth system for enhanced services”, identifies the need to harness progress in areas of scientific and technical research that can enhance the science-for-service value chain, improve predictive capabilities and advance policy-relevant science. The related areas of advances in exascale computing, artificial intelligence (AI) and data handling have been identified by the WMO Research Board as relevant areas with the potential to improve predictive capabilities and enhance services across the weather, water, oceans, climate and broader environment (hereafter, WWOCE) domains. Success will be dependent upon leveraging progress and overcoming challenges in these three rapidly developing areas. The Research Board has therefore commissioned, through the Task Team on Exascale Computing, Data Handling and Artificial Intelligence (hereafter, the Task Team), the production of concept notes to provide a synthesis of the current state of activity in these areas, and to provide recommendations for the short and long term to guide progress and initiate coordinated activity to enable the WMO community to benefit from these advances.

In recognition of the broad scope of exascale computing, AI and data handling, the Research Board has split the work into two related concept notes: the first covering the exascale technology challenges; the second covering the AI and data handling aspects. The themes of these concept notes inevitably intersect; for example, the data-handling challenges are in part a result of the increased data volumes arising from use of exascale computing. The two concept notes jointly provide a coherent set of recommendations that span the themes as a whole. The present concept note constitutes the second note, covering the data-handling and AI aspects.

Data-handling challenges affect both the production and the consumption of data. The WMO community therefore needs a collaborative approach that enhances the ability to share and make use of increasingly large data sets. The challenge arising from production of large data volumes through use of exascale computing is discussed in the first concept note commissioned by the Task Team, on exascale computing. In the present concept note, the focus is on the data-handling challenges arising from consumption of data produced by the modelling systems. These challenges arise from consumption of large data volumes in several contexts: for use in development and delivery of so-called downstream services, for use in scientific analysis, and for use within the application of AI methods.[2] Data sharing, mining, analysis, visualization and service provision are day-to-day issues that are becoming increasingly challenging as volumes increase. Volumes are projected to increase by a factor of 1 000 over the coming decade, with the danger that the ability to produce larger data sets outpaces the ability to handle them effectively, particularly in real-time processing systems.

Growing data volumes are placing conventional workflows under increasing strain throughout the processing chain, including in relation to observation handling, processing model inputs and outputs, and generating and sharing data with downstream users. Particular challenges arise when making data available in an analysis-ready form, and when moving large data sets around over networks with limited bandwidth, or when

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[2] In the context of the present concept note “AI” is used to refer to the “field of science … that focuses on attempting to mimic human intelligence in a computer or machine” (https://csuglobal.edu/blog/whats-the-difference-between-artificial-intelligence-and-machine-learning), whereas “machine learning” is defined as the “the process of using mathematical models of data to help a computer learn without direct instruction” (https://azure.microsoft.com/en-gb/overview/artificial-intelligence-ai-vs-machine-learning/#introduction). The term “AI methods” is used interchangeably with “machine learning”.

using a cloud service provider that charges based on bandwidth utilization. There is a risk that these challenges exacerbate the difficulties experienced by developing nations in obtaining timely access to high-quality weather data and forecasts. WMO has begun to address these challenges with the joint efforts of the WMO Information System (WIS) and the Global Data-processing and Forecasting System (GDPFS, Figure 1).

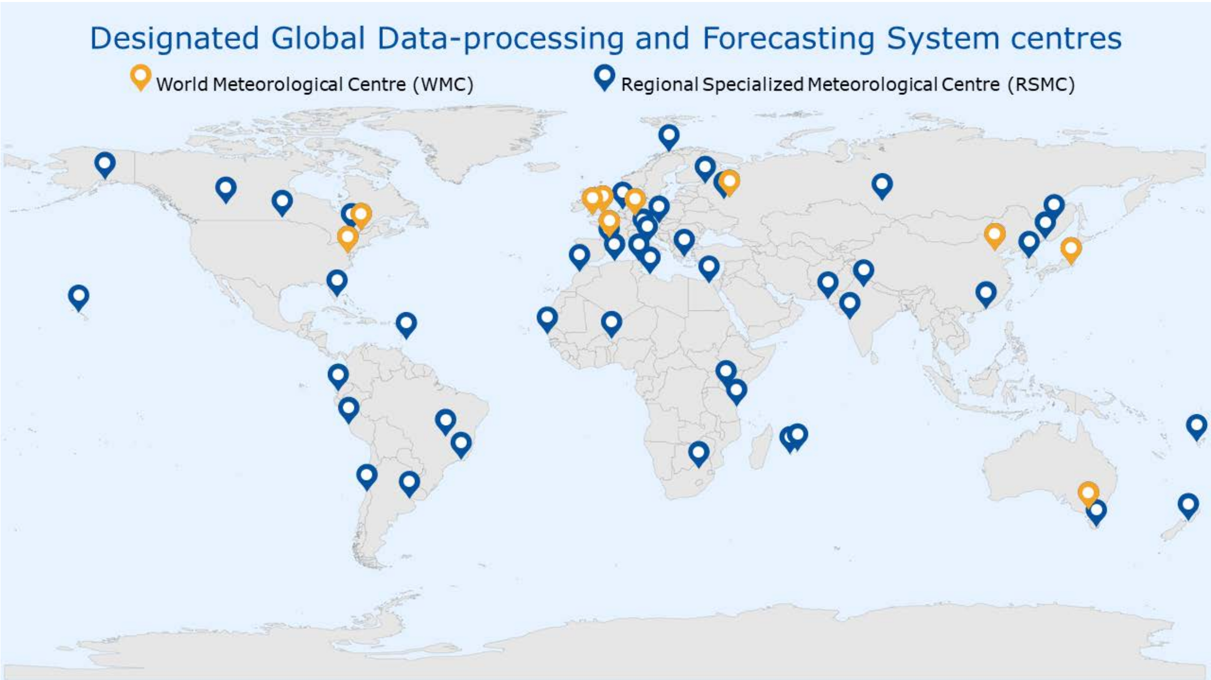

Figure 1. WMO designated Global Data-processing and Forecasting System (GDPFS) centres. A worldwide network of operational centres makes defined products and services for applications related to weather, climate, water and environment operationally available among WMO Members and relevant operational organizations.

Nevertheless, the continued increase in pressure on workflows will require new approaches. For example, a more rigorous adoption of data-in-place approaches (which allow users to run their own analysis codes on computer servers attached to the data repository) is anticipated to be necessary to mitigate data transfer challenges. Indeed, the next generation of the WIS, WIS 2.0, is being designed to be much better suited to bringing the user to the data and to supporting AI workflows (Figure 2).

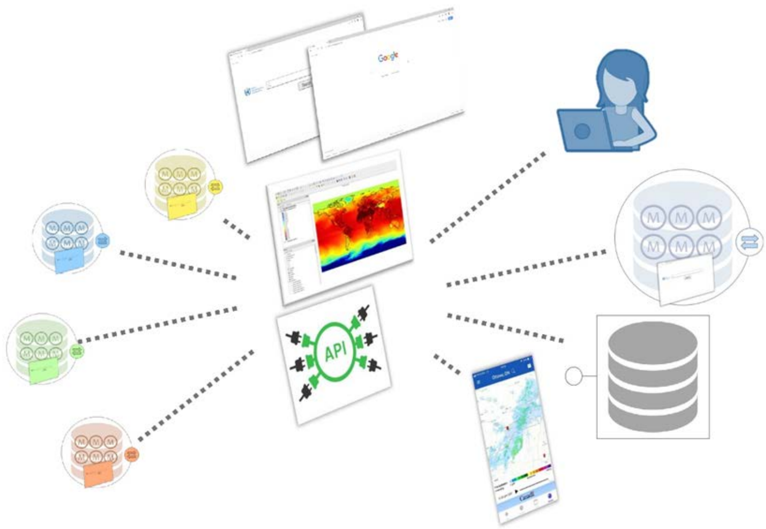

Figure 2. Conceptual view of WIS 2.0

The rapid rise in interest in the use of AI methods in the WWOCE domains creates both opportunities and challenges for the WMO community. AI methods may not only enable a more efficient production of established forecasting and analysis products, they may also open the path to novel combinations of data, and more customized forecasting products. The ability of AI methods to extract complex information from large data volumes can enable more efficient data analysis workflows; the ability to integrate diverse data opens up the possibility of innovative use of new data sources, for example, from low-cost sensors or social media. The application of AI methods may be disruptive to conventional workflows, but this could also constitute an opportunity, given that conventional workflows are already challenged as a result of newly emerging computer technologies (Bauer et al., 2021; this issue will also be addressed in the upcoming WMO concept note on exascale computing). However, the rapid evolution of research into the application of AI within the WWOCE domain is challenging to navigate. Despite a growing evidence base from research studies, it is not yet clear where AI methods provide greatest added value in production workflows, or generate equal quality data products with known uncertainties. Furthermore, it still remains to be demonstrated that the total computational costs are lower than for traditional simulation workflows, particularly if frequent (re-)training must be considered as part of a production cycle. Nonetheless, the opportunity for improvements and efficiencies through harnessing AI techniques, combined with the challenges of exploiting new technologies and ever-larger data volumes, creates an imperative to take action. There is a growing recognition among the WWOCE community (comprising National Meteorological and Hydrological Services (NMHSs) and the wider research community) of the urgent requirement to identify strategies for adoption of AI methods within operational and production systems. Given the potential disruption to long-established workflows, there is also a need to understand and manage the impacts of this change on the personnel involved, in order to ensure buy-in.

In view of the above, there is an opportunity for WMO to guide and facilitate the uptake of new data-handling approaches and AI among Members, and to ensure the effective engagement and support of developing countries to enable the potential benefits to be realized. The present concept note sets out the state of play in the WWOCE domains with regard to data handling and the application of AI methods, and makes recommendations that aim to support WMO in this endeavour.

2. Data handling

Data handling constitutes a growing challenge that arises from flows of increasing volumes of data at all stages of the processing chain and from increased demands on data interoperability and re-use (FAIR principles: https://www.go-fair.org/fair-principles/). Therefore, data-handling challenges interact with the application of exascale computing for data production (described in the Task Team's first concept note, on exascale computing), the application of AI methods (described in the preceding section) and the delivery of data for downstream consumption in scientific applications and services.

Conventional workflows are under increasing strain throughout the processing chain. Volumes of observational data for ingestion into observation-processing and data assimilation systems are increasing as novel observation types become available (see, for example, Alpert et al., 2016). These novel observation types pose challenges due to their greater heterogeneity and use of non-standard formats. Models are generating larger volumes of output data as model resolution and ensemble size increase and additional complexity is added. The development of the application of AI methods is driving an appetite for increasingly precise and accurate data for use in downstream applications. Further, the increased focus on risks and impacts is placing greater emphasis on the combination of data sets from different domains, including combinations of hazard, vulnerability and exposure data to evaluate and reduce risk, and the combination of information from other domains to improve decision support capabilities. Consequently, data handling is becoming a potential bottleneck that prevents effective use of data as volumes exceed the level that traditional methods can handle. Rethinking effective data-handling approaches is needed in order to meet growing demands to improve decision support and cross-domain evaluation of risks and impacts.

Data-handling challenges fall within three broad areas: (1) the ability to handle system inputs and outputs within the centres running end-to-end modelling systems; (2) the ability to share data effectively between data producers and data consumers; and (3) access to suitable platforms for data processing. Effective data sharing (point 2) encompasses both the sharing of real-time data and the sharing of static data sets (for example, for training machine learning (ML) algorithms); it is worth noting that the characteristics of the two may be very different in terms of volume and form.

Centres running end-to-end modelling systems face the need to adapt their workflows to deal with increasing data volumes. Examples of such adaptation may include: exploiting greater levels of parallelism in processing steps; use of tiered storage strategies; more considered and targeted selection of model diagnostics; and greater levels of in-line processing of outputs. AI methods offer the potential to optimize workflows with innovative and disruptive approaches. The benefits of such approaches rely on foundational data-handling requirements, including data formats, metadata, interoperability and data access improvements.

Some of the specific challenges relating to data handling are considered in the following paragraphs.

Data formats and standards: Effective exchange of data between data producers and data consumers depends on the use of appropriate data formats. Interoperability is enhanced by the use of standardized, self-describing and extensible data formats, with sufficient metadata to enable re-use. Some such formats are described as "analysis-ready" (a term borrowed from the satellite imagery community), meaning that the data have undergone enough preparatory pre-processing for the data consumer to ingest the data for immediate use. The use of "cloud optimized" formats, which are compatible with object storage with access via HTTP, is also gaining ground.

While the WWOCE community has a long history of development and adoption of standardized data formats, some of the formats widely used in the community are not well suited to facilitating effective exchange of data and have inherent limitations. For example, GRIB data are not self-describing, and netCDF data may not be sufficiently standardized, and so these formats have not been adopted outside of the WWOCE community. There is therefore a need for the WWOCE community to consider use of data formats and metadata standards that can facilitate data exchange, particularly with other scientific and technical communities. The development of common standards and best practice guidance for data formats and metadata, alongside protocols for data exchange, would facilitate the effective exchange of data between producers and consumers, and would complement existing efforts to facilitate data exchange (such as the CliMetLab tool: https://climetlab.readthedocs.io/en/latest/). Any such standards will need to address the requirement to inherently allow for massive scalability. For example, the geographic information community has developed widely used standards and formats implemented in geographic information system (GIS) software, however there is no efficient parallel software which could be applied to scale such formats to the level of WWOCE data. Efforts to establish suitable guidance and standards for data exchange need to take account of existing efforts in this area, both under the auspices of WMO, and beyond.

Data interoperability: Overcoming technical barriers to data interoperability is a necessary step to enabling the use of WWOCE data by other scientific and technical communities, yet may not by itself be sufficient. Data exchange between communities is also generally reliant on a constructive dialogue, a shared commitment to work together and sustainable access to suitable infrastructure for data sharing. Investment of effort in these social aspects of exchange between communities, and in the underpinning infrastructure, is also therefore required.

One exception, that avoids the need for interaction between communities, is the consumption of data delivered through provision of Application Programming Interfaces (APIs). Data provided through APIs may be consumed without any direct interaction with the data provider, often by software developers without any background in the scientific domain. This poses a particular challenge for data producers to ensure that any such data are suitably well described and validated, to protect against inadvertent inappropriate use. Individual WMO centres will need to identify their appetite for, and approach to, provision of data via APIs.

Data ownership roles and responsibilities: Conventional approaches to data exchange within the WWOCE community have focused on delivery of data from production platforms to consumers' local IT systems for subsequent processing and analysis. This has meant that the computing power and tools required have been entirely the consumer's concern. With increasing data volumes, moving data to local IT systems across networks with limited bandwidth is becoming increasingly untenable. There is therefore a need to consider the alternative of enabling processing and analysis to be undertaken on a system with local access to the data, that is, close to the data. A change of this nature would mean that data consumers would no longer have complete control over their access to processing power and tools, and represents a potential shift in the balance of responsibilities between data producers and data consumers. Furthermore, such changes raise the prospect of data consumers needing to reconsider their processing chain in its entirety in order to take advantage of a combination of non-local and local data. Alongside this, the adoption of AI methods is driving a requirement for suitable architectures to optimize AI workflows, placing an onus on those providing data and platforms to respond to this requirement. These changes may create new opportunities and an increased imperative to support developing countries and academic research communities by opening up the possibility of application of data without the need to invest in procuring and supporting local hardware. The WMO Commission for Observation, Infrastructure and Information Systems (Infrastructure Commission) will take this into account in its work to document the future role of NMHSs.

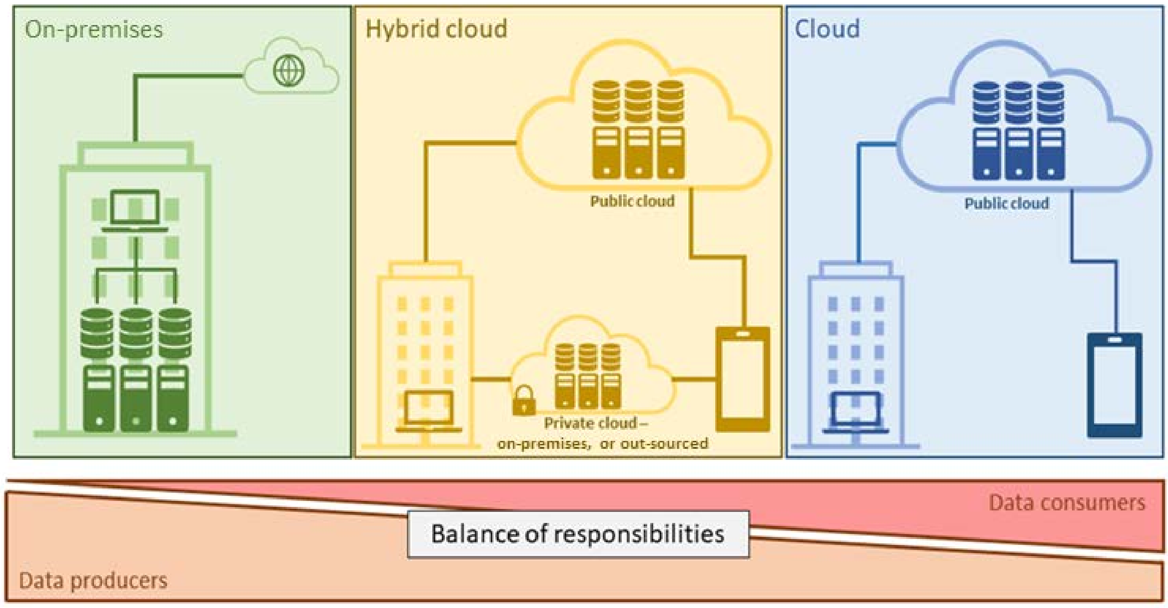

Figure 3. Schematic view of approaches to adoption of cloud computing. As processing and analysis is brought closer to the data through cloud computing approaches, there is a potential shift in the balance of responsibilities between data providers and data consumers.

Cloud computing: The growing requirement for access to collocated data sets and compute platforms constitutes a shift towards a cloud computing approach, either through use of "public cloud" services or commercial cloud computing providers. In practice, adoption of cloud computing is often achieved through a "hybrid cloud" approach, employing a combination of public or commercial cloud services alongside a private cloud with restricted access, either hosted on-premises or outsourced (Figure 3). Many organizations provide access to public cloud services, with initiatives such as the European Open Science Cloud (https://eosc-portal.eu/) seeking to federate resources for the benefit of multiple communities. Nonetheless, the ample scalable computing power and data storage provided by commercial cloud computing providers raises the question of their potential role in meeting the requirements of the WWOCE community. However, the consumption-based charging models used by such providers may not be well suited to patterns of data production and consumption in the community, and addressing IT security requirements may be perceived as more challenging than with on-premises computing. In addition, governments may impose restrictions on the operation of national infrastructure outside of the country, which may preclude the use of cloud computing. Furthermore, unless the high-performance computing (HPC) centre is also in the commercial cloud, it is an open question whether data can be efficiently moved from the originating HPC centre to the commercial cloud. Nonetheless, the role of commercial cloud computing providers, in particular working in partnership with the WWOCE community, remains an aspect that is likely to need further exploration. This role will be strongly dependent on the ability of NMHSs to develop sustainable business models.

Data analysis: The concept of undertaking data processing and analysis close to the data may create some additional challenges for applications that require multiple data sources. The data science community have adopted the term "data gravity" (https://datagravitas.com/2010/12/07/data-gravity-in-the-clouds/) to reflect the fact that the larger the data set, the greater the pull on other data and applications to be located close by (Figure 4). Within the WMO community, this is reflected in the Global Data-processing and Forecasting System through the concept of World Meteorological Centres, which act as centres of data gravity. This may be a helpful concept when considering the future of data exchange, and in particular the organization of applications that require multiple data sources. Enabling users to effortlessly port their analysis workflow across the centres of gravity requires enhanced harmonization of software stacks and working environments in the HPC and data centres.

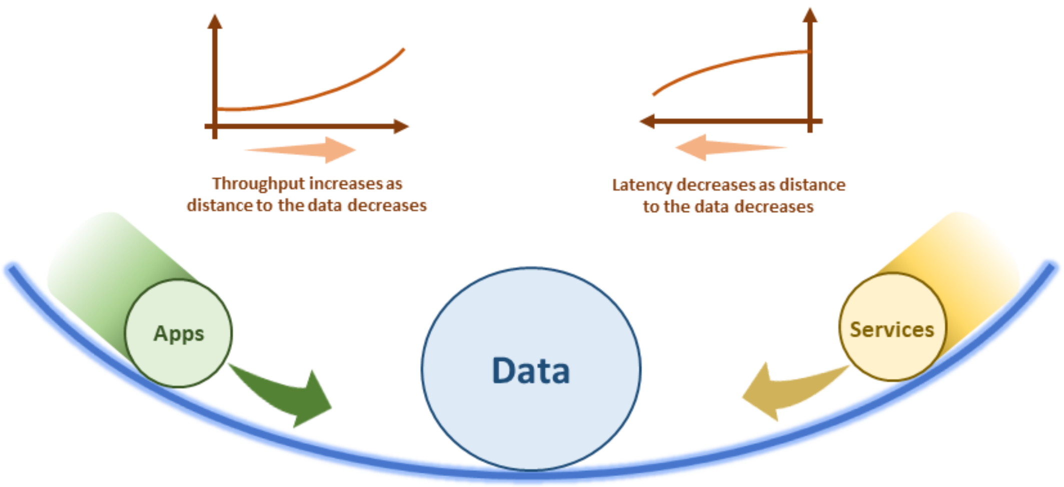

Figure 4. The concept of data gravity: latency typically decreases and throughput typically increases as applications and services are moved closer to the data. This creates a pull that gets larger as the data volume increases.

Data policies: Alongside the technical challenges of data handling, the potential use of personal data, particularly in the development and application of AI methods, raises the requirement to consider ethical aspects of handling personal data and of privacy. Many organizations have produced guidelines on the ethical application of AI (see, for example, Leslie, 2019), and many Members have guidance and regulations in place to govern use of personal data and privacy in AI applications (for example, the Office of the Privacy Commissioner for Personal Data, Hong Kong, 2021). It will be important to ensure that any WMO guidance in this area is not in conflict with any such regulations.

3. Application of artificial intelligence in the weather, water, oceans, climate and environment domains

The performance of numerical weather prediction and climate projections has improved steadily over recent decades (Bauer et al., 2015). This has been the result of incremental advances in understanding of physical processes combined with increases in computing power which have enabled more complex and higher resolution models and larger ensembles to be used. This period has been characterized by sustained steady progress, with few disruptive advances; the emergence of the application of artificial intelligence techniques to weather and climate data has the potential to change this.

While some variants of machine learning (ML) have been explored in the weather, water, oceans, climate and environment (WWOCE) community for many years, it is only through recent developments of new AI methods (in particular deep neural networks) that the great potential for application across the environmental modelling processing chain has been recognized. This methodological potential is enhanced by new processor technologies allowing heavy-duty, parallel data processing. The long history of observational data records, reanalyses and operational forecasts constitutes a great resource for learning from existing data and for deriving intelligent analytics methods for operational use. ML methods present opportunities for progress with forecasting systems on two fronts: (1) through accelerating systems to reduce run-time, for example, through emulation of computationally expensive elements of the system; and (2) through improving accuracy over traditional approaches, especially in areas where new data sources can be exploited and combined with traditional data, or where there is no clear understanding of the physics. A wide range of open-source ML frameworks (such as TensorFlow, PyTorch and Keras), together with programming languages like Python or C++, support the development of such AI applications. However, the integration of such applications into modelling workflows poses some logistical challenges. Such challenges relate to, for example, integration between AI applications and FORTRAN-based model codes (or alternatively, coding AI methods in lower level languages), training strategies, integration into complex time-stepping schemes, and operation on unstructured grids. The efficient integration of AI methods into individual components in a modelling workflow depends upon the ability to isolate those components, requiring a well-modularized modelling system. Furthermore, there are currently only very few AI applications which can efficiently exploit the massive parallelism of multi-core HPC systems.

Given the potential benefits, research into the use of AI is becoming ubiquitous across all steps in the environmental modelling processing chain: observations, data assimilation, model forecasts, post-processing and product generation (Figure 5). Observation-based “nowcasting” applications have been a natural area of application of ML techniques (Prudden et al., 2020; Ravuri et al., 2021) due to the inadequacies of conventional methods, and the need to process large data volumes in a timely manner. Similarly, the use of AI techniques has been a natural extension to the use of advanced statistical methods in data assimilation, allowing more complete estimation of uncertainties (Irrgang et al., 2020). Meanwhile, many studies have explored the potential of ML techniques to improve on parameterizations of subgrid-scale processes in models (Rasp et al., 2018; Yuval et al., 2020) through use of training data from process resolving models. Other applications have included observational data pre-processing, emulating components of environmental models and forecast model output post-processing (Boukabara et al., 2019). Furthermore, some AI methods (in particular, self-supervized learning and causal inference) may lead to new knowledge generation from data (for example, Denby, 2020; Runge et al., 2019). Appendix 1 provides a snapshot of some of the research that has been undertaken across the processing chain.

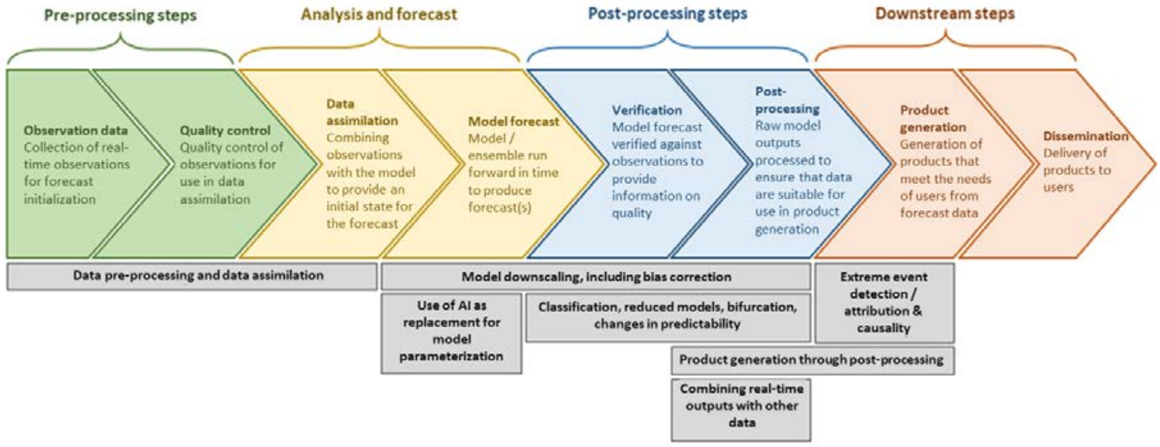

Figure 5. Schematic of a simplified numerical weather prediction processing chain. Applications across the processing chain are described in Appendix 1, organized into the sections identified in the grey boxes, which align with the steps in the processing chain to which they are relevant.

While much of the current research is exploring the potential to replace or enhance components as an evolution of existing workflows (Krasnopolsky, 2007, 2013), there is also growing interest in more disruptive approaches that involve reworking workflows in their entirety (Schultz et al, 2021). Success of such holistic approaches will likely hinge on the ability to impose physical constraints in AI methods, an area of active research. As a shorter-term target, combination approaches (hybrid models) that can use AI to increase the spatial or temporal resolution of a classic model during run-time are actively pursued. AI methods also have the potential to open up opportunities to use new data sources that cannot readily be used in conventional methods, for example, social media reports of impactful events, and novel Earth observation data sets (for example, Hilburn et al., 2020).

Applications of AI methods are not restricted to the data production part of the environmental modelling value chain; work has also been undertaken to explore the application of AI to the forecasting process (for example, Karstens et al., 2018). Such applications are becoming increasingly important to enable forecasters to make efficient and effective decisions faced with large increases in the data being presented to them.

Adoption of AI into processing workflows more broadly will depend upon progress on a number of challenges that are briefly described in the following paragraphs.

Collaboration between the WWOCE and AI communities: To fully exploit the potential of AI in the WWOCE domains, close collaboration between domain experts and ML experts needs to be established. Co-development of methods between the AI and WWOCE communities may help to accelerate progress. Beyond the WWOCE community, there is a much broader community engaged in research and application of AI methods across a wide range of applications. This community encompasses the public, academic and private sectors. There is much commonality between the practical challenges of the application of AI methods across different domains, and therefore an opportunity exists to exchange insight and leverage expertise from other disciplines. However, as discussed in Schultz et al. (2021) and Boukabara et al. (2021), there are also certain properties of

WWOCE data that differ from data in other disciplines. This may prevent the adoption of some AI methods in the WWOCE domains.

So far, few publications list authors from both WWOCE and AI fields. Effective exchange and collaboration of this nature is dependent upon technical aspects such as data standards and interoperability, and common language. For example, one aspect that could boost such collaborations is the definition of benchmark ML problems and data sets for objective evaluation of methods; such benchmarks have greatly contributed to the successes in image recognition and other ML application areas. Initial steps in this direction have been taken (for example, Rasp et al. 2020; http://mldata.pangeo.io/preprocessed_datasets.html; the MAELSTROM project, https://www.maelstrom-eurohpc.eu/). Successful collaboration is also reliant upon suitably skilled and motivated individuals to drive the exchange forward. In reality, the prospect of individuals possessing the skills and knowledge to span both the AI and WWOCE domains is very limited. Collaboration between the communities is therefore going to be essential to make effective progress. Concerted action, for example through WMO Capacity Development action on skill development, may be necessary to facilitate progress.

Interdomain collaborations: To increase the scope and benefit of AI to address complex inter-relationships, stronger cross-domain collaborations are needed. Such efforts would increase the reach of insight into weather and climate events and their associated impacts. There is the opportunity to work jointly across multiple disciplines to tackle problems that require combined analysis of data from multiple domains. Such problems entail the combination of data from different sources that may have very different characteristics, either in terms of temporal and spatial sampling, or in terms of the type of data (for example, categorical versus continuous data). AI methods provide a means to combine such disparate data sets, opening the opportunity for interdisciplinary working, for example between the WWOCE community and the social sciences or medical research communities.

Operational adoption: The rapid growth of research into the application of AI methods in the WWOCE domains has not yet been matched by the rate of application of the research into operational and production systems. In part, this is due to the scaling issue of AI applications. Often, ML solutions are developed on smaller, well-defined test data sets (for example, coarse-resolution model output), while operational systems operate at much finer resolutions. While the ML community is very large and growing, there are relatively few experts who can employ AI methods on massively parallel computer systems. Research creates new opportunities for increased efficiency and accuracy that operational centres are keen to exploit. The need for application of the research in a rapid, systematic and well-planned manner creates some impetus for these centres to organize a process for adopting AI methods and developing strategies for the integration of such methods in operational systems. Some centres, such as the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Oceanographic and Atmospheric Administration (NOAA), have developed and published strategies for this work (Düben et al, 2021; NOAA, 2020); others are still developing their approach. Effective strategies will need to address the trade-offs inherent in the choice between conventional methods and AI approaches. This may be based on, for example: the relative importance attached to accuracy versus time to solution; understanding of appropriate metrics based, for example, on value or impact; and the importance (or otherwise) of the representation of underlying physical processes.

Post-processing: One area where adoption of AI methods has been more rapid is the area of post-processing systems. Haupt et al. (2021) provide a summary of the state of play regarding application of AI to post-processing of weather and climate model output, highlighting that this is the area of greatest maturity in the application of AI within the weather and climate community. They describe applications across all timescales, and spanning efforts aimed at forecast improvement, through to work to improve downstream applications. The authors call for five initiatives to overcome current challenges with the application of AI techniques:

1. Development of a data repository for fast development of post-processing techniques;

2. Data standardization methods (Figure 6; **F**indability, **A**ccessibility, **I**nteroperability, and **R**e-use, FAIR, https://www.go-fair.org/fair-principles/);

3. Studies on interpretability methods;

4. Metadata and model documentation for labelled training data;

5. A database of recorded AI failures to limit duplication of effort across the research community.

These initiatives highlight areas where research community effort is required to facilitate the wider uptake of AI across the weather and climate community. Note that these areas are not unique to the WWOCE community, and there is therefore a potential opportunity to learn from other communities.

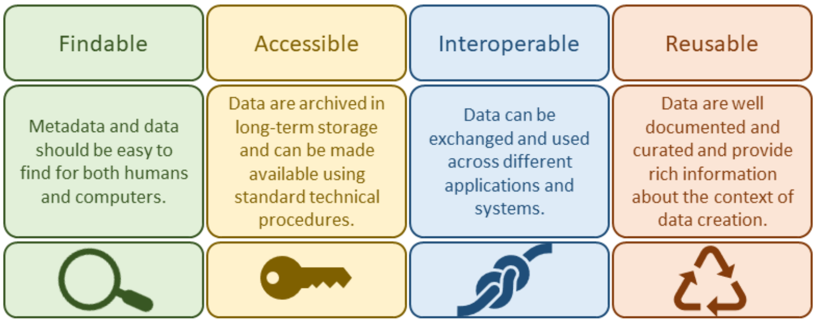

Figure 6. FAIR data principles

Further adoption into processing chains will depend upon progress with a number of practical challenges. For example, while AI methods can in principle harness the value of increasingly large data volumes, the practicalities of doing so in operational, time-critical workflows need further attention. One issue here is the required data parallelism in WWOCE applications: while most AI problems are trained on a massive number of rather small-sized independent samples, WWOCE data samples are not spatially and temporally independent of each other. There is therefore a need to analyse spatiotemporal patterns, which rapidly increases memory requirements and increases the dependence upon parallelization. Thus, new data flow patterns need to be developed for such AI solutions.

Trustworthy AI: While AI models will in any case have to undergo the same rigorous evaluation procedures as traditional WWOCE forecasts, greater understanding of the reliability and accuracy of methods (explainable AI), backed with rigorous, objective analysis is required to build trust in AI approaches, and in particular in projections that extend outside the value ranges seen during the training process. This is a particular challenge because it takes time to build up the evidence needed to engender trust. These challenges may be exacerbated in some regions due to the dependence upon input data, which varies greatly between regions in terms of both coverage and quality. Therefore, the ability to transfer methods between regions with different observational network characteristics, and the optimal approaches to do this, need to be established.

Data sharing: The WWOCE and AI communities need to work together to share data and methods, to define the metrics against which the success of methods needs to be evaluated, and to establish the ability to transfer methods between regions with different characteristics. For example, the AI community, both in the private sector and in universities and research institutes, has been very active in innovating and developing tools for application of AI methods in the WWOCE domains, particularly in the areas of weather and climate impacts and user-focused product generation. At the same time, the WWOCE community holds data sets, and expertise about the data, that could be beneficial in developing such applications in collaboration with the AI community. National Meteorological and Hydrological Services hold extensive data, including real-time forecast and historical data; the broader WWOCE community has research expertise, data and computational facilities that could further evolve; and the AI research community has expertise in development and application of AI methods that could be applied. Bridging the gap between groups is an area where the WMO and AI communities have the potential to offer mutual support and exchange of insight and experience.

Private sector engagement: The private sector has considerable expertise in the development and application of AI methods, and typically has the organizational agility that is beneficial in such a fast-evolving area of activity, together with the focus on customer outcomes that drives progress. However, the algorithms employed by private sector companies are often their key assets and are therefore not made available to the wider community. This often prevents a thorough evaluation of the quality and robustness of commercial systems. Effective public–private collaboration will therefore be dependent upon establishing means for evaluation that respect the restrictions on the ability to share details – for example, through development of objective evaluation measures analogous to those used for evaluating hardware. Furthermore, the greater organizational agility of typical private sector organizations aids the effective exploitation of the fast-evolving AI and ML technologies, while the WWOCE community is more familiar with operating to the level of rigour that is needed for safety-critical services. Therefore, the public and private sectors bring complementary skills, insight and experience. Building trust between private, academic research and public sector actors in this area should be mutually beneficial, and would increase the potential for productive public–academic–private partnerships.

Interaction with downstream users: The increased adoption of AI methods into production chains gives rise to two particular scenarios for the evolution of the interactions between data producers and downstream users. The least disruptive scenario is that the data producers take responsibility for ensuring that the adoption of AI into their production chains delivers benefit to downstream users, without the interaction between producers and users needing to change. This scenario is based upon an assertion that the current production chains are well suited to the requirements of the downstream users. The more disruptive scenario is that the balance of responsibilities between the data producers and the downstream users needs to evolve to enable the downstream users to incorporate AI approaches into their value chains. This scenario may entail changes in the data requirements of downstream users. Operational centres will need to decide on their approach to the evolution of the interaction with downstream users.

4. Recommendations

The preceding discussion has highlighted some of the opportunities and challenges around the use of AI and data handling in the WWOCE domains. Given the nature of AI use and data handling, and the rate at which they are developing, there are many possible directions that the WWOCE community could take. Therefore, there is a clear role for WMO in terms of providing a focus for the WWOCE community. While there may be benefit in WMO influencing the direction of research in this area, much research work is already underway, and the biggest gains are likely to come from a focus on supporting adoption of methods. The recommendations in the present concept note identify some priority areas, and propose actions to assist the community in making progress. It is anticipated that these actions would be taken forward in collaboration with other initiatives that bring together the WWOCE community.

In the recommendations that follow, the term "centre" is used to refer to WMO Global Producing Centres (GPCs) and National Meteorological and Hydrological Services (NMHSs). The term "modelling centres" is used to distinguish the subset of these centres that run end-to-end modelling systems.

Exchange of ideas for adoption of artificial intelligence methods

Proposed short-term action 1: WMO Research Board to promote exchange of insight between centres running end-to-end modelling systems to support development of plans and strategies for adoption of AI methods into operational/production workflows.

Proposed long-term action 1: WMO to develop and promote adherence to good practice guidance for the adoption of AI methods into operational/production workflows.

The rapid expansion of research into application of AI methods in the WWOCE domains, combined with the changing nature of hardware platforms, has created an imperative for WMO Members running end-to-end modelling systems to develop strategies and plans for adoption of AI methods in operational and production systems. This entails overcoming a number of challenges, including the need to prioritize among the potential areas of application, to adapt workflows to accommodate AI methods in a seamless manner, and to objectively evaluate the impact of methods on the quality of outputs. Some modelling centres are well advanced in their thinking in this regard; others have yet to embark on developing such strategies and plans. Efforts of the Working Group on Numerical Experimentation to keep track of progress with application of AI in operational systems could be leveraged to support discussion in this area. There is an opportunity for the WMO Research Board to support this further, in collaboration with the WMO Infrastructure Commission, through establishing a dialogue between modelling centres, for exchange of ideas and insight, and more broadly to facilitate collaboration in this area.

In the longer term, it will be important that the experience gained across the WWOCE community is captured and used to inform good practice guidance on approaches to adopting AI methods into operational and production workflows. This will ensure that modelling centres can avoid common pitfalls, and can adopt methods in an efficient and effective way. It will be important for this guidance to be kept up to date to reflect the rapid evolution in the AI field.

Supporting use of data to improve delivery

Proposed short-term action 2: WMO to explore the potential to improve delivery to customers for centres looking to incorporate data produced elsewhere into their processing chains, including through use of AI methods. This should include elicitation of the requirements for support covering areas such as access to data, computational platforms, selection and validation of methods, and training of staff. Recommendations for how the WMO community can meet these requirements should be made.

Proposed long-term action 2: WMO to develop a roadmap for coordinated provision of support in response to the recommendations identified in short-term action 2.

While the combination of the use of AI methods and the expansion of the range of available data sets creates an opportunity for centres to provide new services through consumption of data for use in AI methods, considerable practical barriers remain. These barriers include establishing suitable access to data sets, understanding the applicability of methods to the data sets available in a particular region, providing appropriate platforms and environments (whether local, or remote) for AI workflows, and accessing appropriate skills and training. Challenges may be particularly acute in centres without end-to-end modelling capabilities, and in particular in developing countries where support may be needed to identify how best to update production chains to integrate the use of AI methods, for example to combine data from Global Processing Centres and Regional Climate Centres with local observations. Centres in developing countries may also face additional barriers due to bandwidth limitations and poor Internet connection. The ability to overcome these barriers is dependent upon first establishing clarity around aspirations and objectives for the uptake of AI methods within the centres, which in turn requires an understanding of the opportunities and their potential to deliver beneficial advances. There is an opportunity for WMO to provide a coordinated approach to exploration of the potential, particularly among developing countries. Subsequently, WMO also has an opportunity to support the uptake by coordinating data, platform and training provision, and addressing technical barriers to uptake, in response to the needs that arise. Such an approach should build upon existing initiatives (such as the WMO Information System 2.0 work that is being undertaken by the Infrastructure Commission) to ensure coherence between related activities, and should draw upon relevant experience in other communities. Long-term training may require WMO capacity development action on: (a) skill development, in order to tackle training needs identified through dialogue; and (b) leveraging of AI to accelerate its adoption into the processing chains for delivery of products and services for developing countries. This should be a joint endeavour between the Research Board, the Infrastructure Commission and the Commission for Weather, Climate, Water and Related Environmental Services and Applications (Services Commission), and should take into account the wide range of training and expert community activity that is already taking place within the WWOCE community.

Development of guidance and standards

Proposed short-term action 3: WMO to collate and develop guidance and standards for: (a) sharing data and tool sets, including for use in AI methods; and (b) objective evaluation of the performance of AI methods. Adherence to the resulting guidance and standards should be promoted across the WMO community.

Proposed long-term action 3: WMO to identify a suitable body for long-term ownership and promotion of guidance and standards for: (a) sharing data and tool sets, including for use in AI methods; and (b) objective evaluation of the performance of AI methods.

The ability to share data and methods effectively and efficiently both within the WWOCE community, and between different communities, is dependent upon common standards and practice. Given the diversity of data sets and applications, a single set of agreed standards covering all sharing of data, code and tools may not be a realistic goal. Instead, a set of good practice guidelines for data, code and tool sharing, with agreed standards in specific cases where appropriate, may be more practical. Such guidelines should cover requirements for data formats and metadata, methods for data exchange, approaches for assuring data quality, and guidelines for sharing of code and tool sets. In the context of data sharing for AI, guidelines should cover provision of benchmark data sets for objective evaluation of AI methods, and guidelines for communicating the quality of methods.

Guidance and standards should be designed to accommodate data policy requirements (for example, in relation to "open data") that will often be determined at the national or organizational level. Guidance and standards should also take into account the requirements of other communities, with a view to facilitating exchange and interoperability between disciplines, and should draw upon efforts already underway in those communities to develop such standards. Therefore, the required effort is a combination of collating existing and emerging standards, and identifying how these can contribute (and be extended) to providing a coherent set of guidance and standards for the WWOCE community. Efforts to establish good practice guidance should draw upon the extensive experience of WMO in developing guidance and standards, and should align with broader WMO policies and initiatives, such as the WMO Unified Data Policy Resolution and existing agreements with the Open Geospatial Consortium. In addition, guidance and standards should take into account ethical considerations around use of personal data and privacy. Consideration should be given to longer-term stewardship of guidance and standards, including mechanisms for regular review and evolution to adapt to emerging requirements and to keep pace with the development of AI methods. There is therefore an associated requirement to establish a suitable body for longer-term ownership and oversight.

Public–private partnerships

Proposed short-term action 4: WMO public–private partnership development efforts to specifically include efforts focused on the application of AI methods to WWOCE data, delivered through sustainable partnerships, in particular in support of improving product delivery for developing countries.

In contrast to conventional modelling efforts, the growth of the application of AI methods has been in part driven forward by the private sector, which has pioneered techniques and applications as part of its commercial activities. Positive progress has been made across a range of organizations from small and medium-sized enterprises, through to the big technology companies. The need for private sector companies to protect their intellectual property creates a barrier to the ability to share details of methods openly, which has limited the extent of public–private partnership activity to date. However, applying private sector methods to public sector data sets could potentially increase the value derived from the data, enhancing the utility of the data while enabling the private sector to deliver improved products. There is particular potential for public–private partnerships to deliver benefits to developing countries through providing new opportunities for enabling access to a combination of data, platforms and methods. Progress in this area will be dependent upon establishing sustainable business models for partnership working, and developing mutually beneficial partnerships. WMO is already engaged in development of public–private partnerships with the aim of improving service delivery. The application of AI methods to WWOCE data would be a beneficial area of focus for this.

Collaboration for data handling

Proposed short-term action 5: WMO Research Board to promote collaboration between centres running end-to-end modelling systems on approaches to adapting workflows to handle increasing data volumes.

The emergence of the data-handling challenge, in part driven by the development of exascale computing and the growth in application of AI methods, requires action across the WWOCE community. Conventional workflows are coming under increasing strain, creating an imperative for changes in approach. This is a multi-faceted problem, with tensions between the need to process larger data volumes and the need to meet targets for time to delivery, requiring a combination of scientific and technical advances. However, this is not a challenge that is unique to the WWOCE community; there is a broader community engaged in developing data-handling techniques and tools and workflow management. At present, few modelling centres have clear strategies for tackling this challenge, and there is therefore an opportunity for the WMO Research Board, in collaboration with the Infrastructure Commission, to provide coordination across the community to lead efforts to rise to this challenge. Note that this recommendation (Proposed short-term action 5) involves the same modelling centres as proposed short-term action 1, and in practice it is anticipated that the two actions would be tackled together.

Taken together, all of the foregoing proposed actions will facilitate the uptake of AI methods among the WMO community, enabling the adoption of AI methods to improve WWOCE data sets, and to deliver increased value by enhancing products and services derived from these data.

Appendix 1. Examples of applied artificial intelligence research within the weather, water, oceans, climate and environment domains

There has been a rapid growth in research into the application of artificial intelligence (AI) throughout the environmental modelling processing chain in recent years, and increasing uptake of AI methods in production systems. A comprehensive summary is therefore beyond the scope of the present concept note. Reviews of some AI and machine learning (ML) applications in the weather, water, oceans, climate and environment domains (WWOCE) are presented in Krasnopolsky (2007, 2013) and Boukabara et al. (2019). The present appendix instead presents a snapshot of current research and production activities, with the aim of providing a sense of the current state of play and future directions.

Data pre-processing and data assimilation

In the area of data pre-processing, in the United Kingdom of Great Britain and Northern Ireland, the Met Office has undertaken a project to apply machine learning to improve classification of expendable bathythermograph (XBT) data. The aim was to enhance the metadata relating to probe type in the historical data records. Such metadata are frequently missing in historical observations, thereby increasing the uncertainty in the historical ocean temperature data set. The application of a decision tree algorithm was demonstrated to lead to significant improvement in probe classification compared to previous manual methods (Haddad et al., 2022).

A first class of problems consists of using ML to emulate or improve the data assimilation (DA) procedure. Geer (2021) explored the crossover between ML and DA, focusing on how Earth system models could be learnt directly from observations. Performing DA at a low cost is of prime concern in Earth system modelling, particularly in the current era of big data, where huge quantities of observations are available. DA and deep learning (DL) can take advantage of each other, as they are complementary and have similarities. Therefore, coupling DA and DL is quite a natural approach. Research work has included the proposition of a new framework to reduce computational cost and memory storage for the ensemble Kalman filter algorithm, by performing calculations in reduced space (latent space), and to improve accuracy by exploiting the latent structure and surrogate network (Peyron et al., 2021). Penny at al. (2021) integrated DA with ML in order to perform entirely data-driven online state estimation. Examples using singular value decomposition for the truncation illustrate the importance of the choice of the truncation parameter in the case of air flow prediction and pollution transport (Arcucci et al., 2019).

For variational assimilation, data-driven strategies have also been tested (Fablet et al., 2020). Numerical experiments on Lorenz-63 and Lorenz-96 systems report significant gain with regards to a classic gradient-based minimization of the variational cost both in terms of reconstruction performance and optimization complexity. These methods still need to be tested on higher-dimension models and questions remain as to the design and selection of the dynamical prior in variational assimilation systems.

ML and DA can also be combined, with ML being used to learn a particular model or model error, and DA being used to correct the model state. It was shown, for example, by Bonavita and Laloyaux (2020) that artificial neural networks (ANNs) can reproduce the main results obtained with weak-constraint 4D-Var in the operational configuration of the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecast System (IFS) model .

An additional application for 4D-Var systems is the use of ML emulators to generate tangent-linear and adjoint code (Hatfield et al., 2021).

Other goals are to go beyond the use of high-resolution simulations and train ML-based parameterizations using direct data, in the realistic scenario of noisy and sparse observations (Brajard et al., 2021). Further proofs of concept have been developed, for example adopting a Bayesian formulation and stating this as a data assimilation problem with unknown model parameters (Nguyen et al., 2019). The important point is that the learning problem is carefully formulated such that the physical model explains as much of the data as possible, while the data-driven component only describes information that cannot be captured by the physical model (Guen et al., 2020). More generally equivalences have been found between ML and DA (Abarbanel et al., 2018; Bocquet et al., 2019).

Houtekamer et al. (2021) explored the use of AI methods to optimize parameter settings. They used a genetic algorithm with an ensemble Kalman filter that uses parameter perturbations (for both continuous and categorical parameters) to explore the ability to optimize parameters based on the performance of the ensemble members. They concluded that for most model parameters, there is not enough information available to produce improved distributions.

Use of artificial intelligence as replacement of model parameterizations

The replacement of parameterizations for complex representation of clouds and their associated processes has been a very active research area. Research has shown the feasibility of using deep learning for climate model parameterization, with the caveat that it might not be able to reproduce conditions outside its training manifold (Rasp et al., 2018).

A new strategy has been proposed for modelling the subgrid-scale scalar flux in a three-dimensional turbulent incompressible flow, using physics-informed neural networks (NNs) and tested in large eddy simulations (Frezat et al., 2021). Very encouraging results demonstrate the capabilities of the model to generalize to unseen flow regimes compared to NN models that do not embed physical knowledge. This echoes previous attempts to infer subgrid parameterizations in the ocean context, that prove to be efficient when limited to a particular area (Krasnopolsky, 2007; Bolton and Zanna, 2019).

Other studies that have looked at modelling subgrid stresses for large eddy simulations have attempted to parameterize them as model selection problems, where NN classifiers attempt to pick optimal closure models to satisfy local energy balances (Maulik et al., 2021). There have also been studies that have explored models of subgrid-scale processes purely from the perspective of removing extra variables in the coupled state to accelerate computations (Maulik et al., 2019; Hijazi et al., 2020). Such studies require data obtained from numerical solutions to train NN regressors or classifiers for online deployment. This is in contrast to outer-loop intelligence-based frameworks such as reinforcement learning (Novati et al., 2021) or solver-in-the-loop training using adjoint-based optimization (MacArt et al., 2021). These methods are valuable for situations where finely resolved information is unavailable for a suitable subgrid parameterization but “true” quantities of interest, such as sparse measurements or energy balances, are available.

In the context of ocean dynamics, for example, neither in situ nor satellite observing systems can provide direct observations for all state variables, as is the case for sea-level anomalies. Promising methods are under development, consisting, for example, of identifying an augmented space of higher dimension than the manifold spanned by the observed variables, where the dynamics of the observations can be fully described by an ordinary differential equation (Ouala et al., 2020).

A wider review of the application of machine learning in ocean science can be found in Sonnewald et al. (2021). Methods have also been applied to problems in the field of hydrology (for example, Romanov et al., 2013).

Model downscaling, including bias correction, and model output processing

There is an increasing number of new methodologies being used for statistical downscaling, including bias corrections. Some of them allow not only the univariate distributions to be adjusted, but also their inter-variable and inter-site dependence structures (Vrac, 2018), opening the way for multivariate estimates that can be used for impact studies (Vrac and Thao, 2020; Robin et al., 2019).

Other studies have looked at downscaling, using generative adversarial networks that allow for uncertainty quantification (Leinonen et al., 2021), and using deep learning to downscale meteorological variables (Sha et al., 2020a, 2020b; Wang et al., 2021).

Extreme event detection/attribution and causality

There is much interest in extreme events, their detection/attribution and possible changes arising from different climate states. Over the past decade (2010–2020), statistical methods and experimental designs based on numerical models have been developed, tested and applied. These typically involve analysing large ensembles, and frameworks using extreme value theory have been developed to better characterize their uncertainties (Naveau et al., 2020). Challenges remain in relation to compound extreme events and compound sources of uncertainties.

Characterization of extremes, their detection/attribution and unprecedented climate events are issues of concern for society and for several economic sectors. Characterization and detection/attribution requires large ensembles, and there is interest in the use of weather generators that incorporate AI to improve their physical properties for different applications (Yiou and Jézéquel, 2020).

There is also interest, for example, in the probability density of events that would severely damage some ecosystems. An extremely large ensemble of simulations is required for estimating the probability densities, and specific models based on AI are being developed that can be applied to observations, reanalyses or climate simulations (Yiou and Viovy, 2021).

Classification, reduced models, bifurcation, changes in predictability

Analysis of climate simulations and identification of key elements for specific sectoral needs has for a long time used a hierarchy of classification methods (k-means, expectation-maximization models, Kohonen maps and so forth), that can provide pattern identification or different types of clustering.

More recent developments based on AI have embedded entropy and a new δ-MAPS clustering procedure (Fountalis et al., 2018) to identify regime changes from long simulations and changes in chaotic climate teleconnections depending on trends in the climate mean states. These promising results open new ways of analysing chaotic signals, and identify linkages between changes in the mean climate state and short-term variability, of relevance for the development of adaptation strategies (Falasca et al., 2020).

An alternative strategy combines extreme value theory, clustering methodologies and pattern recognition to better understand extreme events and metastable states of the atmospheric circulation. This approach is specifically designed for small-scale turbulent flows, and observational uncertainties are considered as noise (Faranda et al., 2017, 2019).

Product generation through post-processing of deterministic model outputs

In 2020, the China Meteorological Administration (CMA) launched the Sciences of Meteorology with Artificial intelligence in Research Technology – Forecast Demonstration Project (SMART2022-FDP) for the Winter Olympic Games in Beijing in 2022, with demonstrations of state-of-the-art, high-resolution regional numerical weather models and artificial intelligence and other objective forecasting technologies, systems and methods. The weather forecast demonstrations during the Olympic Test Games in 2021 and the Olympic Winter Games Beijing 2022 provided more and better technical product support for the meteorological forecasting team. CMA has developed improved short-term forecasting, based on use of a new generation weather radar network, automatic station network and satellite observation data, combined with the rapid assimilation of the numerical model forecast results, to produce a 0–12-hour intelligent rainfall forecasting system with 1 km spatial resolution and minute-level update frequency.

At the National Centers for Environmental Prediction (NCEP, United States of America), a relatively simple NN model was developed that was able to reduce the systematic errors in short-range forecasts of the NCEP Global Ensemble Ocean Wave Forecast System (Campos et al., 2020). The accuracy of day-10 forecasts, using a reasonably simple post-processing NN model with low computational cost, indicated a gain of two days in predictability when compared to the regular ensemble averaging procedure.

In the United Kingdom, the Met Office has undertaken a pilot study to explore the improvement of site-specific wind and temperature forecasts using machine learning within the Integrated Model Post-processing and Verification (IMPROVER) post-processing system (Roberts et al., 2023). The study has shown that a shallow multi-layer perceptron, trained using a rolling store of recent forecast data (15–30 days of data) produces significant enhancements to spot forecasts. In addition, initial explorations into deep learning techniques have shown promise, although the data volumes and processing power required to fit models to run at all lead times and grid points has been noted as a significant barrier. The work within the pilot study has also included an approach for manipulating very large, gridded data sets as “analysis-ready” objects, to facilitate the further development and application of machine learning methods. During the development of this approach, one aspect was considered successful enough to be included in the operational system, and since December 2019, minimum and maximum site-specific temperature forecasts have included machine learning in the post-processing chain.

To satisfy a wide range of end users, rainfall ensemble forecasts have to be skilful for both low precipitation and extreme events. Local statistical post-processing methods have been developed based on quantile regression forests and gradient forests, with a semiparametric extension for heavy-tailed distributions (Taillardat et al., 2019). These have been shown to provide improved results for operational forecasts (Taillardat et al., 2016).

Product generation through post-processing of ensemble outputs (single model and multimodel)

ML methods have been used to improve the skill of ensemble forecasts. At NCEP, a NN model was successfully applied in order to average a multimodel ensemble for 24-hour precipitation forecasts over continental United States (Krasnopolsky and Lin, 2012). NN was also used to improve the NCEP Climate Forecast System week 3–4 precipitation forecast and 2-metre (2m) air temperature forecast (Fan et al., 2021). Hewson and Pillosu (2021) demonstrated improvements in the skill of forecasts from the ECMWF ensemble by applying a statistical post-processing method. Deep learning methods for post-processing ensemble outputs have been developed by Rasp and Lerch (2018), and Grönquist et al. (2021).

The WMO Science and Innovation Department held an open competition to promote the World Weather Research Programme (WWRP)/World Climate Research Programme (WCRP) Sub-seasonal to Seasonal (S2S) prediction project database by using cutting-edge AI methods. This further supported efforts towards the new AI and exascale computing research focus within WMO. The competition aimed to gain new insights in the domains of ensemble atmospheric modelling and probabilistic weather forecasts. The competition provided the “best possible” forecast of 2m temperature and precipitation at forecast lead times of weeks. All of the created software, codes, documentation and results from the competition were made publicly available.

Combining real-time outputs with other data

WMO Global Atmosphere Watch (GAW) is working on data fusion methods to be applied to related air-quality data. The Measurement-Model Fusion (MMF) project has been developed to merge the best available measurements for both wet and dry deposition, with the best available chemical transport models (CTMs) using advanced computing. The results of this method are more accurate maps of atmospheric deposition. The WMO GAW is supporting the Measurement-Model Fusion for Global Total Atmospheric Deposition (MMF-GTAD) initiative to retrieve high-resolution, high-quality, global-scale representation of total atmospheric deposition, aimed at meeting societal needs arising from environment issues and the drive for global sustainable development.

Applications of AI to combine real-time forecast outputs with sector-focused impact-related data are being developed across a wide range of industry sectors by both private and public sector organizations. This is a particular area of focus for big technology companies, with IBM’s Watson AI, Google’s DeepMind, and Microsoft Azure all offering commercial services in this area, alongside a wide network of small and medium enterprises offering sector-specific services.

Appendix 2. Examples of platforms that bring together data, processing power and tools

There are many examples of platforms that allow access to co-located data, processing power and analysis tools to enable research work and application development in the WWOCE domains. A small number of representative examples are described below.

Within the United Kingdom, the JASMIN data analysis system (https://jasmin.ac.uk/) was established to address data-handling concerns and encourage industrial use of environmental data. It has high-performance petascale disk resources, tape archives, a large batch cluster, co-located community cloud, and (from 2021) a large graphics processing unit (GPU) cluster. JASMIN therefore represents an attempt to separate at a fundamental level the data management and analysis workflow (which generally involves large communities) from the data production workflows on supercomputers (which involve many fewer individuals and very different technical challenges). JASMIN takes data from multiple satellite downlinks, and directly from many supercomputers. The environment provides both curated data and large “group workspaces” to support community collaborations around (many simultaneous) petascale workflows using both traditional (batch) and more recent (cloud) tools. A range of tiered storage is provided, including file systems which can present the same object through the Portable Operating System Interface (POSIX) and object store interfaces. The JASMIN environment is foundational to the United Kingdom approach to mitigating difficulties in exploiting machine learning and AI on the very large-scale outputs of environmental simulation.

In 2017, the China Meteorological Administration (CMA) formulated the Meteorological Big Data Action Plan to vigorously promote the co-construction and sharing of meteorological big data resources, coordinate the construction of a meteorological big data cloud platform, promote the openness of meteorological data, improve the accuracy of early warning and forecasting, assist with disaster prevention decision-making, and support cross-industry data value mining. Based on meteorological big data, the actions within the plan provide machine learning, deep learning and other operating environments to support intelligent forecasting services. In 2019, the Chinese Academy of Meteorological Sciences (CAMS) established the Institute of Artificial Intelligence for Meteorology (IAIM) to promote research into the application of AI technology in the field of meteorology, and set up a meteorological big data and AI research team at the newly established Nanjing Joint Institute for Atmospheric Sciences (NJIAS).

In the United States, the National Oceanic and Atmospheric Administration (NOAA) has partnered with Google, Microsoft and Amazon to develop the Big Data Program, subsequently known as the NOAA Open Data Dissemination (NODD) Program (https://www.noaa.gov/information-technology/big-data), which provides public access to NOAA’s open data on commercial cloud platforms through public–private partnerships. These partnerships facilitate full and open data access, while also encouraging innovation by bringing the data together with the tools available from the commercial partners.

In Germany, the German Climate Computing Centre GmbH (DKRZ) has a long-standing tradition of supporting climate research in Germany with high-performance computing and large-scale data resources. It also offers an extensive portfolio of services that goes beyond actual modelling and includes the areas of visualization, data curation and archiving, and also the development of AI methods. With its thematic focus on climate computing, DKRZ is pioneering new concepts for improving climate model workflows, for example, by offering highly flexible services (such as jupyterhub), as well as differently tailored options in virtual research environments (VRE), which are increasingly being realized at DKRZ on the basis of cloud infrastructure. The closer coupling of simulations with data processing and AI workflows is also a strategic topic at the Jülich

Supercomputing Centre (JSC) and at other computing centres in Germany. DKRZ and JSC are leading the data-related activities in the WarmWorld project, which aims at achieving exascale performance for the entire Icosahedral Nonhydrostatic (ICON) Weather and Climate Model workflow.

Within Europe, Copernicus (https://www.copernicus.eu/) provides access to a wide range of environmental monitoring and forecast data. Data are made available on a free and open basis. Data access is accompanied by a set of cloud-based Data and Information Access Services (DIAS) platforms which provide users with the ability to discover, manipulate, process and download Copernicus data and information. Alongside the free and open Copernicus data sets, each of these platforms also provides access to a set of additional commercial data sets as a premium offer.

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