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Technical Note

The Weather On-Demand Framework

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Abstract: This paper describes the Weather On-Demand (WOD) forecasting framework which is a software stack used to run operational and on-demand weather forecasts. The WOD framework is a distributed system for the following: (1) running the Weather Research and Forecast (WRF) model for data assimilation and forecasts by triggering either scheduled or on-demand jobs; (2) gathering upstream weather forecasts and observations from a wide variety of sources; (3) reducing output data file sizes for permanent storage; (4) making results available through Application Programming Interfaces (APIs); (5) making data files available to custom post-processors. Much effort is put into starting processing as soon as the required data become available, and in parallel where possible. In addition to being able to create short- to medium-range weather forecasts for any location on the globe, users are granted access to a plethora of both global and regional weather forecasts and observations, as well as seasonal outlooks from the National Oceanic and Atmospheric Administration (NOAA) in the USA through WOD integrated-APIs. All this information can be integrated with third-party software solutions via WOD APIs. The software is maintained in the Git distributed version control system and can be installed on suitable hardware, bringing the full flexibility and power of the WRF modelling system to the user in a matter of hours.

Keywords: API; data assimilation; NWP framework; WRF

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1. Introduction

In this paper, we will describe the Weather On-Demand (WOD) forecasting framework, which has been developed by the Icelandic private entity Belgingur Ltd. At Belgingur, we focus on research and development in meteorology and have during the past 15 years gradually been improving our software stack used to run operational and on-demand weather forecasts.

The WOD system has its roots in the long history of Belgingur's contributions to search and rescue operations through our collaboration with the Icelandic Urban Search and Rescue (SAR) Team and the UN Global Disaster Alerts and Coordination System (GDACS) (https://www.gdacs.org accessed on 25 December 2024). In the aftermath of the horrific earthquake that devastated Haiti in January 2010, the Icelandic team was the first international SAR team to arrive in Haiti (https://reliefweb.int/report/haiti/iceland-sends-search-and-rescue-team-haiti, https://sagafilm.is/film/icelandic-search-rescue-teams-ice-sar-haiti/ accessed on 25 December 2024), and it asked Belgingur to set up and run high-resolution weather forecasts, in operational mode, for the region. This request was fulfilled in less than two hours, with the forecasts being updated four times per day over the next six months. This paved the way for Belgingur to become a certified service provider for the GDACS through the SARWeather [1] forecasting system (https://www.sarweather.com accessed on 25 December 2024). In 2015 Belgingur provided services

to the United Nations Economic Commission for Africa (https://www.uneca.org accessed on 25 December 2024) via provision of the operational and on-demand WOD weather forecasting systems for the National Meteorological and Hydrological Services (NMHSs) of the Seychelles and Cabo Verde [2]. The operational forecasting system was installed on in-house hardware at these NMHSs in 2016 and 2017, respectively. In 2022, the system was installed at the Faroe Islands meteorological agency, again on in-house hardware.

The backbone of the WOD weather forecasting system is the WRF-Chem atmospheric model [3], with several in-house customizations. Initial and boundary data can be taken from the Climate Forecasting System (CFS), Global Forecasting System (GFS), Global Ensemble Forecasting System (GEFS), and the RAPid refresh forecasting system (RAP), all operated by the National Oceanic and Atmospheric Administration (https://www.noaa.gov accessed on 25 December 2024) (NOAA) in the USA. Operational forecasts use cycling of chosen parameters, mainly deep soil and surface fields. Cycling means that parameter values from previous forecasts are used to overwrite initial value data coming from the global or regional model used to force the simulation. This is conducted to minimize spin-up effects and to ensure proper book-keeping of hydrological fields such as snow accumulation and runoff, as well as the constituents of various chemical parameters.

With access to a wide variety of input data, the WOD system can be used to create deterministic short- to medium-range weather forecasts for any location on the globe, as well as regional climate outlooks and ensemble forecasts. In addition to being able to create forecasts and climate outlooks, users are granted access to both global and regional weather forecasts, as well as seasonal outlooks from the NOAA through WOD-integrated APIs (URL of WOD RESTful API: https://wod.belgingur.is/api/v2/ui/, and for further information see https://github.com/Belgingur/WOD-Documentation/wiki/Getting-Started-With-WOD-APIs both sites accessed on 25 December 2024). Open access global forecasts from the European Centre for Medium-Range Weather Forecasts (ECMWF) and regional forecasts from the Deutscher Wetterdienst (DWD) and the Danish Meteorological Institute (DMI) can be accessed further via the APIs. Through the WOD API system, users can also access weather observations from over 30,000 locations worldwide. All this information can be integrated with third-party software solutions via the WOD APIs.

The WOD system can be used for air quality purposes (e.g., dispersion forecasts from volcanic eruptions; see, e.g., [4]) and as a tool to provide input to other modelling systems, such as hydrological models. A wide variety of post-processing options are available, making WOD an ideal tool for creating highly customized output that can be tailored to the specific needs of individual end-users. One option worth mentioning is the ability to create output files that are compliant with the Verif (V1.3.0) verification tool [5], developed at the Norwegian Meteorological Institute and the University of British Columbia. Through this, users can compare not only forecasts created by the WOD system itself but also forecasts from a wide range of providers to observations.

The task of installing and running an atmospheric modelling system like, e.g., WRF-Chem [3] can be a daunting one. Not only is it a question of configuring and compiling a large and complex modelling system, but also of correctly configuring and compiling a plethora of underlying libraries, necessary for the seamless operation of the atmospheric model. Luckily, one can now find guidelines on how to run the model in the cloud (https://catalog.workshops.aws/nwp-on-aws/en-US/0-preparation accessed on 25 December 2024) or even access pre-compiled binary stacks to run on one's own in-house hardware (see, e.g., [6]). Considering the complexity involved in installing and running an atmospheric model from the bottom up, the concept of an on-demand forecasting system is indeed tempting. The idea of such a system is also not a new one; back in 2004, Warner et al. [7] described a system where users could, through a graphical

user interface, rapidly configure and deploy the MM5 [8] atmospheric model. In 2007, Stauffer et al. [9] described a nowcasting system, again based on the MM5 model, that could be deployed in the field on computers that were physically located in, e.g., army vehicles. To our best of knowledge, neither of these systems were ever made available to the public as both projects were either funded by, or designed for, various branches of the US military. In 2010, Belgingur launched the SARWeather on-demand forecasting solution and more recently the US-based company TempoQuest offered their cloud-based on-demand WRF (https://wrfondemand.com/ accessed on 25 December 2024) forecasting services to the public.

There are several differences between WOD and the above-mentioned solutions. The biggest one is perhaps the notion that the user can be given the rights to install the whole software stack on his/her own in-house, or cloud-based, hardware. Secondly, the WOD framework offers the potential to use data assimilation to improve forecast accuracy. Thirdly, users are granted access to a wide range of both global and regional forecasts from a plethora of third-party providers through a uniform API. This is conducted in such a way that data are made available on the fly, which can be quite valuable for time-critical downstream solutions such as energy trading and search and rescue operations.

According to [10], only half of the world's countries had access to a multi-hazard early warning system (MHEWS) at the end of 2023. It is our belief that the WOD system can play an important role in two of four pillars that make up a successful MHEWS, especially in infrastructure-sparse regions. These are observations and forecasting, as well as dissemination and communication. The remaining two pillars are disaster risk knowledge and the preparedness to respond, which are outside the scope of the WOD framework.

In the next section, we will describe the current version of the WOD forecasting system, focusing on design philosophy, software architecture, and data assimilation capabilities. Following that, we will give some examples of applications and finally wrap up with general discussions and thoughts on future developments.

2. System Description

The backbone of the WOD forecasting framework is the WRF-Chem [3] atmospheric model and its accompanying WRFDA [11] data assimilation software suite.

2.1. Design Philosophy

The system is primarily based on open-source software tools and components, allowing for seamless updates, scalability, and deployment without concerns about licensing fees. Predominantly coded in Python, it leverages essential libraries such as NumPy, netcdf4, Flask, and Sqlalchemy. Executed on clusters of Linux machines, the system integrates PostgreSQL as its relational database, while communication is facilitated through RabbitMQ and XML-RPC. Automated deployments are orchestrated through SaltStack, ensuring consistency across environments.

The forecasting system operates on an event-driven model, triggering processing in response to the availability of necessary data. Subsequently, tasks are scheduled to appropriate workers and modelers, rendering the system flexible and easily scalable to accommodate increased workloads.

2.2. Software Architecture

The component at the heart of the WOD system is referred to as the conductor (cf. Figure 1). The conductor actively monitors events, such as the availability of upstream data or the initiation of a modelling job via the API. Its core function is to orchestrate the execution of the weather model across a distributed infrastructure. The modelling process

is structured as a series of tasks, with each task assigned to a suitable worker (lightweight tasks) or modeler (heavy tasks, such as WRF execution). The resulting forecast files, generated at the conclusion of the modelling process, are stored in a shared file system. Details about the tasks constituting the modelling process are stored in a PostgreSQL database.

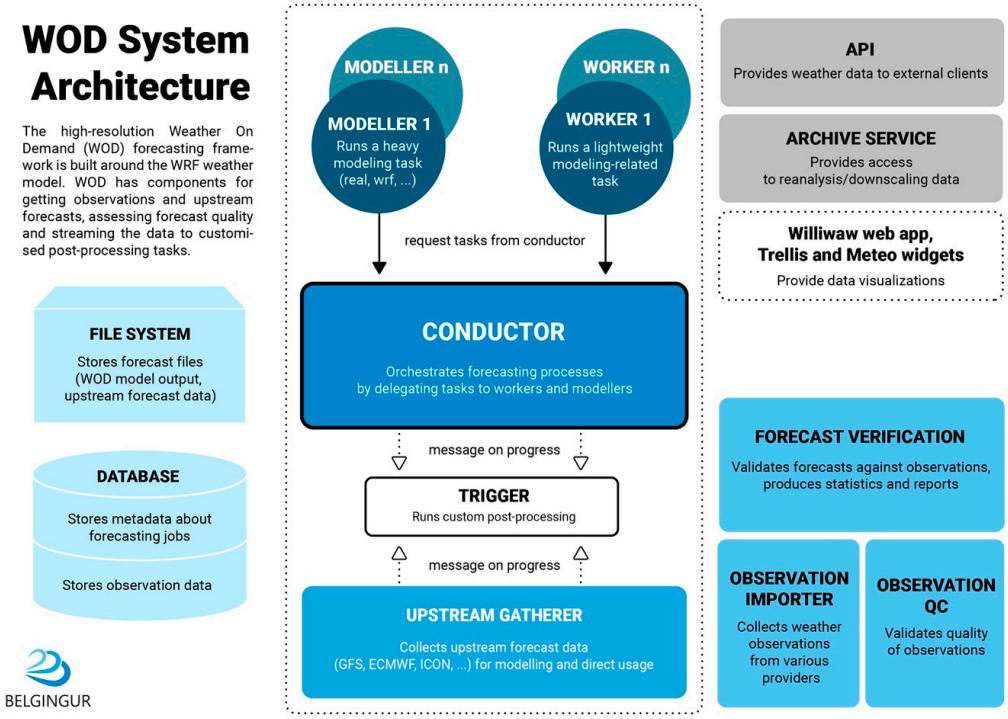


Figure 1. Diagram of essential components of the WOD system and their interconnections. See text for further details.

Next to the conductor and the workers/modelers tasked with executing its components, the WOD system comprises a suite of smaller services dedicated to handling weather data.

- Upstream gatherer: It retrieves data from a variety of upstream sources, including the NOAA, ECMWF, Icelandic Met Office, and more. It notifies the conductor upon the availability of initial and boundary condition files to initiate modelling. Additionally, the service converts incoming data to the WOD standardized comprehensive netCDF file format, allowing convenient access to upstream data through the WOD API.
- Post-processing trigger: A service connected to the conductor via a message broker, receiving notifications about the completion of diverse modelling tasks. Configurable triggers enable the execution of various post-processing actions in response to these events.
- Observation importer: This module handles surface observation data from different sources, whether pulled from external providers or received from third-party providers. The processed data are then stored in a PostgreSQL database.
- ObservationQC: A service responsible for evaluating imported observation data and assigning credibility scores to the observations.
- API: A RESTful API that enables access to the forecasting results and upstream data, starting on-demand forecasts and browsing observations. It is the main gateway for accessing the weather data from outside of the system.
- Archive service: A service providing access to reanalysis data series.
- Frontend components: Diverse clients designed to visualize both forecasts and observations.

- Forecast verification: This service enables the comparison of WOD forecasts and those from upstream sources against observational data.

2.3. Data Assimilation Capabilities

The WRFDA [11] data assimilation system has been integrated with the WOD framework. To date, users can take advantage of both the 3DVar and 4DVar options (see [3,12]) within WRFDA, as well as the hybrid data assimilation option described in Wang et al. [13,14]. Examples of observational data that can be used are satellite radiance data in the BUFR format and a plethora of observations in the PREPBUFR format made available by the NOAA (https://nomads.ncep.noaa.gov/pub/data/nccf/com/obsproc/prod/ accessed on 25 December 2024). The WOD system further accommodates user-provided surface observations that are converted to the LITTLE_R format required by the OBSPROC pre-processing tool. To create domain-specific background error statistics, users need to use a utility program called *gen_be* (V2.0) [15]. The input data for *gen_be* are previous WRF forecasts, which are used to generate model perturbations, used as a proxy for estimates of forecast error (https://www2.mmm.ucar.edu/wrf/users/docs/user_guide_v4/v4.4/users_guide_chap6.html#_Domain-specific_background_error accessed on 25 December 2024). The WOD framework allows for the automatic post-processing of WRF forecasts over a user-defined period to create the necessary set of data to be used as input to the *gen_be* software tool. A step-by-step description of how to run an on-demand forecast and how to create an operational schedule from the said forecast, along with the necessary steps needed to implement variational data assimilation, is given in Appendix A. An extensive overview of uncertainties in relation to variational data assimilation and filtering is given in Potthast [16].

In addition to the WRFDA data assimilation system, users can take advantage of observation nudging, also called Four-Dimensional Data Assimilation (FDDA) [17], of both conventional surface observation and atmospheric profiles. In FDDA, observations are merged into the model simulation to prevent the model solutions from drifting away from the observed values. In situ profiles from, e.g., uncrewed aircraft systems (UASs) have been shown to have a beneficial impact on the accuracy of model simulations (see, e.g., [18,19]). Indeed, the World Meteorological Organization (WMO) has organized a global UAS demonstration campaign (https://community.wmo.int/en/uas-demonstration accessed on 25 December 2024) to investigate the efficacy of UASs to contribute to the WIGOS (WMO Integrated Global Observing System) Global Basic Observing Network (GBON) routinely and operationally. The campaign focused on the near-real-time provision of the measurement of the atmospheric variables required for assimilation in numerical weather prediction systems.

2.4. Observation and Forecast Verification

To ensure data quality, the WOD framework includes an automatic quality control (QC) service of surface observations that are collected, where each observation coming to the system is assessed by several measures. The QC component leverages the best practices described in [20] and those implemented in NCEP's Meteorological Assimilation Data Ingest System (MADIS) [21]. Quality-assured surface observations serve as the base for forecast verification. The Verif tool (V1.3.0) [5] can be used to monitor the accuracy of WOD-based and third-party forecasts alike, as well as reanalysis datasets used for training machine learning models. The solution includes a graphical tool to browse and visualize verification results. This graphical tool is described in Appendix B.

3. Examples of Applications

In response to the Icelandic Mt. Eyjafjallajökull eruption in 2010 and Mt. Grímsvötn eruption in 2011, efforts were initiated to enhance the WOD system so it would be able to forecast the dispersion of volcanic ash and SO_2 (see, e.g., [22]). This addition [4] came on-line in 2014 when the Holuhraun eruption (for general information on the Holuhraun eruption see, e.g., https://en.wikipedia.org/wiki/Holuhraun accessed on 25 December 2024) started and has been used on a regular basis over the past few years now that eruptions are occurring frequently on the Reykjanes peninsula in SW Iceland (cf. Figure 2).

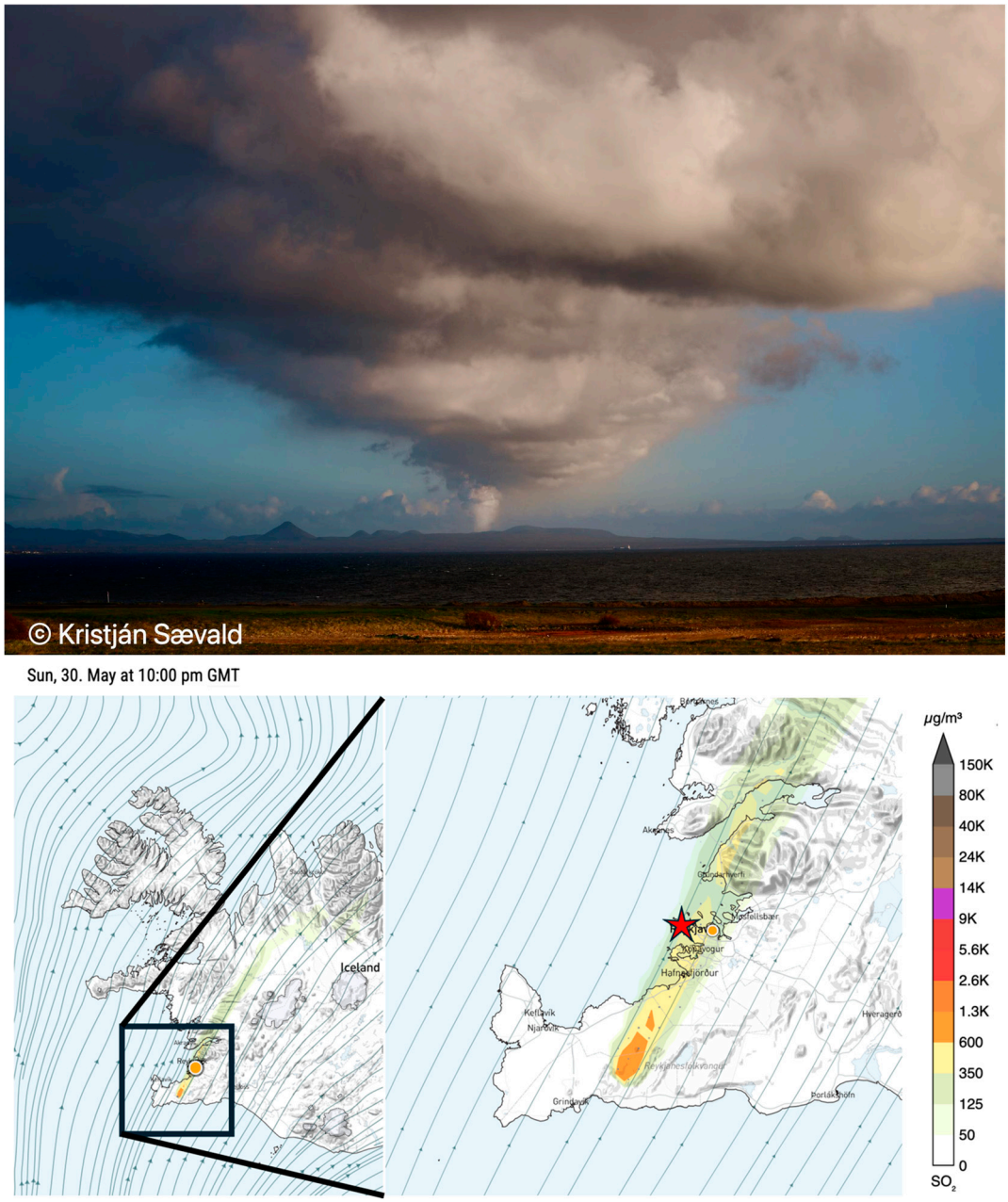


Figure 2. Volcanic cloud (**top panel**) emanating from the Mt. Fagradalsfjall eruption, SW Iceland, on 30 May 2021 (photo courtesy of Kristján Sævald) and a dispersion forecast (**bottom panel**) of SO_2 at 500 m AGL, valid at the time of the photoshoot, created by the WOD system. The red star shows the approximate location from where the photo was taken.

The use of data assimilation in regional models fosters broader and more collaborative integration among various meteorological stakeholders. For instance, users with an

observation network (cf. Figure 3) can have their data assimilated into the meteorological model, significantly enhancing prediction accuracy. However, ensuring rigorous quality control of the data before ingestion is paramount, as inaccuracies or inconsistencies can undermine the reliability of the forecasts. The more users provide data, the better the predictions for everyone, fostering a virtuous cycle where the quantity and quality of provided data help drive the precision and accuracy of forecasts, attracting more collaborators and consequently more observational data.

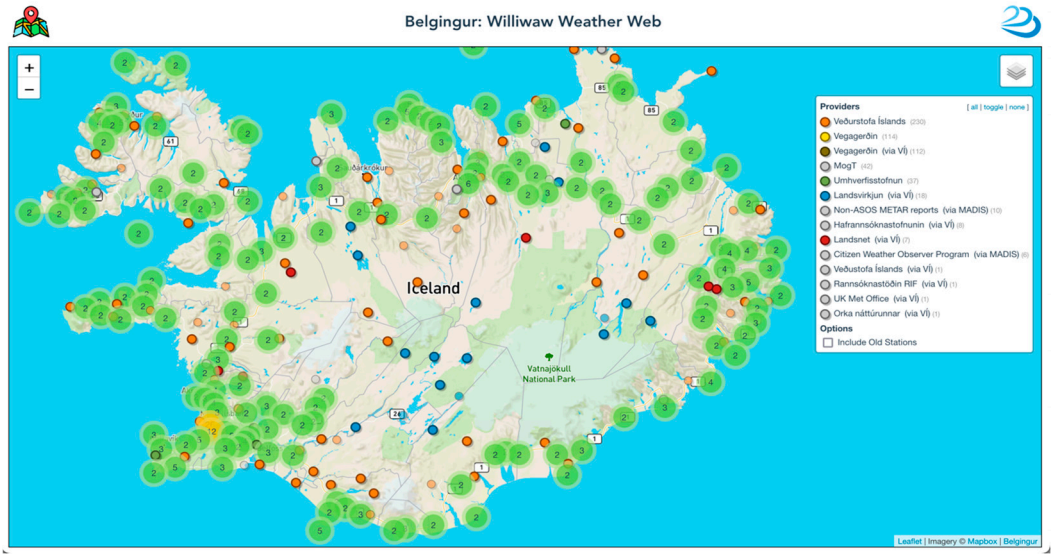


Figure 3. Example of how the location of observation sides in Iceland, from a wide range of providers, can be presented within the WOD framework. Screenshot taken from https://obs.belgingur.is on 11 July 2024.

In addition to traditional meteorological sector applications, such as media and governments, the WOD system also offers significant commercial and strategic benefits for sectors that maintain observational data networks, such as the electrical sector, agribusiness, and infrastructure (cf. Figure 4).

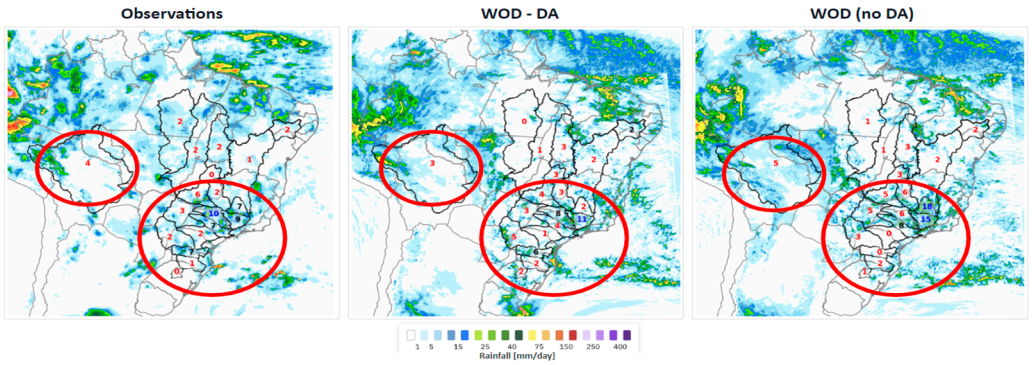


Figure 4. Comparison between observations (**left**) of 24 h rainfall [mm/day] over South America on 19 January 2023 estimated by the MERGE system of the Brazilian Centre for Weather Forecast and Climatic Studies (CPTEC in Portuguese), the results of a one-day-ahead WOD system with data assimilation (**centre**), and the same results without data assimilation (**right**). Areas limit the main hydro basins used for hydropower in Brazil, and numbers show the average precipitation over each basin. Numbers in red are precipitation significantly below daily average, while blues are significantly above daily average. Red circles highlight the regions where precipitation has the greatest impact on the Brazilian electric sector and where we identified the most significant improvements using the data assimilation system.

In Brazil, the WOD system has been utilized since 2018 by Tempo OK Tecnologia em Meteorologia Ltda., Sao Paulo, Brazil, a leading meteorological consulting company specializing in providing tailored weather forecast solutions. By 2024, over 90 Brazilian entertainment festivals and shows, including major events such as Lollapalooza, Tomorrowland, and Rock in Rio, benefited from WOD forecasts. In the infrastructure sector, the WOD daily forecasts support operations for more than one thousand kilometres of railways. In the energy trading sector, over 80 companies, including large banks and major power producers, representing over 85% of traded energy rely on WOD system forecasts as inputs for energy pricing models. Additionally, approximately one-third of Brazilian wind farms integrate WOD outputs into their power production forecasting systems. In agribusiness, the system is used by numerous farms and two prominent agro-insurance companies as a key input for their intelligence systems.

Wind farms, for example, have wind, temperature, and humidity measurements on towers at heights exceeding the first model levels. These data can be directly assimilated into the meteorological model without the need for boundary layer parameterizations to extrapolate information to the correct model level. On the other hand, these entities require accurate forecasts to better plan their operational and maintenance activities, as well as estimate their future power production (cf. Figure 5).

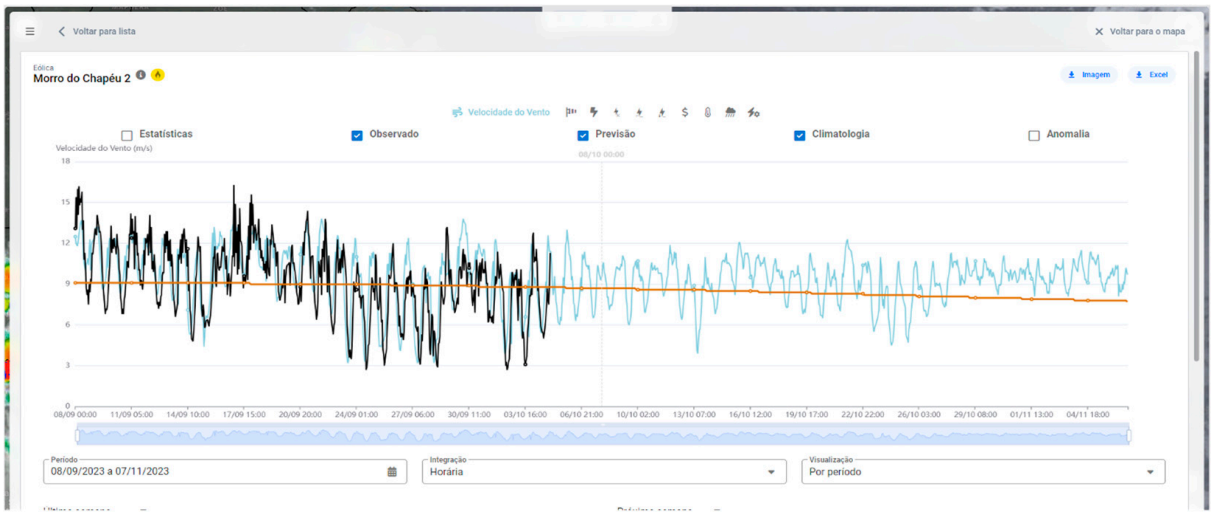


Figure 5. Example of a power production forecast where WOD model output has been post-processed using a novel machine learning software that takes observed winds and power production, among other factors, into account.

Another example of application lies in precision agriculture, which increasingly employs systems for measuring rainfall, temperature, and humidity in agricultural fields. Agricultural companies with private measurement networks can provide a significant amount of data collected in regions distant from major urban centres, where observational data from the government network are typically sparse. While this expanded data coverage for the data assimilation system can improve predictions for agricultural management in remote locations, it is essential to consider the representativeness error. The additional data may not fully capture the spatial variability of weather conditions, especially in heterogeneous landscapes. Addressing such errors through rigorous quality control and proper station siting is critical to ensure the reliability and value of these data in improving agricultural forecasts. Furthermore, the agrology sector is not only measuring the atmosphere with traditional weather stations, but with UASs as well. Like towers from wind farms, the UASs can measure atmospheric parameters at heights corresponding to the first model

levels and in a vertical profile and therefore bring more valuable information to the data assimilation system.

Finally, the infrastructure sector, encompassing ports, railways, roads, waterways, and construction projects, has also experienced rapid growth in atmospheric measurements, in line with the Industry 4.0 revolution and the expansion of the Internet of Things (IoT). This sector also heavily depends on accurate weather forecasts to enhance the efficiency and planning of its operational activities.

Regardless of the integration of data assimilation systems, high-resolution meteorological models, such as WRF, play a vital role in supporting applications across various sectors. These models offer detailed insights into local weather patterns, which are critical for decision-making processes in agriculture, infrastructure, and the energy industry. For instance, Hong et al. [23] and Kioutsioukis et al. [24] demonstrated how WRF enhances agricultural planning by accurately characterizing soil moisture deficits and improving evapotranspiration and irrigation forecasts, particularly in complex landscapes. In their 2020 paper, Nahian et al. [25] highlighted the model's superior performance in predicting meteorological conditions over an open-pit mining facility in northern Canada, aiding operational reporting of greenhouse gas emissions. Similarly, the energy sector relies on high-resolution models to anticipate weather-driven variability across all time scales in production and demand, as underscored by Dubus et al. [26].

4. Discussions and Future Development

In this paper, we have described the current status of the Weather On-Demand weather forecasting framework, focusing on design philosophy, software architecture, data assimilation capabilities, and its field of potential applications.

The data on which a numerical forecast is based and their impact on the uncertainty of the forecast are to a great extent influenced by the weather situation, the characteristics of the land, sea surface temperature, and topography and vary according to time of day, seasons, and the geographical location. In the vicinity of orography, or in cases of conditionally stable airmasses, middle- to low-level tropospheric stability may be of essential importance for accurately predicting precipitation, gravity waves, or orographic jets (see, e.g., Ólafsson and Ágústsson [27]). Consequently, it may be hard to reach general conclusions on the importance of different data sources.

The possibilities for the application of a regional meteorological model system with data assimilation technology are diverse and encompass both the private and governmental sectors, especially in the context of climate change. In these circumstances, where statistical methods often fail to represent phenomena that have rarely been observed in the past but may become increasingly frequent, this approach stands out by preserving the dynamic characteristics of the atmosphere, akin to any other deterministic model. Therefore, error reduction techniques in post-processing, such as machine learning algorithms, are still recommended to be applied to the forecast results.

Improving a system like WOD will hopefully lead to improved forecasts and forecast-based applications for a multitude of human activities. Improvements of this kind will inevitably be limited by the development of the underlying science of numerical weather prediction, including the acquisition of data, data assimilation, numerical techniques, the parameterization of sub-grid processes, and the statistical post-processing of numerical data (see review in Ólafsson and Bao [28]) and the employment of machine learning.

As the WOD framework is continuously being improved with new features under development, we conclude this paper with a review of ongoing amendments and near-future additions to WOD.

4.1. Cloud Deployment

The current version of the WOD system can be deployed on cloud services, which gives the flexibility to allocate the necessary resources as needed for a specific deployment, with the possibility to adjust these later. The benefits of cloud installation are clear in cases where the necessary High-Performance Computing (HPC) infrastructure is lacking. A cloud installation as a back-up service, in case of unforeseen disasters, is also a viable option. Another potential advantage lies in the geographical availability of such services—positioning the modelling infrastructure close to the end-users of the forecasts (especially in cases where clients need to access model output files directly, not just the point data APIs) eliminates delays related to network throughput. An option with the highest cost-reduction potential is the possibility of starting modelers (computing nodes responsible for running the weather model steps itself) in an on-demand manner. That means, the CPU and memory resources are allocated only for the time when the computationally expensive weather model is being run and are turned off as soon as the simulation is finished. The system is ready to serve this purpose through WOD's trigger mechanism (described in more detail in Appendix A). For optimal performance, the WRF model source code may also have to be recompiled to take full advantage of the underlying hardware (both CPU and intra-node network fabric). These issues are by no means a showstopper for a successful cloud deployment but rather emphasize the need to fully understand the pros and cons of available HPC cloud provider solutions.

Usage of on-premises HPC infrastructure remains a reasonable alternative, and the choice of a particular deployment manner needs to be assessed case by case based on weighing various components of time- and money-related cost.

4.2. Hybrid Options

It is possible, using the current infrastructure, to use data from different upstream sources to create initial and boundary data for WOD forecasts. Notably, using high-resolution sea surface temperature observations from NASA (data description is available online: https://www.earthdata.nasa.gov/learn/articles/tools-and-technology-articles/mur-sst-in-the-cloud accessed on 25 December 2024) is a straightforward task. It is also possible to use input data from, e.g., the ECMWF as initial analysis and then data from the NOAA for forcing the model at the boundaries. These hybrid forecasts are, however, not as well supported within the WOD framework as forecasts using conventional data flows, i.e., they are not as fault tolerant.

4.3. Additional DA Options

Currently, the WOD system supports neither the assimilation of radar data nor observations of precipitation. Integration of these data sources has intentionally been given less priority than, e.g., radiances and UAS profile data. The reason is mainly that it is quite difficult to gain real-time access to high-quality Doppler radar and gridded precipitation observations.

4.4. Very High-Resolution Simulations

We must keep in mind that fluxes of momentum and heat are necessary lower boundary conditions for any numerical weather prediction (NWP) model. This interaction between the surface and atmosphere is generally handled within a sub-module of the NWP model called the planetary boundary layer (PBL) scheme. Hence, even if we have a "perfect" PBL scheme that could handle equally well sub-filter-scale turbulences at a 10 km grid as on a 10 m grid, we would still be riddled with errors in the model results if the lower boundaries are not of equal quality. Hence, the quality of the land surface model is becom-

ing ever more important as well as the accuracy of the underlying land use characteristic and topography data.

It is possible to run the WRF model operationally at resolutions below 1 km, e.g., by taking advantage of the three-dimensional scale-adaptive turbulent kinetic scheme described in Zhang et al. [29]. Indeed, the WRF model has been run at horizontal resolution below 100 m on numerous occasions. Cui et al. [30] ran the model at 333 m horizontal resolution in a Large Eddy Simulation (LES) mode to investigate the model's capabilities to simulate radiative fog. Liu et al. [31] ran the model down to 37 m horizontal resolution when testing the model's potential for capturing atmospheric circulation characteristics on the microscale in preparation for the 2022 Olympic Winter Games. Simulations at such high horizontal resolution do, however, call for high-resolution topography and land-use data. With the exception of the continental US, such data are not available as part of the default WRF installation datasets. For the bulk of the globe, the highest resolution is 30 arc seconds, which equals to about 900 m. To make the most of WRF's LES capabilities, it would be very useful to integrate high-resolution topography data, e.g., from the Shuttle Radar Topography Mission 1 arc second (~30 m) dataset (SRTM1) (details can be found at https://cmr.earthdata.nasa.gov/search/concepts/C1220567890-USGS_LTA.html accessed on 25 December 2024) and high-resolution land-cover classification maps (updated annually) from the Copernicus Climate Change Service [32] into the WOD framework.

4.5. Importance of Aerosols

Grell and Baklanov [33] point out that aerosols can influence the weather by directly changing the atmospheric radiation budget as well as through cloud formation. In this paper, the authors argue in favour of integrating weather and chemistry for both NWP as well as air quality and chemical composition forecasting. In Grell et al. [34], the authors demonstrate the important role aerosols can play in cloud formation and storm development. This was linked to the interaction of aerosols with radiation (through an increase in CAPE) as well as the interaction with cloud microphysics. In more resent papers (cf. López-Romero et al. [35] and Xi et al. [36]), the authors demonstrate that the inclusion of aerosols in the numerical simulations can have considerable effects on the local-scale precipitation structure. These scientific findings strongly indicate that the presence of aerosols should not be ignored if one is trying to simulate the atmospheric flow in areas that are frequently affected by biomass burning, extensive resuspension of dust, and/or air-pollution from megacities. To date, the authors are aware of four global forecasting models that provide information on atmospheric aerosol composition and that could provide the necessary initial and boundary condition to the WOD system. These are the GEOS-Chem (https://gmao.gsfc.nasa.gov/weather_prediction/GEOS-CF/ accessed on 25 December 2024) from NASA, GEFS-Chem (https://www.nco.ncep.noaa.gov/pmb/products/gens/ accessed on 25 December 2024) from the NOAA, ECMWF-CAMS (https://confluence.ecmwf.int/display/CKB/CAMS:+Global+atmospheric+composition+forecast+data+documentation accessed on 25 December 2024) from the ECMWF, and ICON-Art (https://www.imk-tro.kit.edu/english/10581.php accessed on 25 December 2024) from the DWD. Properly prepared, this kind of data could serve as the initial and boundary forcing for the Goddard Chemistry Aerosol Radiation and Transport (GOCART) aerosol module available as part of the WRF-Chem model, and hence the WOD framework.

4.6. Machine Learning-Based Forecasting

Over the past couple of years, research institutes and private companies have been working on developing large machine learning (ML) models for weather forecasting.

Most recent papers introduce models such as AIFS, CorrDiff, and GenCast (for references, see [37–39]) trained on the ERA5 dataset (see [40,41]) and producing results comparable to, or better than, those of analogous NWP models. Parallel to that, at Belgingur we took one of the earlier models, ClimaX [42], to build a high-resolution (2 km) ML weather model for Iceland, using our own high-resolution reanalysis for Iceland (called IceBox). The ClimaX model has been made available open source including a pre-trained checkpoint, so we can both adjust its architecture and use a pre-trained component as a base for fine-tuning to our purposes.

The main advantage of the ML models over traditional NWP models is that, after the primary phase of model training and experimentation is conducted, the models can produce forecasts in a fraction of time and on a fraction of resources compared to NWP. Developing a high-resolution regional machine learning model and including it in the WOD framework will pave the way for ML models to serve day-to-day forecasting applications.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The WOD (V2024.11.0) software suite repository is stored on Github—https://github.com/Belgingur/ (accessed on 25 December 2024). The software is closed source but interested readers are advised to contact the authors for a user license.

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Conflicts of Interest: Ólafur Rögnvaldsson and Karolina Stanisławska are employees of Belgingur Ltd. And Joao A. Hackerott is an employee of Tempo OK Ltda. This paper reflects the views of the authors and not that of the two companies.

Appendix A

In this appendix, we give a step-by-step instruction on how to set up typical operational forecast, including the use of variational data assimilation. When typing in the URL of the WOD API landing page, the user is greeted by a list of options as shown in Figure A1.

Clicking on the meta button, encircled in red in Figure A1, the user is given the option to create a new job (cf. Figure A2).

The user now needs to type in the geographical centre point of the outermost model domain (also frequently referred to as "MOAD", or Mother Of All Domains). A pre-defined model configuration, referred to as "job_type", needs to be chosen, as well as the forecast duration and a short descriptive title (cf. Figure A3).

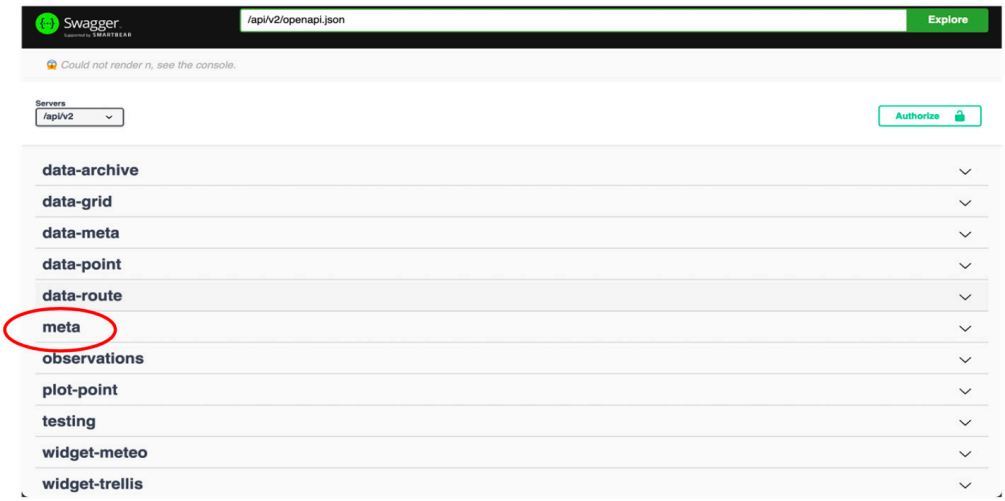


Figure A1. Example of a typical landing page for the graphical user interface (GUI) of the WOD API.

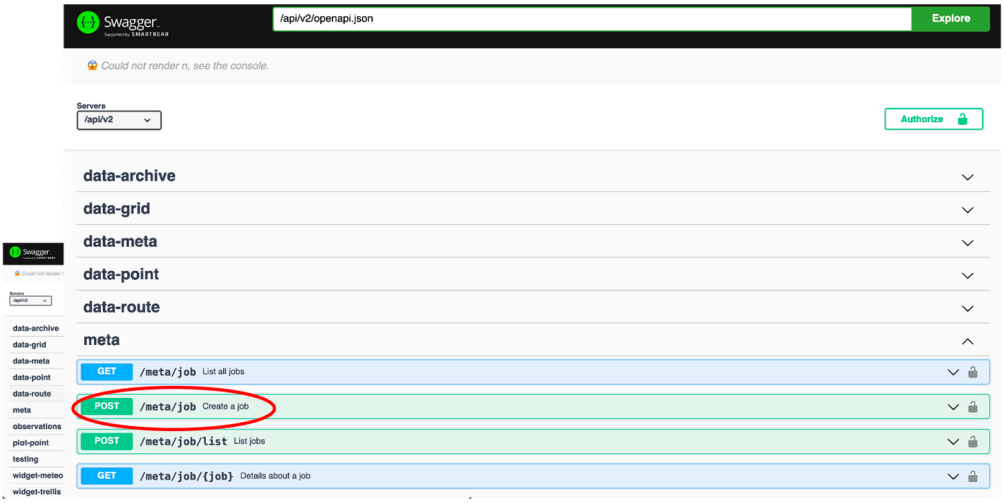


Figure A2. Step two in running an on-demand forecast; click the encircled `/meta/job` button.

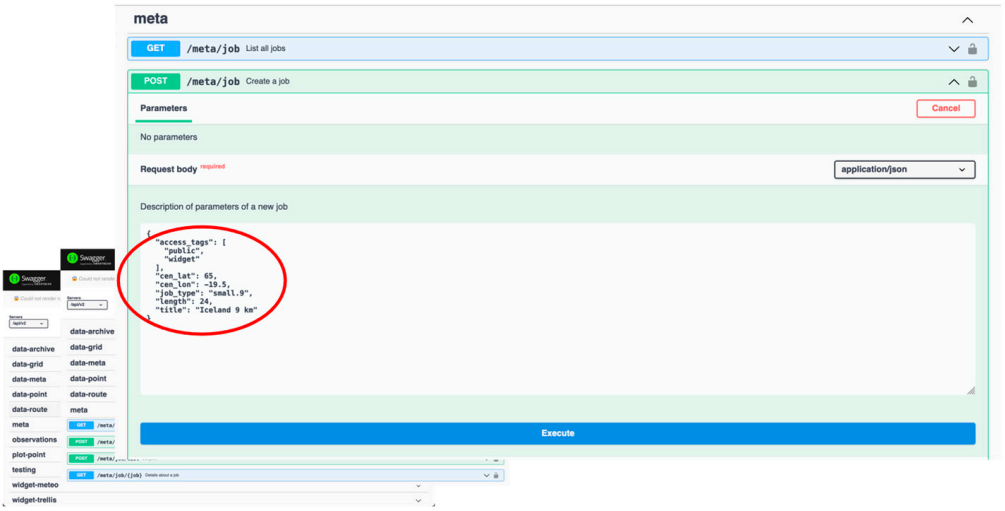


Figure A3. The user now types in the latitude and longitude of the centre point of the outermost domain, in addition to the specific, pre-defined model configuration and forecast duration. In the encircled example shown here, the name of the job_type is `small.9`.

The "job_type" definitions for the example shown in Figure A3 are set in a directory named `/wodroot/job_types/small.9`. Here, the user needs to edit a set of template files that govern the behavior of the WRF model. These are as follows:

- Geogrid.tpl—handles the "geogrid" part of the conventional `namelist.wps` file
- Iofields.txt—here, the user can control which variables are written to the history files
- Meta.yml—here, the user defines parameters such as model resolution and history interval
- Metgrid.tpl—handles the "metgrid" part of the conventional `namelist.wps` file
- Wrf.tpl—handles the "wrf" part of the conventional `namelist.input` file
- Da_wrfvar_XXX.namelist.input—(optional) handles the specifics of the variational data assimilation method in question, and the available options currently include 3DVar, 3DEnVar, 4DVar, and 4DEnVar

Once the forecast has run, and the user is satisfied with the results, it is possible to create a "schedule", i.e., a set of rules that govern how the WOD framework creates forecasts at regular intervals, based on the specific prototype forecast created earlier. This final step is encircled in Figure A4.

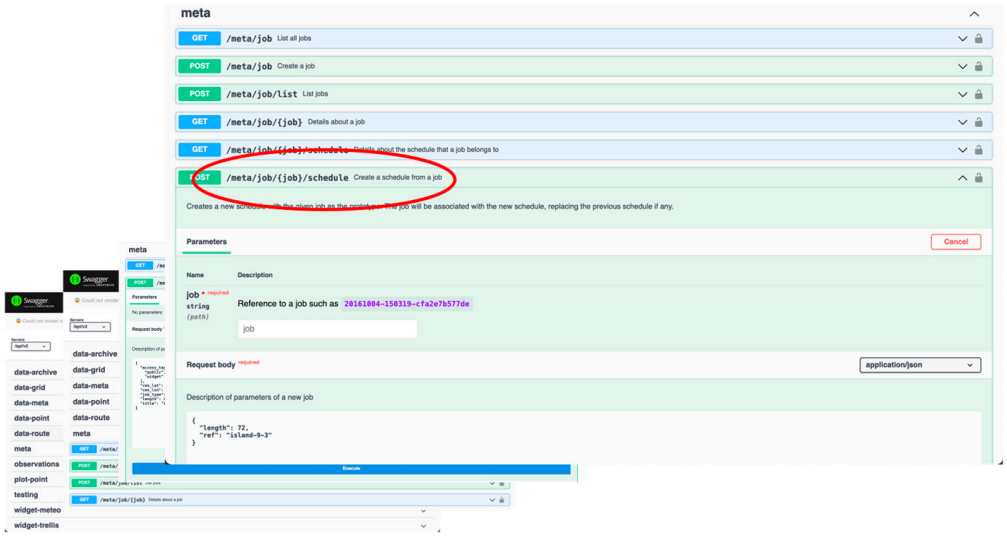


Figure A4. The final step to set up an operational forecast is to set the unique identification number of the prototype forecast as the "Job" the schedule should be based on. In addition, the user should define the forecast duration and choose a (preferably) sensible name for the new schedule. More fine-tuning can be conducted by modifying individual entries linked to the schedule in the WOD database.

To implement the use of variational data assimilation in the schedule just created, one needs to change a few default settings for the prototype forecast in the WOD database. Specifically, one needs to set `da_type='da3d'` and `da_bufr='true'`. This sets the 3DVar as the variational data assimilation method of choice where radiance data in the BUFR format, provided by the NOAA, will be used. In the absence of domain-specific background error statistics, e.g., when the schedule is quite recent and the user does not have a long history of forecasts, it is possible to use a default background error statistics file, supplied with the WRFDA source code. However, it is recommended to collect the necessary information from the scheduled forecasts to build up the dataset needed to run the *gen_be* program, described in Section 2.3. This can be conducted by taking advantage of the trigger mechanism of the WOD framework. As the status of each task within the WOD system is known, this information can be used to trigger, or run, a custom-made program when the status of a particular task changes. This trigger mechanism is controlled via configure files called `trigger.yml`. An example of such a file is given below.

```
#!jinja|yaml
# Config fragment for the trigger daemon.  It is included from /etc/wod/trigger.yml
# After changing, restart ‘wod_trigger‘ to re-read config e.g., by running ‘trigger_restart‘.
# Then follow the log to verify that changes work.
tasks:
  subset_wrf_out_dk:
  exchange:  jobs
  key:  job.admin.dk-9-3-da3d.*.done
  show_stdout:  True
  cmd:  ‘.  /wodroot/bin/in-clickless python subset_wrf.py --input
/wodroot/jobs/{dir}/wrf --analysis {analysis} --d01 2 4 --d02 6 12
>> /wodroot/post_process/dk-9-3-da3d/log_subset.log’
timeout:  10
```

In this example, a python program called `subset_wrf.py` is run every time a forecast task for a schedule called `dk-9-3-da3d` is finished. This program extracts the necessary variables (and from the correct time steps) needed to run the *gen_be* program, from the WRF atmospheric model output files. These data are then written to a dedicated output file. Once the user has collected a sufficiently long series of forecasts, the *gen_be* solution can be applied to create a domain-specific file that describes the background error statistics. It is recommended to update this file at regular intervals as the statistics change over time.

Appendix B

In this appendix, a graphical tool, built on top of the Verif [5] solution, is described. This tool can be used to browse and visualize verification results from any atmospheric simulation, as long as the data have been converted to the WOD standardized netCDF file format. This includes forecasts created via the WOD system, a third-party provider, and/or simulations from reanalysis projects. General guidelines on how to prepare data for the Verif solution can be found on Verif's Wiki page (https://github.com/WFRT/verif/wiki/Arranging-my-own-data accessed on 25 December 2024). There, the user can find information on how the Verif package specifies the data format and how to load the data into the NetCDF files to be read by the Verif system. The WOD API system can be used to download data, observations, and model data alike, which then are fed into Verif's pre-processing tools (again, we refer to the Verif Wiki page for further instructions) to create the files that are eventually interpreted by Verif. This simplifies considerably the process of comparing results from different modelling systems as the task of converting model data into a unified format has already been conducted within the WOD framework. That is, the user can use the same API to access results from a plethora of atmospheric models.

The landing page for the Verif web service is shown in Figure A5 (top panel). Once the user has logged on, he/she needs to select a file containing observations and model simulations of one variable. This is how Verif works, i.e., it operates on one file at a time, where the said file contains the observed and simulated data of a single variable.

If a single observation station is chosen, the user can also download observed and simulated data in a text format by clicking the "Download CSV" button. In addition to creating scatter plots, Taylor diagrams, and quantile–quantile plots (cf. Figure A6, top panels), the user can also plot three different types of maps (cf. Figure A6, bottom panels).

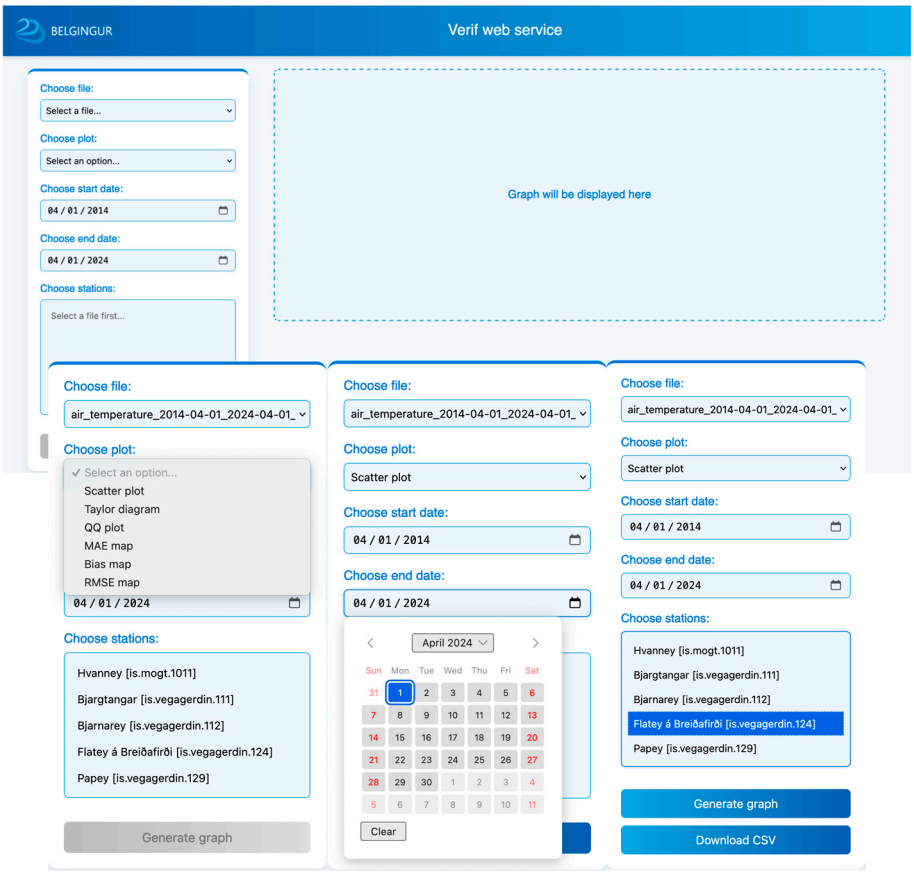


Figure A5. The landing page (**top panel**) of the Verif web service offers the user the choice of a set of observed and modelled variables as well as plot options (**lower panel, left**); data range options (**lower panel, middle**); and the option of customizing which observation locations are to be investigated (**lower panel, right**).

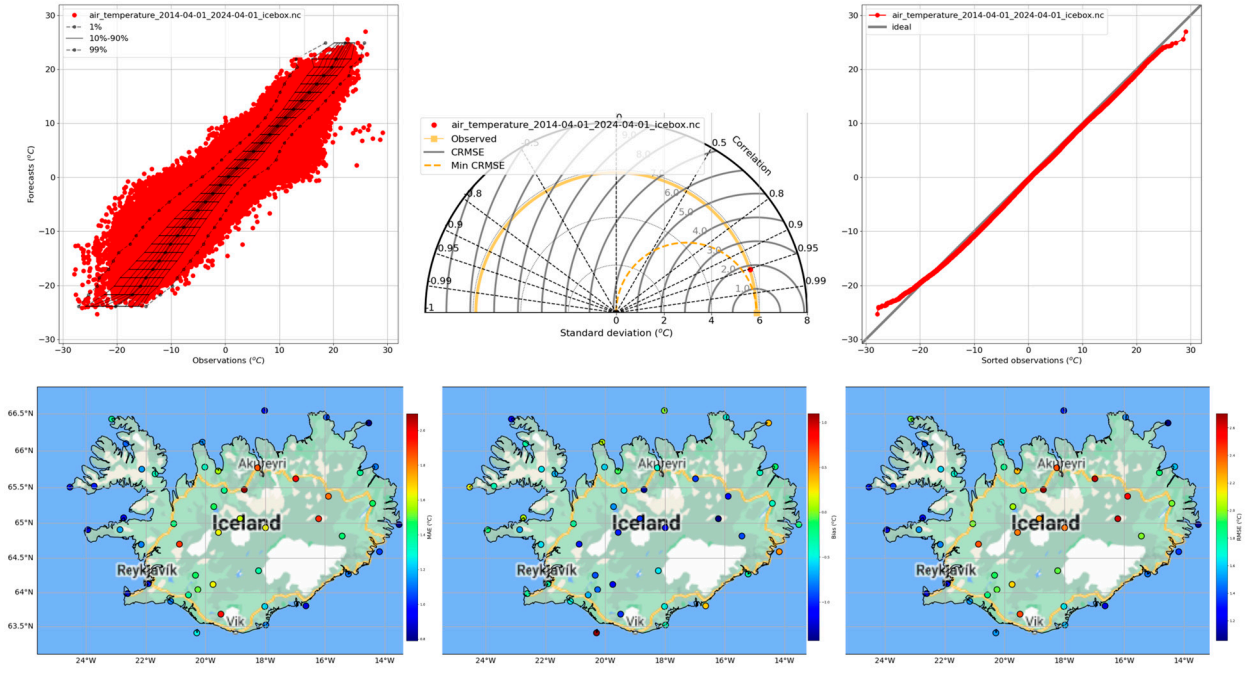


Figure A6. The Verif web service offers six types of graphs. These are scatter plots (**top left**), Taylor diagrams (**top centre**), quantile–quantile plots (**top right**), and maps showing mean absolute error (**bottom left**), bias (**bottom centre**), and root-mean-square error (**bottom right**).

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