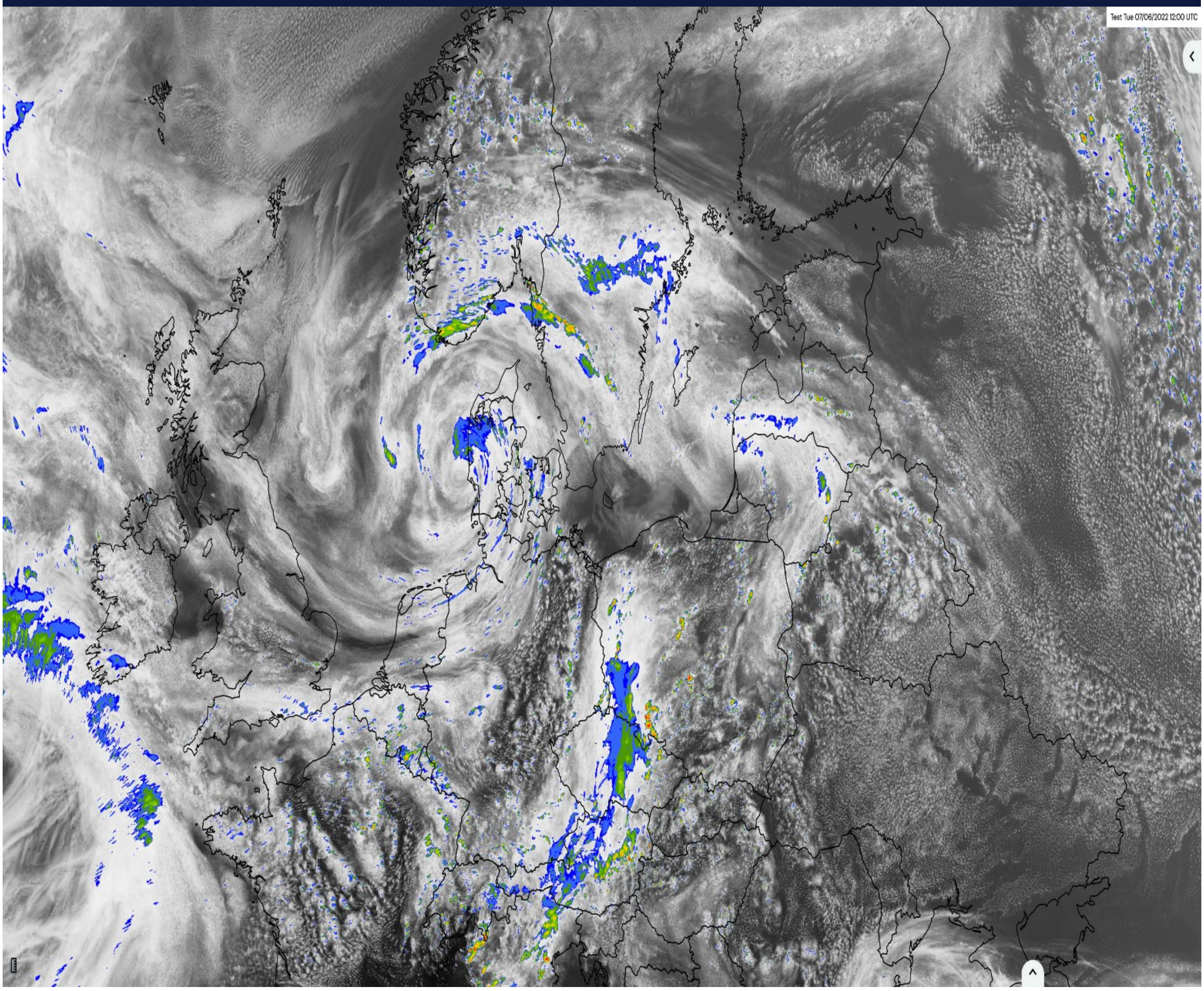
GONDUL: EURO1k model validation

Quantitative comparative analysis of met model forecast and historical data with observations

Report | No. 2-2025 – NORCE Energy and Technology: Observation systems



Report title	Gondul project: EURO1k model validation
Institution	NORCE Research AS
Report number	2-2025, NORCE Energy and Technology
ISBN number	978-82-8408-400-8
Project number	60080-108233
Client(s)	Meteomatics AG
Classification	Open
Licence	CC BY 4.0
Authors	Øistein Johnsen
Quality assurance	Dr. Rune Storvold
Keywords	Meteomatics, EURO1k, MEPS, Meteorology, Arctic, Army, Intelligence, UAV, Risk

NORCE Research AS, Postboks 22 Nygårdstangen, 5838 Bergen, Norway

E-POST post@norceresearch.no WEB norceresearch.no TEL. +47 56 10 70 00 ORG NO. 919 408 049

Summary

Project Gondul is a scientific research project related to the technology transfer of the Meteomatics EURO1k model weather forecast and its Meteodrone data collection capability to Norway. Project Gondul will focus on estimating the value of information these weather forecasts represent for tactical decision making and plans for Norwegian military Arctic land operations. The project combines both natural science and social science for collection of reliable data and creating new relevant knowledge. The Norwegian Army school of intelligence and electronic warfare is the subject matter expert (sponsor) for project Gondul.

Project Gondul will focus on how this new weather intelligence technology can contribute to risk reduction for the Norwegian Army's arctic land operations, specifically addressing adverse operation of military NATO class 1 Unmanned Aerial Vehicle (UAV) systems in adverse conditions.

The focus of this report is on performance evaluation of meteorological forecast data as weather intelligence input to risk evaluation and operation of UAVs in cold climate. The evaluation uses measurements at meteorological stations as ground truth for quantitative comparative analysis of the performance of forecast products EURO1k delivered by Meteomatics, and MEPS delivered by the Norwegian Meteorological Institute. The aim is to provide an objective basis for a Value of Information analysis (VoI) for the Euro1K weather intelligence potential role in Norwegian Army UAV operations.

The qualitative assessment, objective statistical analysis and calculated score matrices obtained from directly comparing EURO1k and MEPS data with real weather observations from 249 measurement stations demonstrates that EURO1k outperforms MEPS on all selected meteorological parameters considered relevant for the Gondul project. EURO1k provides, on average, more accurate predictions than MEPS 2.5 km in more than 70 % of the cases. Conversely, MEPS 2.5 km are deemed more accurate in approximately 27 % of the cases.

Note that the conclusion is preliminary as the period for accumulated data is still limited. Analysis will be subject to updates according to weather forecast accumulation for an extended period later in the project.

In next phase of the Gondul project a new report will document forecast performance based on validation against observations collected by Meteodrones.

Contents

Definitions and abbreviations

Weather forecasts and observations	
ABL	Atmospheric boundary layer.
EURO1k	Regional weather forecast for Europe with 1 km horizontal resolution.
ff	Forecasted time for a given time ahead, typically given in hours. I.e. ff000 represents the time of the current weather (nowcast) and ff012 represents the time of the forecast 12 hours from now.
Forecast	Weather conditions for a given time ahead as calculated by numerical weather prediction models.
LAM	Limited-area models, models covering only part of the Earth as opposed to global models that cover the entire earth system.
MEPS	MetCoOp Ensemble Prediction System. A short-range ensemble weather forecasting system used in the Nordic region. Operated by the Norwegian Meteorological Institute.
Meteodrone	Drone-based weather observing system equipped with measurement devices providing direct measurements of critical meteorological properties. The system is developed by Meteomatics AG.
Nowcast	Current weather conditions as calculated by numerical weather prediction models.
NWP	numerical weather prediction, mathematical models of governing atmospheric and oceanic processes to simulate and predict weather based on the current weather conditions.
Observations	A collection of real time measured quantities describing the physical properties of a system over time, either by in-siu or remote methods.
PBL	planetary boundary layer.
Reanalysis	Reanalysis models, i,e. reanalysis forecast, uses measurements and/or past corrected data as input to adjust model predictions.

Meteorological parameters	
a.g.	Height ‘above ground’ of a given measurement and forecast model variable.
icing_potential_2m:idx	Icing potential given 2 m above ground given as index [0-100]
low_cloud_cover:p	Low cloud cover, i.e. areal coverage at altitudes less than ~ 2 km [%]
medium_cloud_cover:p	Medium cloud cover, i.e. areal coverage at altitudes less than ~ 2 – 7 km [%].
msl	Mean sea level.
msl_pressure:hPa	Mean sea level pressure [hPa].
precip_1h:mm	Hourly precipitation [mm]. Precipitation refers to any form of water – liquid or solid – that falls from the atmosphere and reaches the ground. This includes various types of weather phenomena such as rain, snow, sleet, and hail.
precip_type_intensity_1h:idx	Precipitation type given by indexed category [index].
relative_humidity_2m:p	Relative humidity 2 m above ground [%].
PR	Precipitation rate. Amount of water [mm] deposited per time interval. Precipitation refers to any form of water – liquid or solid – that falls from

	the atmosphere and reaches the ground. This includes various types of weather phenomena such as rain, snow, sleet, and hail.
RH	Relative humidity [%]. Height unspecified.
SFIP	Simplified forecast icing potential, a practical indicator to estimate the risk of icing on an aerial vehicle.
SR	Snow rate. The amount of snow [mm] that falls to the ground within a given time interval.
t_2m:C	Air temperature 2 m above ground [°C].
T	Temperature [°C]. Height unspecified.
wind_speed_10m:ms	Wind speed 10 m above ground [m/s]. The wind speed is assumed to represent the 10-minute mean value.
wind_dir_10m:ms	Wind direction 10 m above ground [°]. The wind direction is assumed to represent the 10-minute mean value.
z	Vertical coordinate in a 3-dimensional system specifying the altitude / height above ground.

Statistics	
Linear regression	A statistical method used to model the relationship between a dependent variable and one or more independent variables, i.e. linear relation $y=mx+b$ between variable y and x.
MAE	Mean Absolute Error: average absolute differences between predicted values and actual values.
MSE	Mean Square Error: average of the squares of the differences between predicted values and actual values
Percentile	A statistical measure that indicate the value below which a given percentage of samples in a group of data/observations falls. For example, the 40th percentile is the value below which 40% of the data/observations may be found.
PCC	Pearson correlation coefficient: Quantifies the strength and direction of the linear relationship between two quantitative variables.
Probability density distribution	A fundamental concept in probability theory and statistics, used to describe the likelihood of a continuous random variable taking on a particular value.
Quantile-quantile (Q-Q)	A graphical tool used to compare two probability distributions by plotting their quantiles against each other. A quantile is a statistical measure that divides a data set into equal-sized, adjacent intervals and calculate a representative number (i.e. median) for the groups.
R^2 determination factor	R^2 (R-squared) determination factor is a key metric in linear regression that measures the proportion of the variance in the dependent variable that is predictable from the independent variable(s).
RMSE	Root Mean Square Error: The root of the MSE.

Other	
API	Application Programming Interface is a connection between computers/servers or between computer programs.
AUV	Unmanned Aerial Vehicle.
DEM	Digital Elevation Model. Topography data that represents the surface of the Earth (as global or regional datasets) including buildings, infrastructure and vegetation.

NMI	Norwegian Meteorological Institute
THREDDS	Thematic Real-time Environmental Distributed Data Services. A project which aims to offer coherent access to a large collection of real-time and archived environmental data.
Watchdog	System to monitor NORCE’s operational coastal forecast models, systems and production performance.
WMO	World Meteorological Organization.

1. Introduction

1.1. Background

Project Gondul is a scientific research project related to the technology transfer of the Meteomatics Euro 1K model weather forecast and its Meteodrone data collection capability to Norway. Project Gondul will focus on estimating the value of information these weather forecasts represent for tactical decision making and plans for Norwegian military Arctic land operations. The project combines both natural science and social science for collection of reliable data and creating new relevant knowledge. The Norwegian Army school of intelligence and electronic warfare is the subject matter expert (sponsor) for project Gondul.

Figure 1-1: ***Risks addressed in project Gondul: Risk related to visibility conditions for the use of the elevated sensor (left) and risk associated with prioritization of sensor platforms, i.e. where/at what height can the elevated sensor operate with low risk of icing and subsequent crash? (right). Image courtesy of the Norwegian Army***

Project Gondul will focus on how this new weather intelligence technology can contribute to risk reduction for the Norwegian Army's arctic land operations, specifically addressing, as illustrated in **Figure 1-1**:

- Flight termination by icing conditions for military NATO class 1 Unmanned Aerial Vehicles (UAV) systems.
- Planning and priorities for the generic UAV capability in Norwegian land operations with regards to snow showers, cloud cover and cloud ceiling.

In addition to technical evaluations, the project also adopts qualitative methods and approaches to explore the adoption of this new technology within Arctic military land operations. Additional key research topics guiding this investigation include:

- Prerequisites and barriers for implementing advanced weather intelligence into decision-making processes related to tactical decisions Arctic land operations.
- Trust in advanced weather intelligence technology and its implications for decision-making processes Arctic land operations
- The relevance of advanced weather technology in the context of climate change and its impact on decision-making processes within Arctic land operations.

The focus of this report is on performance evaluation of meteorological forecast data as weather intelligence input to risk evaluation and operation of UAVs in cold climate. The evaluation uses measurements at meteorological stations as ground truth for quantitative comparative analysis of the performance of forecast products delivered by Meteomatics and the Norwegian Meteorological Institute.

The performance assessment aim to provide an objective basis for selection of weather intelligence most fit for purpose.

1.2. Forecasting modeling – general introduction

Meteorological forecast modeling, also known as numerical weather prediction (NWP), involves using mathematical models of governing atmospheric and oceanic processes to simulate and predict weather based on the current weather conditions.

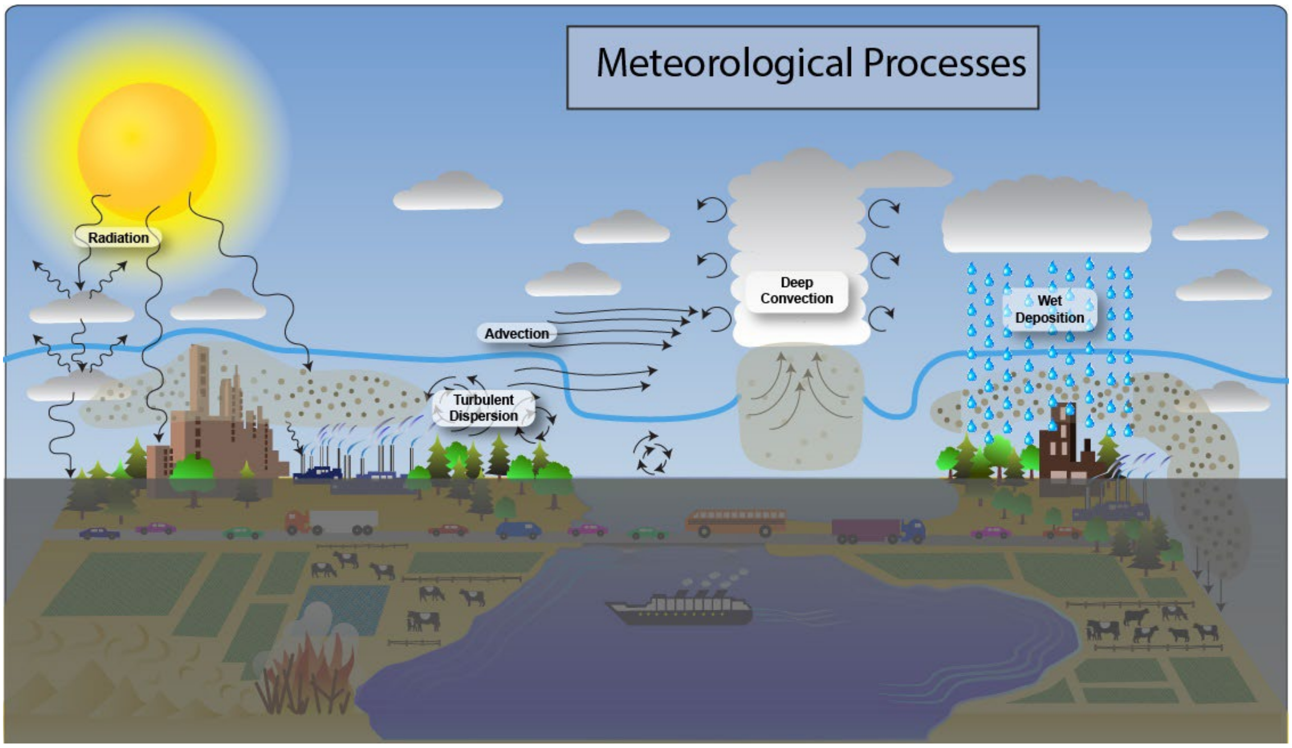


Figure 1-2 Sketch meteorological processes

Such models produce meteorological information for future times at given locations and altitudes. Any modern model applies a set of fundamental physical laws and equations to predict the future state of the atmosphere [14]. These equations—along with the ideal gas law—are used to evolve the density, pressure, and potential temperature scalar fields and the air velocity (wind) vector field of the atmosphere through time. Additional transport equations for pollutants and other aerosols are included in some primitive-equation high-resolution models as well. The equations used are nonlinear partial differential equations which are impossible to solve exactly through analytical methods, with the exception of a few idealized cases. Therefore, numerical methods are necessary to obtain approximate solutions. Different models use different solution methods: some global models and almost all regional models use finite difference methods for all three spatial dimensions, while other global models and a few regional models use spectral methods for the horizontal dimensions and finite-difference methods in the vertical.

These equations are initialized from the analysis data and rates of change are determined. These rates of change predict the state of the atmosphere a short time into the future; the time increment for this prediction is called a time step. This future atmospheric state is then used as the starting point for another application of the predictive equations to find new rates of change, and these new rates of change predict the atmosphere at a yet further time step into the future. This time stepping is repeated until the solution reaches the desired forecast time. The length of the time step chosen within the model is related to the distance between the points on the computational grid and is chosen to maintain numerical stability. Time steps for global models are on the order of tens of minutes, while time steps for regional models are between one and four minutes. The global models are run at varying times into the future.

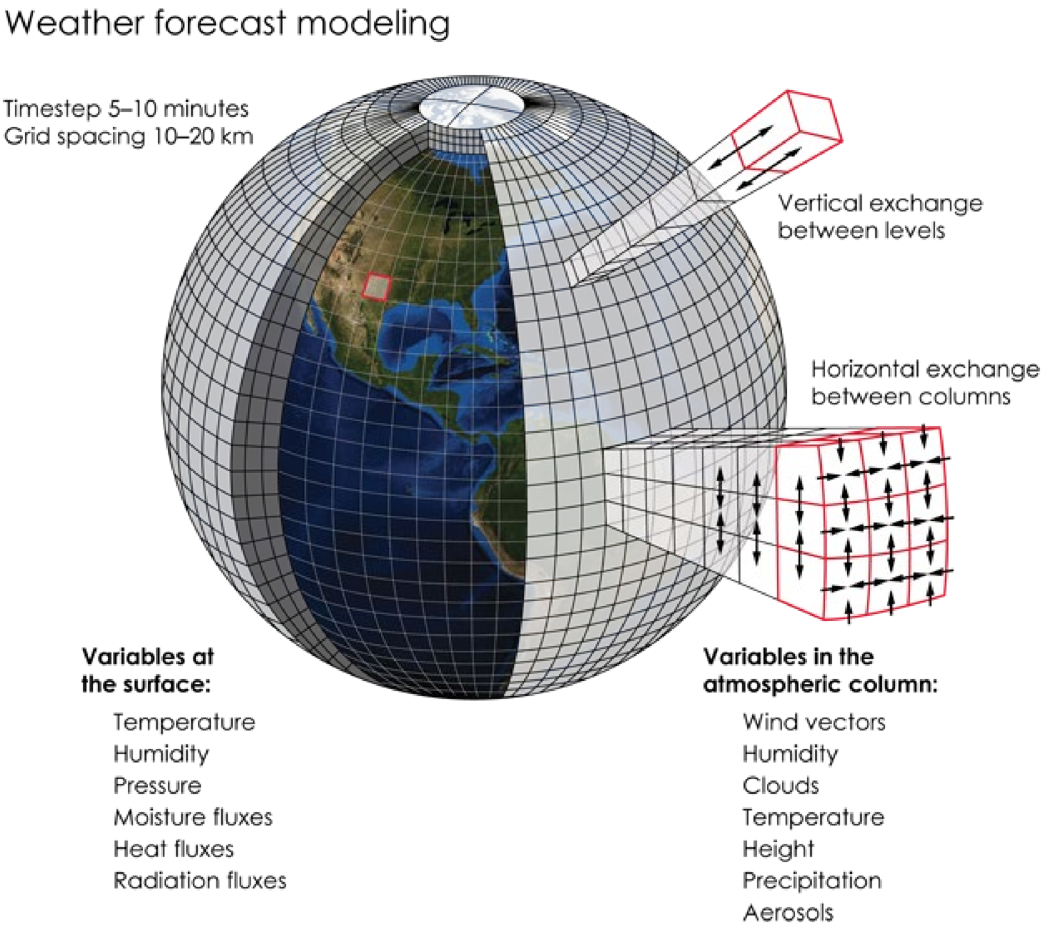


Figure 1-3 ***Illustration of global model build: boundaries, grid and spatial exchange for examples of variables. Credit: K. Cantner, AGI***

The horizontal domain of a model is either global, covering the entire Earth, or regional, covering only part of the Earth. Regional models (also called limited-area models, or LAMs) allow for the use of finer grid spacing than global models because the available computational resources are focused on a specific area instead of being spread over the globe. This allows regional models to resolve explicitly smaller-scale meteorological phenomena that cannot be represented on the coarser grid of a global model. Regional models use a global model to specify conditions at the edge of their domain (boundary conditions) to allow systems from outside the regional model domain to move into its area.

The vertical coordinate is handled in various ways: using the geometric height z as the vertical coordinate or a pressure coordinate system of geopotential heights with constant pressure surfaces of which become dependent variables (which greatly simplifies the solution of differential equations).

Some meteorological processes are too small-scale or too complex to be explicitly included in numerical weather prediction models, in which case parametrization techniques are used to represent sub-grid scale processes by relating them to variables on the scales that the model can resolve. This can be processes such as cloud formation, radiation, turbulence and other.

Ensemble forecasts is a method to cope with the modelling sensitivity and to improve accuracy. It involves analysing multiple forecast realizations created with an individual forecast model by using different physical parametrizations or varying initial conditions.

Accurate forecasting relies on real-time observational data assimilation into the models as exemplified in **Figure 1-4**.

Mathematical models based on the same physical principles can be used to generate either short-term weather forecasts or longer-term climate predictions; the latter are widely applied for understanding and projecting climate change. The improvements made to regional models have allowed significant improvements in tropical cyclone track and air quality forecasts; however, atmospheric models perform poorly at handling processes that occur in a relatively constricted area, such as wildfires.

1.3. Observations

Measuring stations and remote sensing are essential for collecting real-time, hyperlocal weather intelligence. Measurement design and architecture are usually customized for the intended application, i.e. aviation, energy utilities, hydrology, agribusiness, local municipalities etc. for to optimize operational efficiency, plan and respond to adverse weather events, and for public information and safety.

Figure 1-4 illustrates common meteorological observation systems that may be used to assist meteorological modelling and forecasting.

Generally, the information collected are physical parameters pertaining to the conditions of the atmosphere, ground and/or water/ocean. Typical parameters are temperature, humidity, pressure, precipitation, wind speed, wind direction and more.

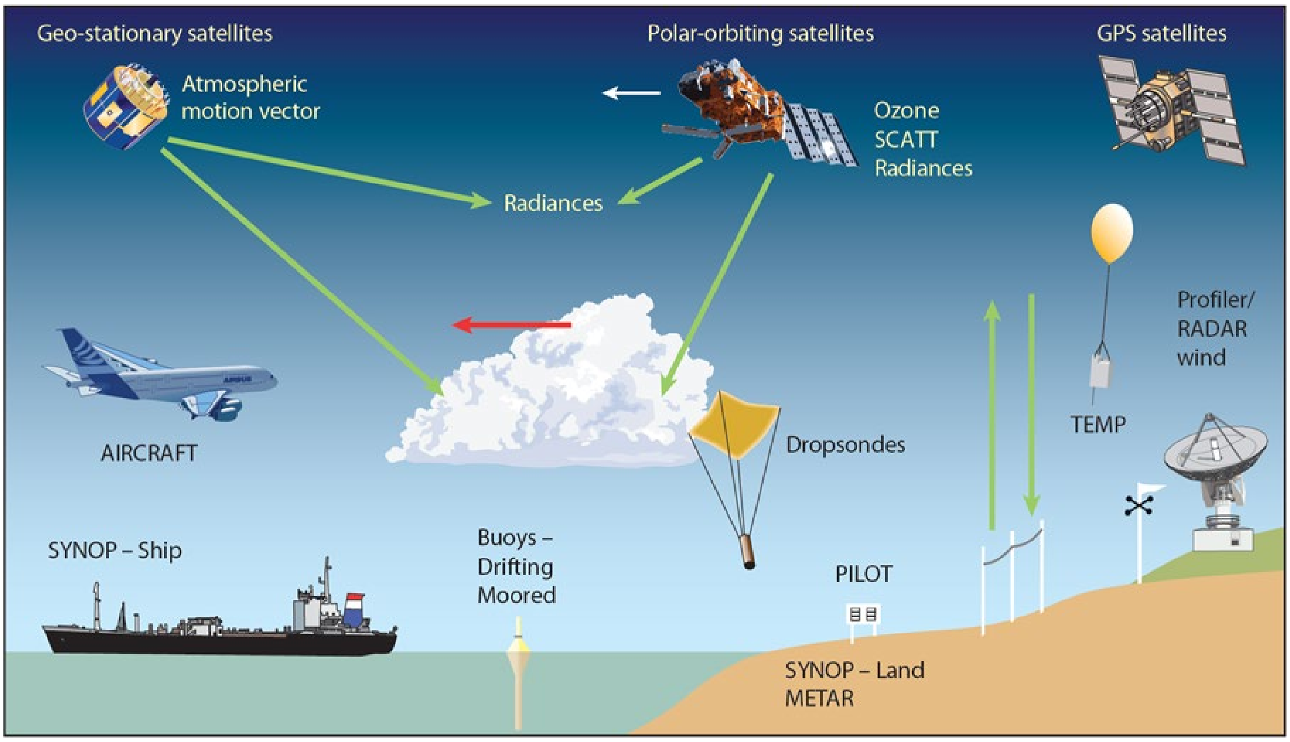


Figure 1-4 ***Meteorological observation systems that may be used to assist meteorological modelling and forecasting.***

For interoperability and quality assurance, measuring is urged to conform to standards, guidelines and recommendations given by the intergovernmental World Meteorological Organization (WMO) [16, 17]. This entails standard practices and procedures, definitions, nomenclature, units, quality assurance, formatting etc. **Figure 1-5** shows the global distribution of the Regional Basis Synoptic Network weather stations (as of 2002).

In this part of the project the observation data pertains to ground based stations exemplified in **Figure 1-6**. When conforming to WMO standards, guides and recommendations the data are available at standards heights above ground: wind at 10 m, air humidity and temperature at 2 m, pressure relative to mean sea level etc. This is essential information for intercomparison of local observations, as well as forecast data with concurrent measurements.

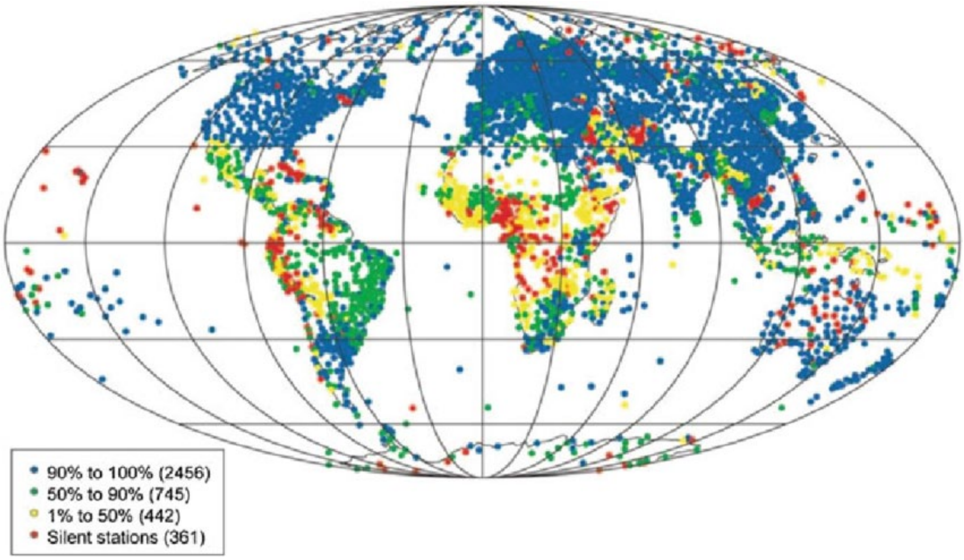


Figure 1-5 The WMO World Weather Watch global distribution of the Regional Basis Synoptic Network weather stations providing SYNOP (surface synoptic observations) reports during October 2002. (WMO 2003). The colour denotes each station's reporting rate.

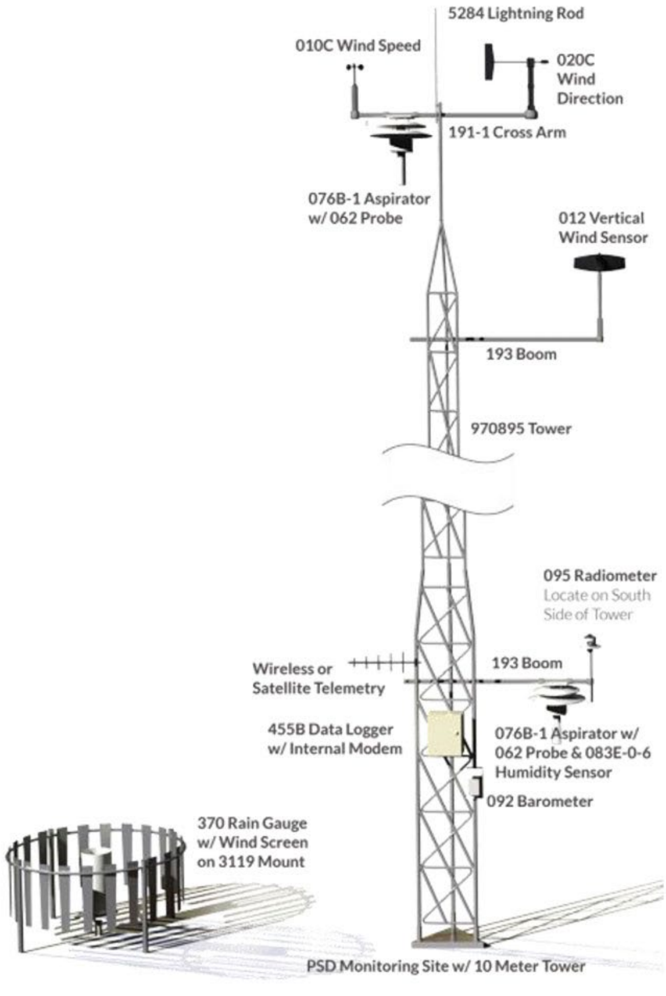


Figure 1-6 Example of a meteorological measurement system.

1.3.1. Meteodrones

The atmospheric boundary layer (ABL), also known as the planetary boundary layer (PBL), is the lowest part of the atmosphere directly influenced by its contact with the Earth's surface. The ABL is associated with high spatial and temporal variability. Understanding and being able to accurately model the atmospheric boundary layer is a crucial element in local weather prediction, yet this part of the atmosphere is quite under-observed both in space and time. The space-time distribution of in-situ measurements i.e. instrumented weather balloons/radiosonde, towers, and aircraft, and remote sensing: technologies such as radar, lidar, and satellites provide data on the ABL's structure and dynamics from a distance is limited.

Towers are strictly limited to observing near ground, and systems to measure over the vertical column (radiosonde, aircraft, remote systems) are very limited to its fly-by (see **Figure 1-7**).

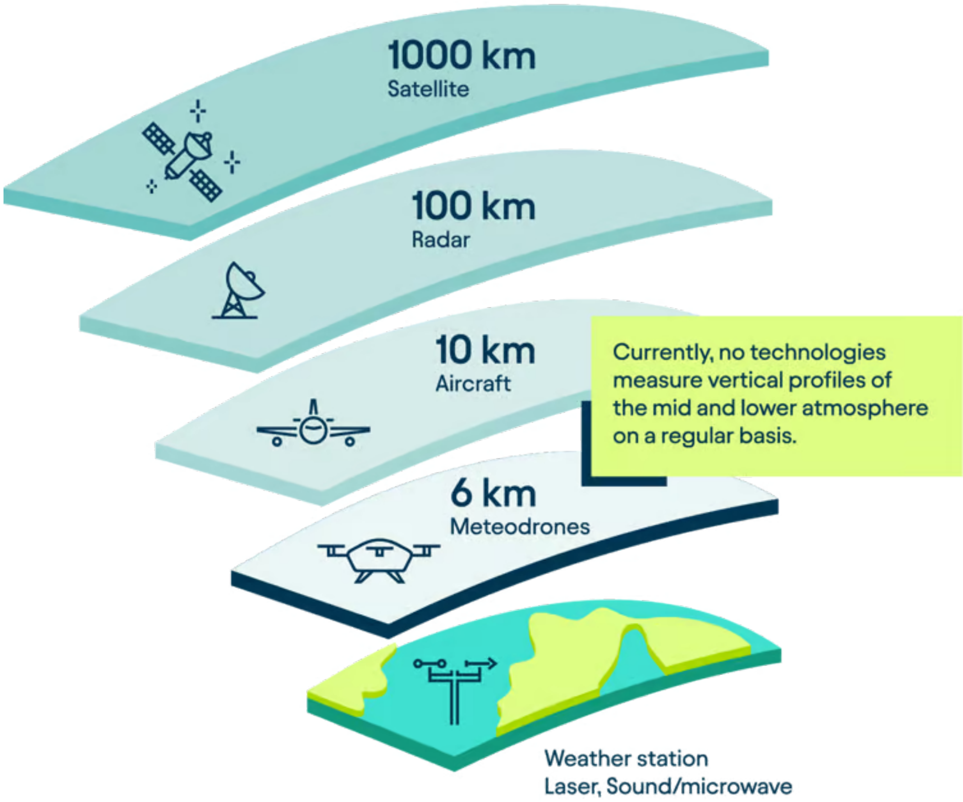


Figure 1-7 Operation domain of in-situ and remote measuring systems. Courtesy of Meteomatics AG.

Weather drones present a solution to bridge this data gap. Meteomatics's Meteodrone (**Figure 1-8**) is a novel concept provide a cost-efficient and sustainable platform to gather weather data from both the lower and middle atmosphere. Equipped to capture high-resolution, direct measurements of critical meteorological elements such as temperature, humidity, air pressure, and wind speed etc. Meteodrones offer reliable in-situ repeated measurements over time to provide insight in ABL dynamics up 6 km altitude – a great leap forward in meteorological sciences. Incorporating these measurements into weather model calculations can demonstrably improve weather forecasts.

Meteodrones [8] and launch base from Meteomatics, (**Figure 1-8**) are currently operating at Meteomatics' Meteodrones and Meteobases are already operational and contribute to improved weather forecasting in several countries, including Switzerland, France, Italy, Romania and the United States. Meteodrones can operate in automated flight mode or controlled, from a launch base or as a mobile unit. The drones are heavily used in meteorological research.

Figure 1-8 Meteodrone and Meteobase by Meteomatics Its design allows for customization with various instruments to meet specific requirements, offering flexibility for diverse operational needs. Courtesy of Meteomatics AG.

A Meteodrone base is scheduled for installation and operation in the late spring / summer of 2025 at Andøya and will be fully implemented and operational by end of 2025. The long-term ambition is to establish a network of 30 Meteodrones in Norway as shown in **Figure 1-9**.

This allows for Meteodrone data to be integrated into EURO1k improving accuracy in in local weather forecasts. This benefits industries that rely on the weather conditions for production management, such as renewable energy, agriculture, transport and maritime industries, as well as safeguarding the society in assisting governmental/municipal responsiveness by prediction of severe weather conditions.

Figure 1-9 ***Meteomatics Meteodrone launch sites (Meteobase) planned for Norway. The sites are indicative and pending permissions from Norwegian authorities.***

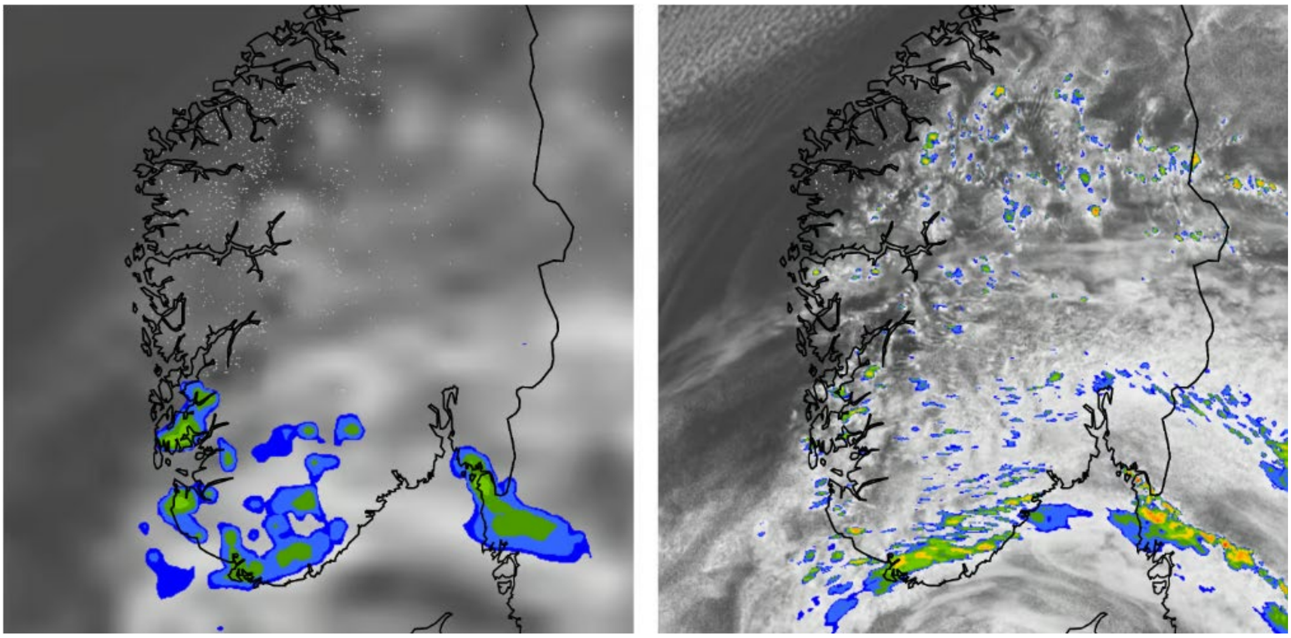


Figure 1-10 ***Precipitation and cloud cover over Norway with the ECMWF model (left, resolution: approx. 9 km) and with the EURO1k model from Meteomatics (right, resolution: 1 km)***

1.4. Scope of work

The quantitative comparative analysis was performed using the EURO1k forecast model operated by Meteomatics and MEPS forecast model operated by the Meteorological Institute of Norway (Met Norway) versus available observations from all met stations in Norway for the period January 2023 to May 2025.

The spatial coverage and period imply assessment of met data for a wide range of climate zones and seasons relevant for drone operations, including adverse conditions in terms of risk of icing and heavy snow.

Both historical forecasts (ff000, or “nowcast”) and forecasts for 0 to 65* hours ahead (ff000 to ff065) have been analysed on a selection of parameters of interest for drone operations. Preliminarily, the variables are investigated at standard heights for direct comparison and validation with met station measurements.

In order to perform the analysis a complete data archive is built considering variables deemed as key weather intelligence for drone operations. The variables given below are collected according to station and model availability (see comments in footnotes**):

- 10-minute mean wind speed 10 m above ground [m/s] (wind_speed_10m:ms)
- 10-minute mean wind direction 10 m above ground [°]. The wind direction is the direction in degrees from which the wind blows, clockwise with reference to North as 0°. (wind_dir_10m:ms)
- Air temperature 2 m above ground [°C] (t_2m:C)
- Relative humidity 2 m above ground [%] (relative_humidity_2m:p)
- Mean sea level pressure [hPa] (msl_pressure:hPa)
- Low cloud cover, i.e. areal coverage at altitudes less than ~ 2 km [%] (low_cloud_cover:p)
- Medium cloud cover, i.e. areal coverage at altitudes less than ~ 2 – 7 km [%] (medium_cloud_cover:p)
- Hourly precipitation [mm] (precip_1h:mm). Precipitation refers to any form of water – liquid or solid – that falls from the atmosphere and reaches the ground. This includes various types of weather phenomena such as rain, snow, sleet, and hail.
- Precipitation type given by indexed category [index] (precip_type_intensity_1h:idx)
- Icing potential/index given 2 m above ground given as index [0-1] (icing_potential_2m:idx)

* 65 hours ahead is the maximum forcasting time of MEPS and limiting over EURO1k’s 72 hours.
** Units are given in [] and short name given in ().

2. Forecast Data

2.1. Sources

2.1.1. Observations

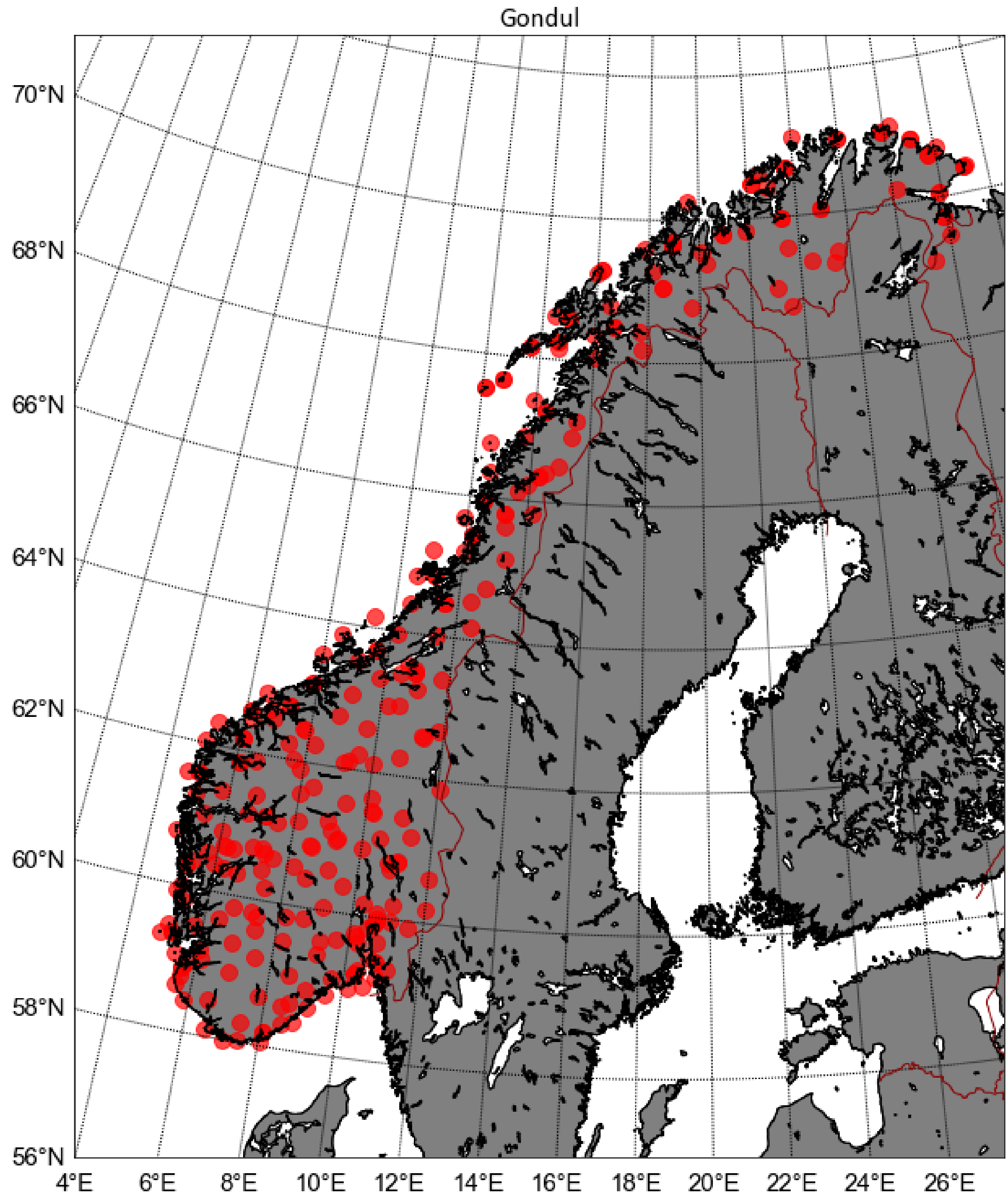


Figure 2-1 Operative met stations in Norway as used for assessing forecast model accuracy in the Gondul project.

Meteorological measurements are available for 249 locations across the country as shown in **Figure 2-1** (Location name, WMO-number, geo-position and from date is given in Appendix 1). The stations are owned by Avinor (The Norwegian Aviation Authorities), The Norwegian Public Roads Administration and The Norwegian Meteorological Institute (NMI). Data from all stations are managed and provided to the public by NMI via the Frost API [11].

Data from Norwegian observing stations are also made available by Meteomatics via their Weather API solution [6, 7]. The Meteomatics API is found to be easier to use, more efficient and reliable than the Norwegian Meteorological Institute's API service and is consequently chosen as the gateway for sourcing met station data in this project.

A location lookup table with met station name, WMO number and station positions in terms of latitude and longitude is generated. The positions are used as input for requesting forecast and archive data from the EURO1k model from Meteomatics and the MEPS model from NMI

2.1.2. Meteomatics EURO1k model

The EURO1k model operated by Meteomatics is a high-resolution weather model with 1 km spatial resolution with a geographical coverage across all of Europe [5]. The temporal resolution is 15 minutes hourly updates with 72 hours forecast lead time are provided. High fidelity is delivered by integrating a wide suite of measurement data and observations from across Europe. It also provides the exclusive integration of weather data captured by Meteodrones (Meteomatics' weather drones) [8].

Downscaling capability allows for resolutions as precise as 90 meters.

The model's level of detail allows it to capture small meteorological phenomena like thunderstorms, hail, storms and extreme events more accurately than traditional (coarser) models.

As many as 1800-weather parameters are available in the model, continuous up to ~20 km altitude.

EURO1k is particularly useful for industries that rely on precise weather predictions, such as renewable energy, transportation, and aviation.

Meteomatics also provides the option to assimilate a pool of nearby local met station data to nudge the forecast data against to improve the skill of weather predictions. These data we term 'calibrated'.

EURO1k data are available via Meteomatics' Weather API solution [6, 7].

2.1.3. Norwegian Meteorological Institute MEPS model

MetCoOp Ensemble Prediction System (MEPS) is a short-range ensemble weather forecasting system used in the Nordic region [2]. It is a collaboration between Norway, Sweden, Finland, and Estonia, providing high-resolution forecasts with a 2.5 km horizontal resolution and 65 vertical levels (up to approx. 10 km).

MEPS operates by generating multiple forecasts (ensemble predictions) instead of a single deterministic forecast. This approach helps meteorologists assess uncertainty in weather predictions and estimate the probability of different weather scenarios:

- Ensemble Forecasting: MEPS runs several variations of the same weather model, each with slightly different initial conditions. This allows meteorologists to see a range of possible outcomes rather than just one.
- High Resolution: MEPS provides short-term forecasts for -2 to 65 hours with a 2.5 km horizontal resolution.
- Nordic Collaboration: It is developed through a partnership between Norway, Sweden, Finland, and Estonia, ensuring accurate forecasts tailored to the region
- Operational Use: MEPS is integrated into platforms like Yr.no, providing real-time weather updates to the public.
- Predicting Extreme Weather: The ensemble approach helps forecast storms, heavy precipitation, and other extreme weather events, improving preparedness and response.

The Norwegian Meteorological Institute also provides *reanalysed* MEPS data with 1.0 km spatial resolution. The reanalysis combines past short-range weather forecasts and local observations through data assimilation to nudge the forecast production to make better weather predictions. The data provided in the MEPS 1.0 km reanalysis product is strictly limited to heights at which measurement are conducted, which is the standard WMO elevations, i.e. 10 m wind, 2 m atmospheric, msl pressure etc.

Data are publicly available at NMI's THREDDS Data Server which provides metadata and data access for scientific datasets, using OPeNDAP, OGC WMS and WCS, HTTP, and other remote data access protocols [12]. THREDDS, which is short for Thematic Real-time Environmental Distributed Data Services, is a project which aims to offer coherent access to a large collection of real-time and archived environmental data

2.2. NORCE data archive

2.2.1. Architecture

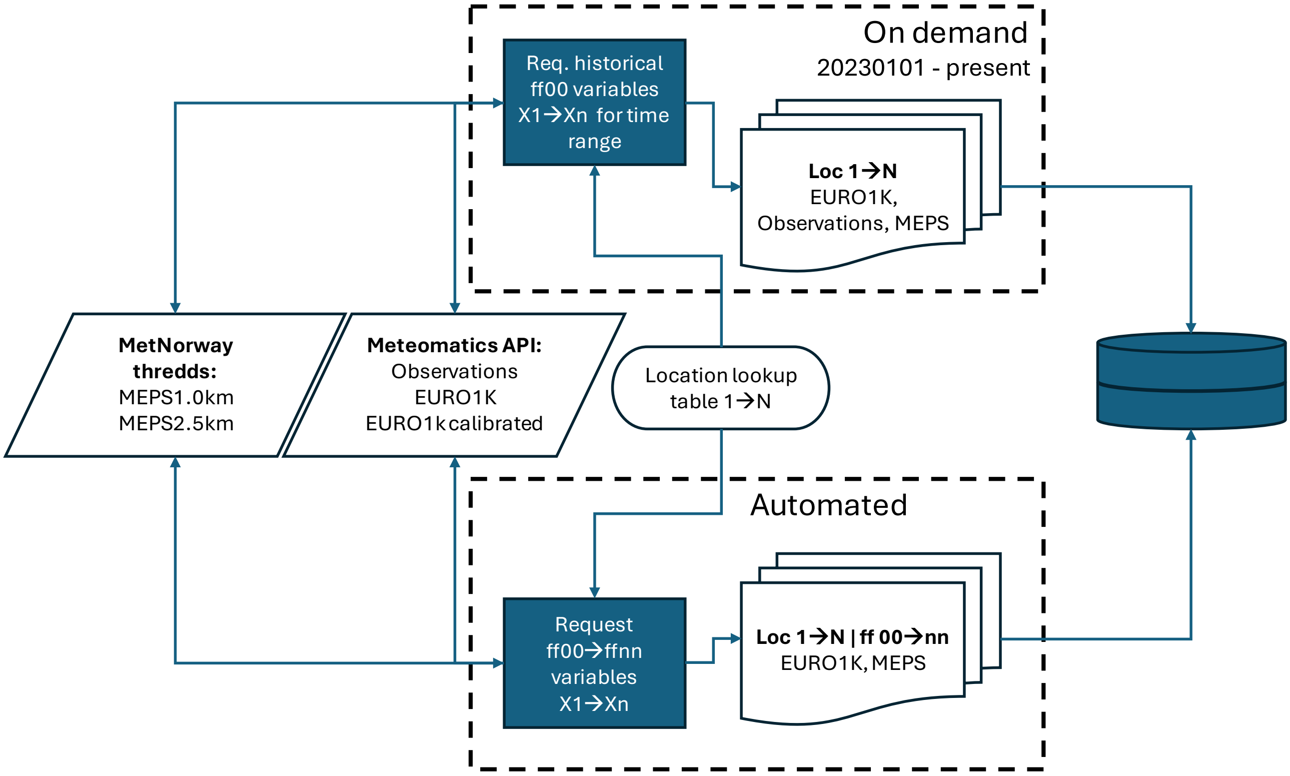


Figure 2-2 Data accumulation workflow.

For both the EURO1k and MEPS models only the latest forecasts ff000 are archived by the provider. Thus, to evaluate the forecasting performance of the respective models the actual forecasts beyond time zero must be downloaded and archived.

NORCE have constructed download managers (batch script operations of python scripts) making hourly request against Meteomatics servers and 3-hourly requests against NMI servers as illustrated in **Figure 2-2**:

1. Automated requests for Meteomatics EURO1k and calibrated EURO1k forecasted variables of interest are passed on an hourly basis. For the given timestep, files for each forecast time ff000 to ff072 are stored for each location.
2. Automated requests for MEPS 2.5 km and MEPS 1.0 km forecasted variables of interest are passed on 3-hourly basis. For the given timestep, files for each forecast time ff000 to ff065 are stored for each location.
3. On-demand requests for Meteomatics EURO1k and calibrated EURO1k historical latest forecast (ff000) variables of interest. For each location, data are concatenated with previously downloaded data and stored.
4. On-demand requests for MEPS 2.5 km and MEPS 1.0 km latest forecast (ff000) variables of interest. For each location, data are concatenated with previously downloaded data and stored.

This will over time accumulate data that allows for a statistically robust comparison with observations.

2.2.2. Monitoring

The processes NORCE have developed for the Gondul project to collect and treat weather forecasts from Meteomatics and NMI are monitored in the NORCE monitoring system called Watchdog. Watchdog monitors all NORCE's operational coastal forecast models, systems and production performance and can be viewed online at https://kystvarsel.no/watchdog/.

The Gondul project relies highly on a reliable influx of data. Therefore, once every hour the age of the last acquired EURO1k and MEPS files is checked. If the age is > 3 for EURO1k and >4 for MEPS an 'age warning' warning is issued, and investigation shall ensue. If left unsolved the status and warning message becomes 'age off spec'.

Figure 2-3 shows a snapshot of the online Watchdog display, at 8 p.m. on Monday May 12th. The Gondul monitoring sorts under the "Systems" panel, in which the increase of forecast age is seen, and to the very right age warnings and accordingly warnings are issued for the EURO1k forecasts. Looking into the case revealed that the source was an unscheduled python update on Saturday May 10th enforced according to our new local IT regulations. This caused version conflict with the meteomatics.api python package and loss of contact with the EURO1k host server, until scripts were updated as response to the software update.

Access and production issues pertaining to NMI's MEPS products are often detected by Watchdog before they are posted on the NMI incident status board (https://status.met.no/).

Figure 2-3 Snapshot of the Watchdog monitoring system

2.2.3. Operation and user experience of weather data download services

In our experience, down-time and or other issues are virtually non-existent for the Weather API solution operated by Meteomatics [6]. Implementation is well described [7], it is exceptionally easy to set up and use, and the API is highly responsive. And importantly, it ensures a reliable and unhindered stream data.

Conversely, working with NMI's THREDDS server is more cumbersome due to its architecture and that it seems associated with frequent management issues on the host's behalf:

- Request response is slow.
- Filenames, formats and timesteps changes over time (unscheduled).
- Frequent unscheduled access issues, down time, and production errors. The incident history for products and services affecting Gondul are summarized in Appendix 2.

2.2.4. Data Quality control

Prior to comparative statistical analysis, weather data are checked and unrealistic values (upper and lower limit), positive and negative spikes (typically 2 standard deviations) and static parts where the values remain invariant over 5-time steps are removed.

Missing data are not remediated by filling in interpolated data.

3. Analysis

3.1. Data selection

Four sources of forecast data are considered; the Meteomatics EURO1k forecast and calibrated EURO1k forecast, and NMI MEPS forecast (2.5 km) and MEPS reanalysis (1.0 km), as described in Section 2.1.

Although the spatial resolution alludes to MEPS 1.0 km forecast to be the appropriate contender to the EURO1k forecast, it is not, as the MEPS 1.0 km forecast is a *reanalysis* product, distinctly different from EURO1k and MEPS 2.5 km. MEPS 1.0 km uses a different assimilation protocol than the other more traditional forecast models: Past short-range weather forecasts and local observations are assimilated into the model to nudge the forecast production. This infer that the data selection is strictly limited to heights at which measurement are conducted, which is the standard WMO elevations, i.e. 10 m wind, 2 m atmospheric, msl pressure etc. MEPS 1.0 km cannot be used to forecast the weather at other altitudes, and it is excluded for comparison with Meteodrone data later in the project. Icing potential/index is not issued for MEPS 1.0 km. Another critical disadvantage is that the MEPS 1.0 km forecasts are issued from 4 hours ahead (ff004) to 62 hours ahead (ff062), which imply that that forecasts for the 3 first hours of, i.e. highly relevant for military operations, are not available. The use of local observations in MEPS 1.0 km does however resemble the "calibration" option for EURO1k. **Figure 3-1** illustrates the difference in vertical coverage and available forecast time ff.

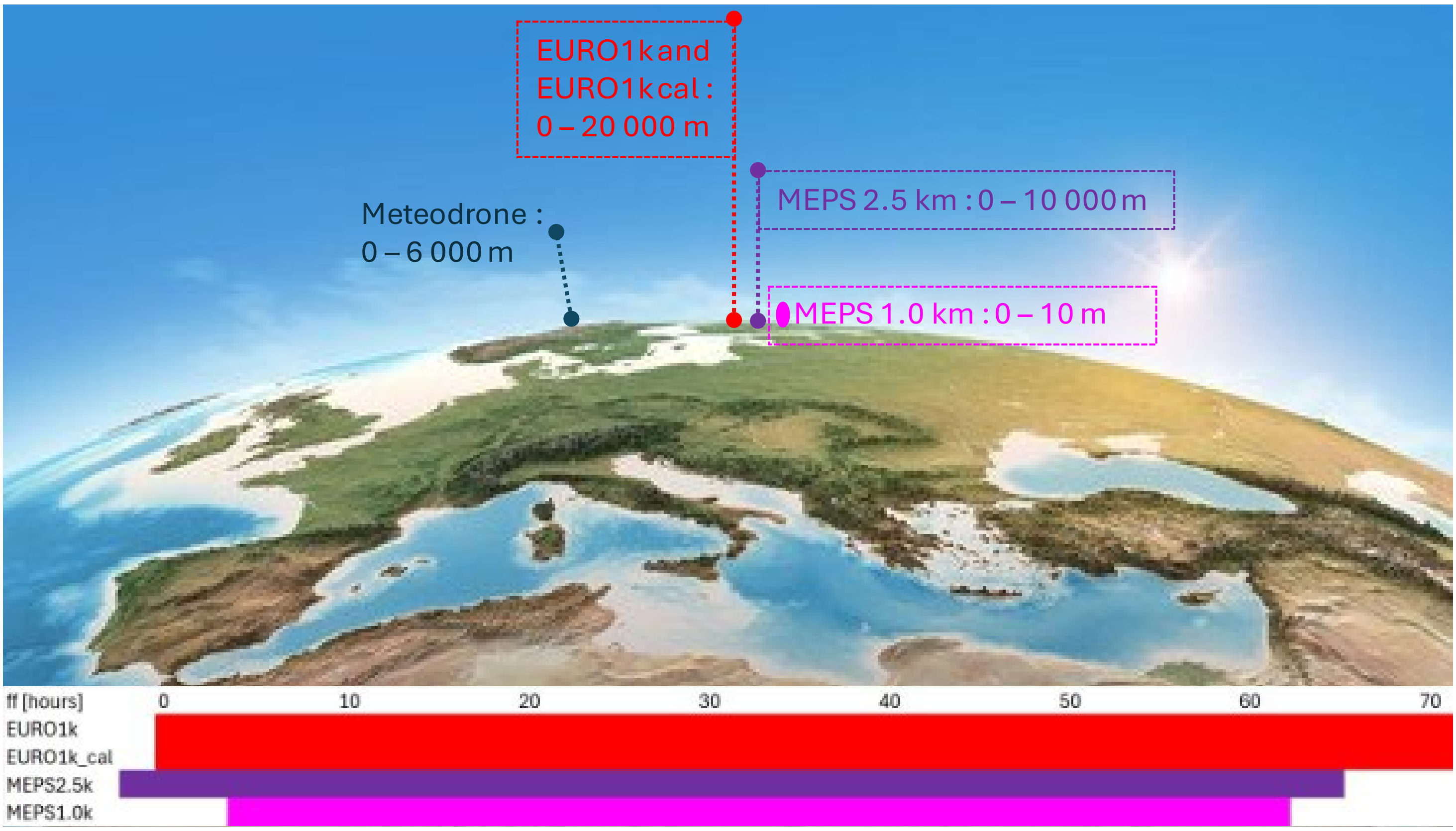


Figure 3-1 ***Vertical coverage and available forecast time ahead (ff) for the EURO1k and MEPS forecast products. Vertical range of the Meteodrone inserted for context.***

Thus, the following sets of models are subject to comparison:

1. Meteomatics EURO1k forecast vs MEPS 2.5 km.
2. Calibrated Meteomatics EURO1k forecast vs MEPS 1.0 km reanalysis.

Where, 1) comparison of Meteomatics EURO1k forecast vs MEPS 2.5 km, is the focus of the comparative analysis, and 2) the calibrated Meteomatics EURO1k forecast vs MEPS 1.0 km reanalysis is complementary.

3.2. Process and methodology

Figure 3-2 shows a schematic outline of the data post processing, statistical analysis and objective evaluation workflow.

For each met station location 1→N and variable of interest X, historical ff000 forecasts (nowcast) and forecasts ff000-ff065 timeseries are constructed and compared with observations and results are synthesized into one-pagers as exemplified in **Figure 3-3** and **Figure 3-4**.

The methods of analysis and statistical estimators and their usage are described in **Table 3-1**.

To provide an objective performance indicator, a score based on which of the models perform best on the statistical estimators R^2, QQ R^2, PCC and normalized MEA, MSE and RMSE (ref. **Table 3-1**). The models subject for comparison will be compared for each calculated estimator, for which the best performing model will receive a point (1 assigned for the best performing, 0 for the momentarily inferior), while if the statistical estimators are within 5 % of each other results are treated equal, and the score point is shared. When all estimators are calculated and points distributed, a total score is calculated by summation, weighting on most important estimators (MEA, MSE, RMSE and PCC), and finally normalized. Thus, the final score is a number between 0 and 1. This is done individually for each variable of interest, and each given nowcast and forecast time, across all met station locations. This provides detailed comparison of the performance locally. The resulting analysis compiled into individual score sheets exemplified in **Figure 3-3**, which shows the forecast 12 hours ahead (ff012) air temperature 2 m above ground, at location Filefjell. In this case, based on the given statistical estimators, EURO1k outperforms MEPS, as highlighted.

The calculated scores pertaining to appointed EURO1k and MEPS forecast variables X are collected into score matrices with stations as rows and ff as columns, i.e. N x nn = 249 x 65 matrix for each variable. This keeps account of the cases (given location and forecast time) where one model outperforms the other, and ultimately stating success rate in % for each forecast time across locations. For the archived nowcasts (historical ff000) the score matrices are reduced to Nx1 = 249x1 for each variable.

For precipitation the analysis is slightly different. Comparative statistics are calculated but the success is determined on hit rate which is a binary evaluation rather than a score based on statistical estimators, i.e. being able to predict precipitation for when it is recorded or not. The example in **Figure 3-4** shows the time series, percentile distribution and sample probability distribution as well tabulated statistics and calculated hit rate [%], for nowcast (historical ff000) precipitation, at location Filefjell.

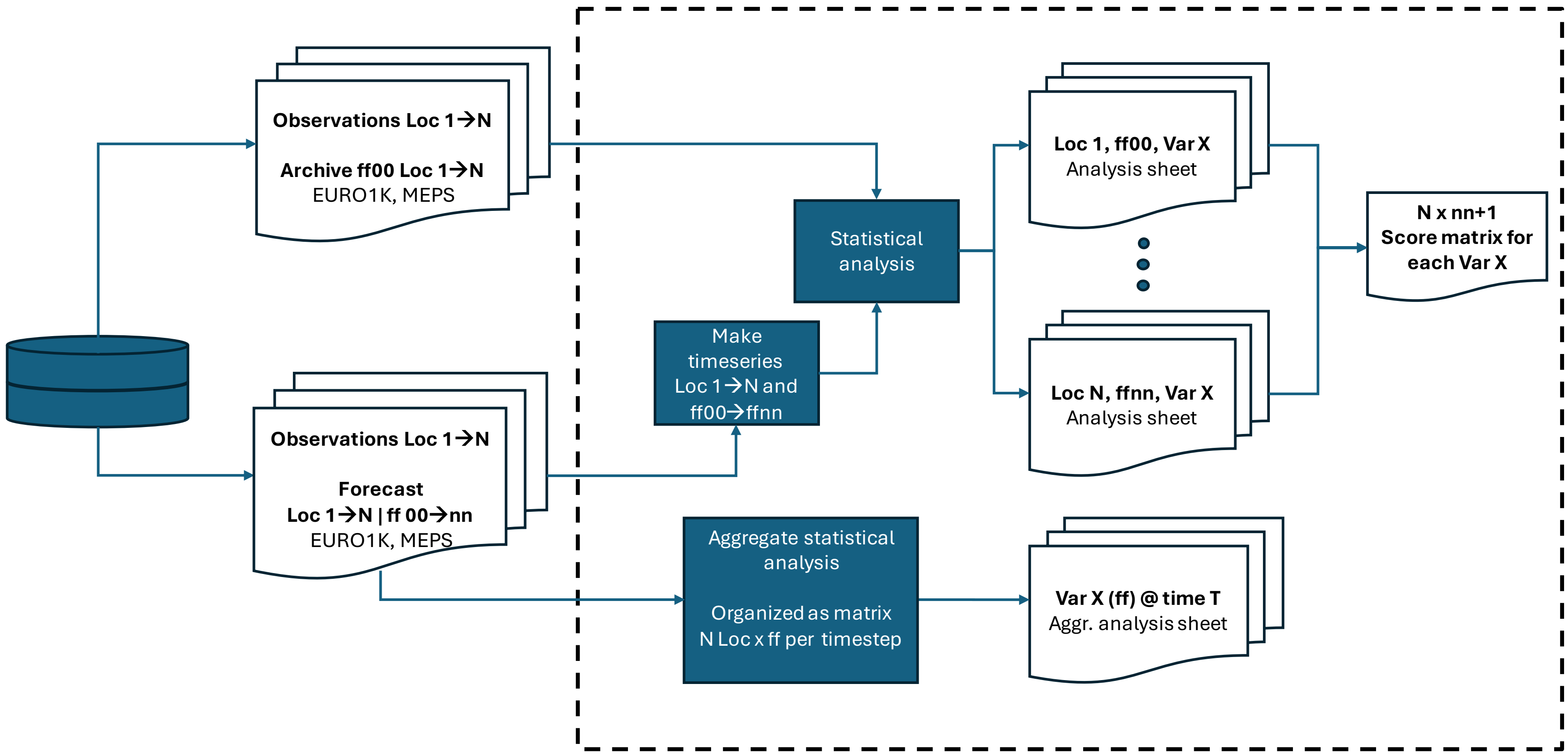
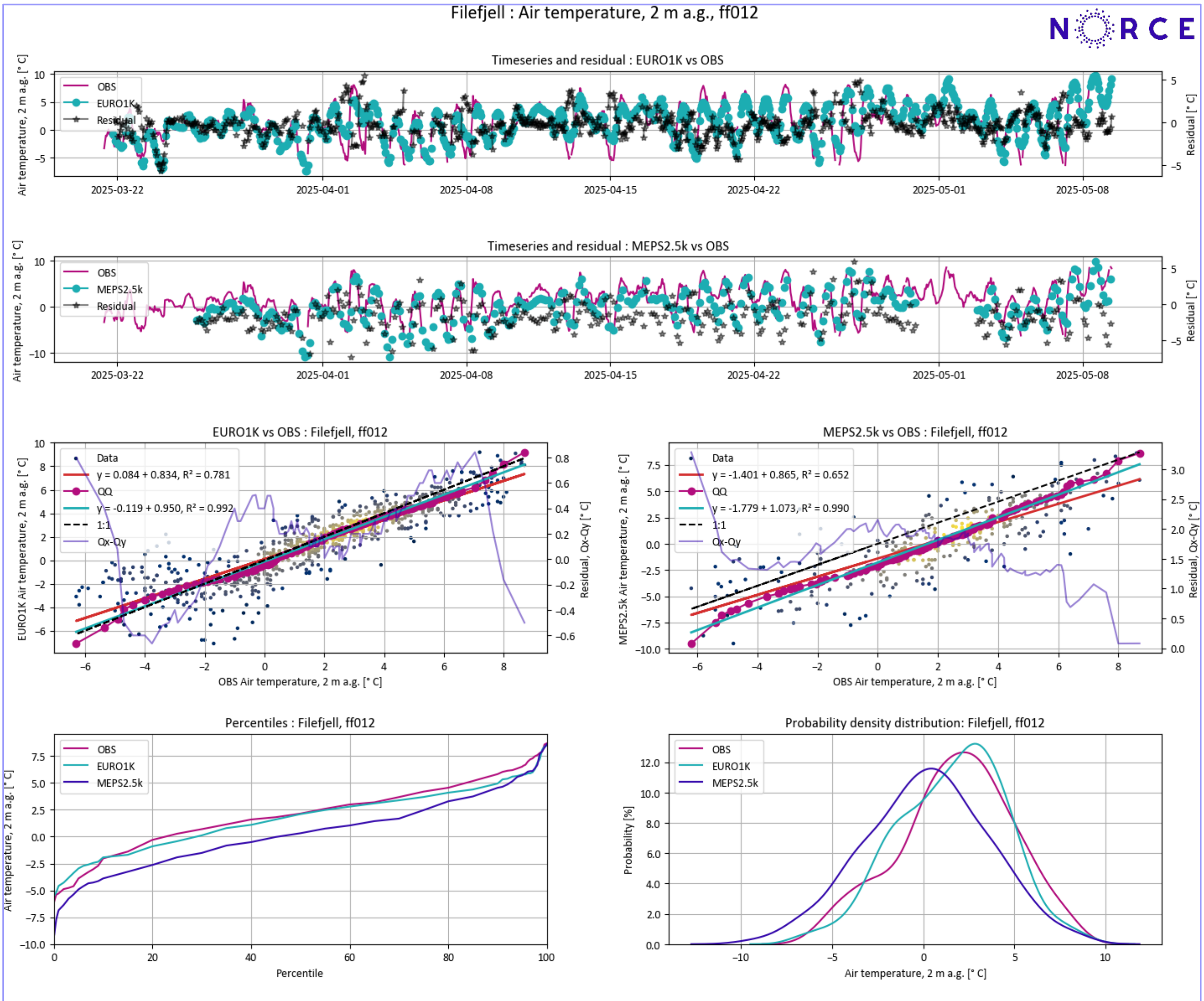
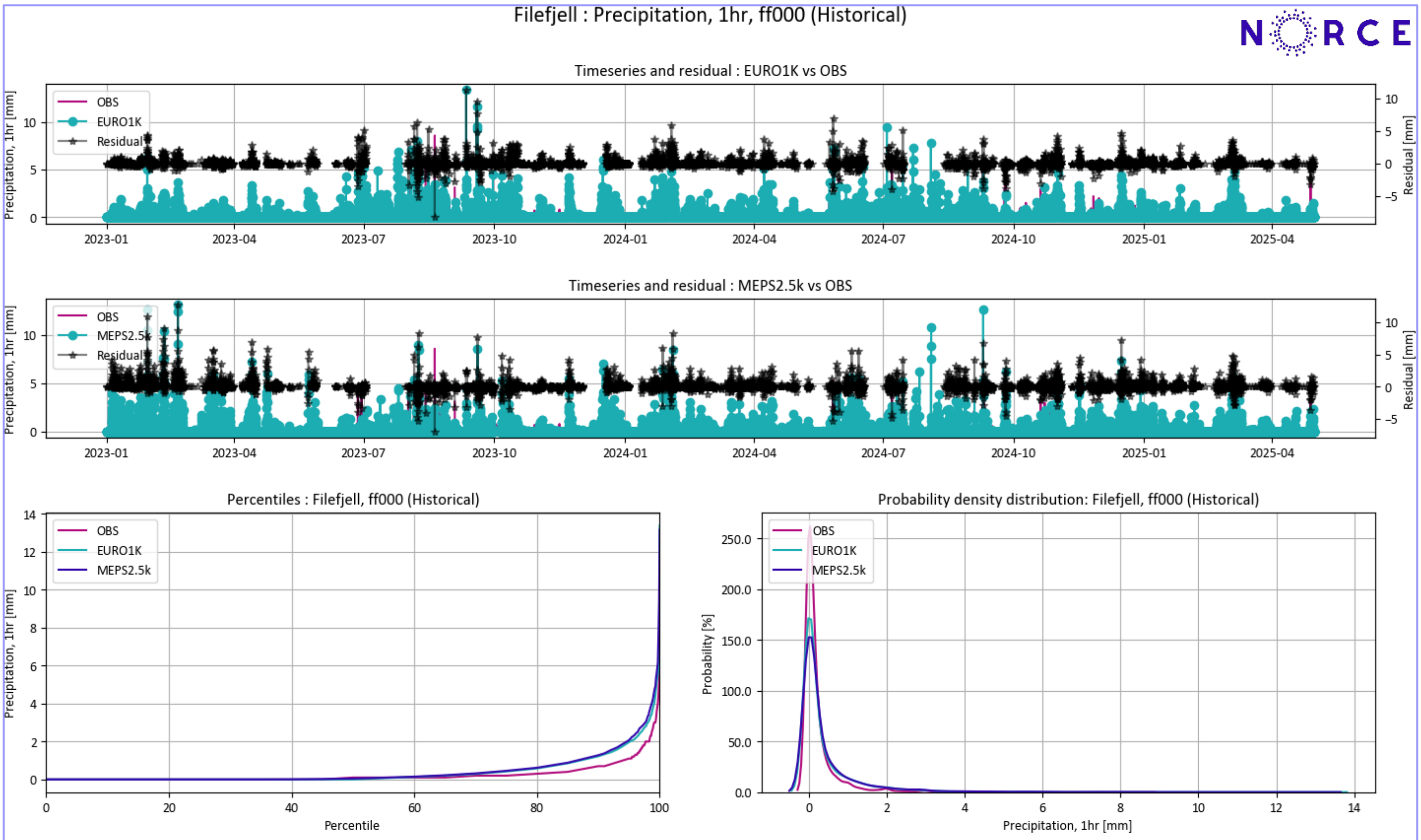


Figure 3-2 Schematic outline: data post processing, statistical analysis and objective evaluation workflow.



Estimator	EURO1K	MEPS2.5k	Estimator	EURO1K	MEPS2.5k
Data regression	y = 0.084 + 0.834x	y = -1.401 + 0.865xx	QQ regression	y = -0.119 + 0.950x	y = -1.779 + 1.073x
R² determination coefficient	0.781	0.652	QQ R² determination coefficient	0.992	0.990
Mean Absolute Error, MAE	1.020	2.201	Mean bias	-0.319	-1.726
Mean Square Error, MSE	1.878	6.869	Pearson correlation coefficient	0.902	0.812
Root Mean Square Error, RMSE	1.370	2.621	Score	**0.964**	**0.036**

Figure 3-3 ***Example of an analysis datasheet produced by NORCE. This data sheet is a synthesis of statistical comparison of 12-hour forecast (ff012) air temperature 2 m above ground from the EURO1k model vs observations and MEPS 2.5 km model vs observations, at location Filefjell.***



Estimator	EURO1K	MEPS2.5k	Estimator	EURO1K	MEPS2.5k
Mean Absolute Error, MAE	0.346	0.449	**Mean bias**	0.153	0.191
Mean Square Error, MSE	0.563	0.897	**Pearson correlation coefficient**	0.488	0.302
Root Mean Square Error, RMSE	0.750	0.947	**Hit rate**	**0.693**	**0.595**

Figure 3-4 ***Example of analysis datasheet produced by NORCE. This data sheet is a synthesis of statistical comparison of archived nowcast (historical ff000) precipitation from the EURO1k model vs observations and MEPS 2.5 km model vs observations, at location Filefjell.***

Table 3-1 Statistical analysis used to determine forecast skill based on comparison vith observations. Table continues on next page

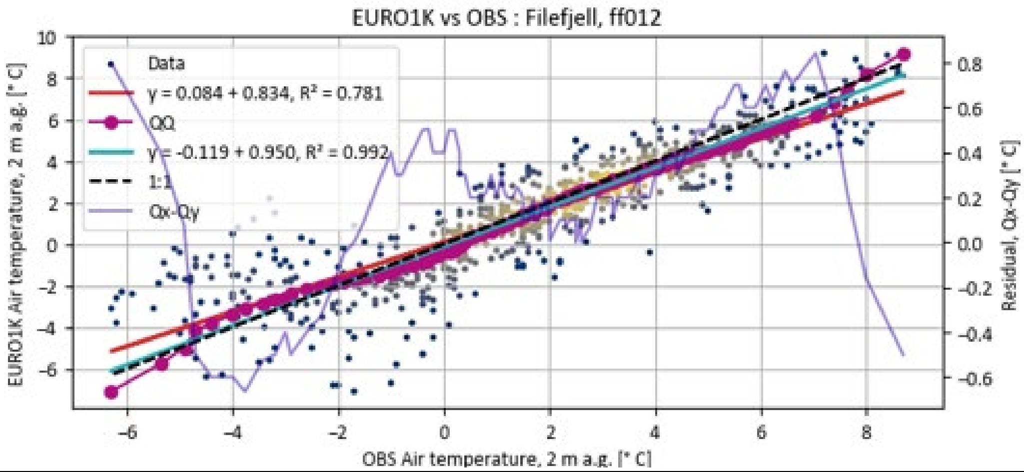
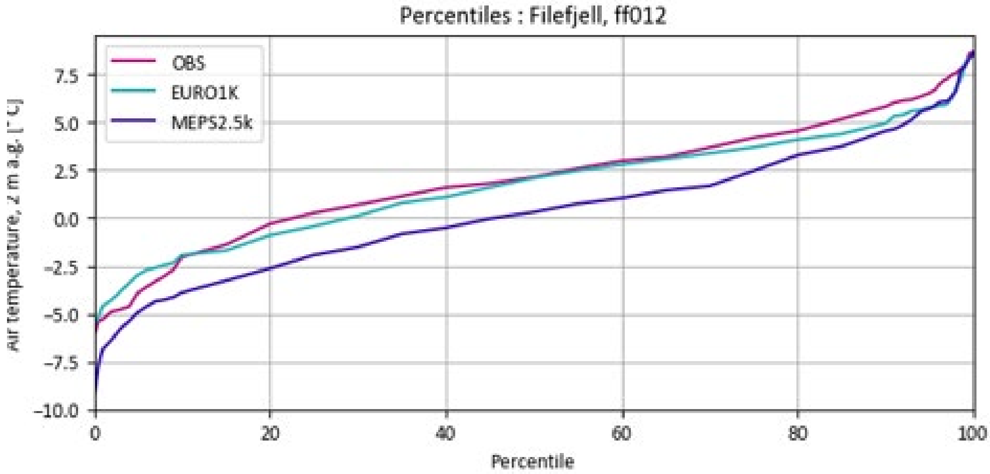
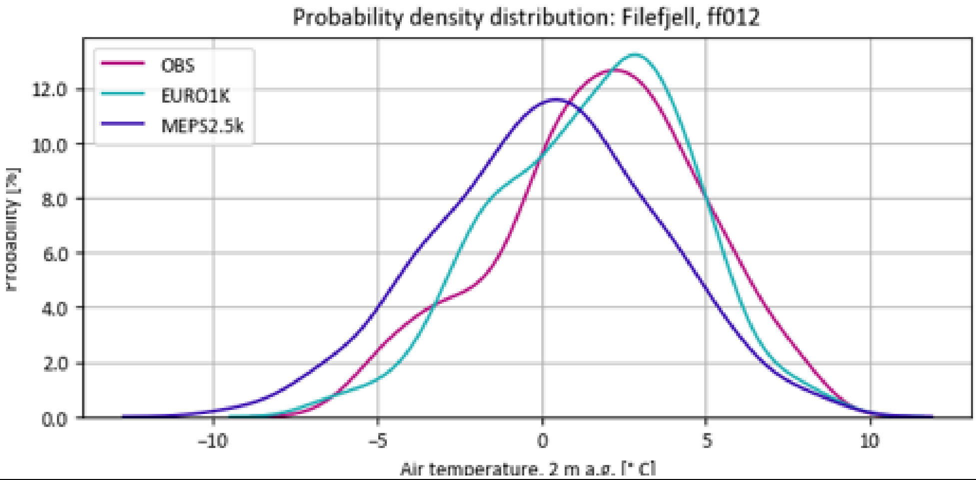
Timeseries comparison and residual: Forecasted value of a given parameter as function of time compared directly with observations of the same parameter. The residual time function, which is the absolute difference between the two timeseries is given on the secondary (right) y-axis
Data scatter plot and linear regression with R^2 determination coefficient: Concurrent forecast and observations data points are plotted against each other (dots labeled 'Data' in the figure below). If perfectly related to each other these points would fall on the 1:1 line, but in as there are minute difference between the two the points are scattered round the 1:1 diagonal. Fitting a line to the scatter data by linear regression we find an expression y = a + bx and a determination factor R^2 which expresses how well the two data sets correlate. **Quantile-quantile (QQ) plot and linear regression with the QQ R^2 determination coefficient:** Sorting the data into N equally sized groups based values (N^{th} quantile) provides another form of statistical assessment of correlation. Since the data are grouped according to value the datapoints are statistically more robust but not necessarily conserving concurrence. Similar for the time series linear regression and R^2 determination coefficient is calculated, as well as the residual between the ordered data Qx (x-axis: which is the observations) and Qy (y-axis: which is the forecast). 

Table 3-1 Continued from previous page. Table continues on next page

Percentiles distribution:
A percentile is a statistical measure that indicate the value below which a given percentage of samples in a group of data/observations falls. For example, the 40th percentile is the value below which 40% of the data/observations may be found. Considering percentiles in the range 0 to 100 we can visualize how the percentiles are distributed for the forecasts and observations and how well they relate.



Probability density distribution:
A probability density distribution (or function) is a fundamental concept in probability theory and statistics, used to describe the likelihood of a continuous random variable taking on a particular value. It can be used to assess how much of the data attains a certain value and comparatively how well different datasets correlate.



Mean Absolute Error (MAE):
A measure used to quantify the accuracy of a model by calculating the average absolute differences between predicted values and actual values. It's a common metric in regression analysis and time series forecasting.

Mean Square Error (MSE):
A common measure used to evaluate the accuracy of a model by calculating the average of the squares of the differences between predicted values and actual values. It is particularly useful in regression analysis and other predictive modeling techniques. MSE amplifies and penalizes larger errors due to squaring the residuals compared to MAE. This helps in identifying critical inaccuracies in the model's predictions. This means it is also highly sensitive to outliers.

Table 3-1 Continued from previous page.

Root Mean Square Error (RMSE): It is the root of the MSE as described above. The metric of the error mirrors the unit of the variable whereas MSE attains the variable unit squared. Makes interpretation a little easier.
Mean bias error (MBE): Measures the average bias in a model's predictions. It helps to identify whether a model tends to overestimate or underestimate the actual values. It does not capture the magnitude of individual errors well but is useful together with metrics like MAE, MSE and RMSE for a comprehensive evaluation.
Pearson correlation coefficient (PCC): Quantifies the strength and direction of the linear relationship between two quantitative variables. The Pearson correlation coefficient is defined as the covariance of the two variables divided by the product of their standard deviations. It ranges from -1 to 1 where; • +1 indicates a perfect positive linear relationship: As one variable increases, the other variable tends to increase. • -1 indicates a perfect negative linear relationship. As one variable increases, the other variable tends to decrease • 0 indicates no linear relationship. There is no predictable relationship between the variables

An aggregated analysis is also performed on the respective forecast model data versus observations in which for each variable the statistical estimators MEA, MSE, RMSE and PCC are calculated across all met station location for a user defined time period. This provides a comparison and adds to the understanding of overall performance of the respective models. **Figure 3-5** shows an example of the aggregated analysis: statistical evaluation of air temperature 2 m above ground for all EURO1k and MEPS 2.5 km forecast data versus observations as function of forecast time ff for the period 20250401 to 20250523.

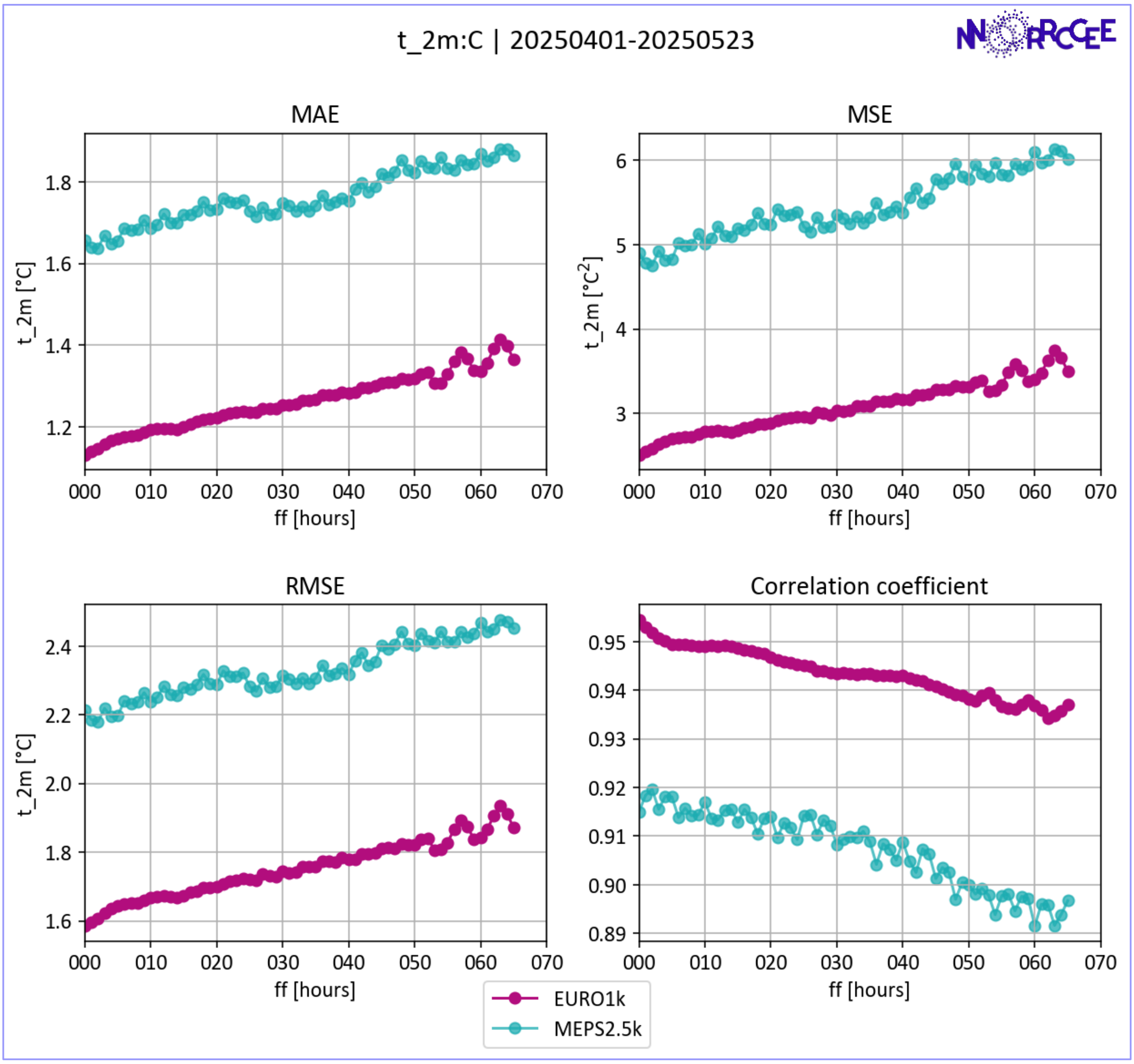


Figure 3-5 Example of the aggregated analysis: statistical evaluation of air temperature 2 m above ground for all EURO1k and MEPS 2.5 km forecast data versus observations as function of forecast time ff for the period 20250401 to 20250523.

3.3. Icing potential

Icing in manned aviation has been studied since the 1940s and 1950s and the processes, risks and remediation are well understood topics. Icing nowcast and forecast for manned aviation are typically issued by national met services.

Unmanned aerial vehicles (UAVs) face several special technical challenges that are different from manned aircraft. The following is a broad overview of the most relevant topics for the occurrence of atmospheric icing [3, and references therein]:

Vehicle type: Icing effects and severity depends very much on the type of UAV. Icing on rotary-wing UAV is dissimilar than icing on fixed-wings. Different types of propulsion system (propeller, rotor, or jet) have their individual vulnerabilities to icing.

Size: Smaller airframes experience higher impingement rates than larger ones. This is because the generate lower aerodynamic deflection forces, while the droplet inertias are unchanged. In practice, this means that smaller air foils collect more ice relative to their size. Since icing penalties are related to the relative ice size, smaller aircrafts experience icing more severe than a larger aircraft in the same conditions.

Flight velocity: High air speeds cause aerodynamic heating of the leading edges of lifting surfaces (wings or rotors). This heating effect can lead to a decrease of icing at temperatures near the freezing point. At the same time, lower airspeeds also generate reduced surface friction, which can decrease ice shedding efficiency for de-icing.

Reynolds number: The Reynolds number is a dimensionless number describing the ratio of viscosity to inertia (momentum) of an object in a fluid between which there is a relative velocity. The Reynolds number is used to characterize the flow with regards to laminar and turbulent effects:

$$Re = \frac{\rho \cdot L \cdot v}{\mu}$$

with the fluid density ρ, characteristic length L, relative fluid speed v, and dynamic viscosity μ of the fluid. The Reynolds number is used to characterize the flow with regards to laminar and turbulent effects. The difference in the Reynolds number regime between manned and unmanned aircraft means that many simulation tools and empirical methods developed for manned aviation may not be applicable for smaller UAVs.

Weight: The additional weight on the airframe due to ice can be an issue since it needs to be compensated with additional lift. Also, the weight can affect the location of the centre of gravity, stability, and manoeuvrability of the aircraft.

Materials: UAVs are often built from composite materials with low heat conductivity. In contrast, manned aircraft wings are mostly built of metal which has substantially higher heat conductivities. This difference can affect the ice accretion process, especially in glaze and mixed ice cases.

Rotor and propellers: Most fixed-wing UAVs rely on propellers for propulsion, with a few exceptions of military UAVs that use jet engines. Rotors are used on many smaller UAVs for lift and thrust generation. Icing on rotating surfaces can occur at high ice accretion rates and acutely affect thrust, power and stability.

Sensors: The most critical sensor with respect to icing is the pitot tube which indicates the airspeed to the aircraft. Erroneous airspeed indications due to iced pitot tubes have led to documented UAV crashes [10]. Camera lenses, antennas, radomes, and other sensors can also be affected by icing which may limit their functionality and add weight to the aircraft.

Autopilot and controls: The autopilot is a key system in UAVs, responsible for flight controls, navigation, path planning, landing, etc. In-flight icing is changing aircraft flight behaviour. Autopilots of UAVs need to be able to identify and adapt (e.g. by increasing speed, reducing altitude, changing path) to icing, to ensure safe operation in all-weather conditions.

Estimating and predicting icing penalties in operation and/or in the design and optimization phase is a complicated matter, involving environmental conditions as much as being vehicle specific, which typically necessitates numerical simulations i.e.:

1. **Calculation of the flow field:** Most modern codes achieve this by solving the Reynolds-Averaged Navier-Stokes (RANS) equations with computational fluid dynamics (CFD) methods. Older codes use panel-methods, often enhanced with empirical functions.
2. **Droplet impingement on surfaces:** The information how much water impinges on a surface can be calculated with either a Lagrangian or a Eulerian method.
3. **Solution of the energy and mass balance:** This step calculates how much of the impinging water turns into ice and is affected by several terms such as aerodynamic heat transfer coefficients, evaporation, latent heat release, aerodynamic heating, IPS loads, etc.
4. **Calculation of the new ice shape:** The new, iced surface is calculated based on the amount of water turning into ice and the ice density at each calculation point. For CFD tools this step includes the re-meshing of the new geometry.

All simulation tools need to be validated with experimental data. In manned aviation, a significant amount of data is available for this task on air foils. Less data is available for rotors on propellers. There is an acute lack of validation data specifically for UAVs with regards to UAV-specific geometries or Reynolds numbers.

The EURO1k and MEPS 2.5 km forecast models provides predictions of the expected occurrence of icing on different altitudes (note that MEPS 1.0 km does not provide icing potential). However, observing stations does not provide such data. Thus in order to obtain an objectively comparable parameter for quantitative comparison we resort to evaluating the conditions of low temperatures and high humidity by acknowledging that [15, 4]:

- Atmospheric icing typically requires high humidity levels, as supercooled liquid water droplets need to exist for ice formation. Relative humidity above 80% is often necessary
- Clouds with tops at temperatures between -5 to -15°C generally consist of supercooled droplets. At -9°C the majority of clouds (over 50%) will be all supercooled water (providing there is no cloud seeding from above), at -14°C – about 75% off all clouds will contain some ice, while at -18°C or colder almost all clouds have ice nuclei. It is in clouds such as this that aircraft are most likely to encounter severe icing conditions since supercooled droplets freeze when they collide with an aircraft/AUV.

The concept of the simplified forecast icing potential (SFIP) [9], a practical icing risk indicator, is adopted, which is reduced to a function of air temperature and relative humidity only:

$$SFIP = M_T \cdot M_{RH}$$

where M_T and M_{RH} are the membership functions for temperature T and relative humidity RH defined as:

$$M_T = \begin{cases} 0 & if\ T < T_1 \\ (T - T_1)/(T_2 - T_1) & if\ T_1 < T \leq T_2 \\ 1 & if\ T_2 < T \leq T_3 \\ 1 - [(T - T_3)/(T_4 - T_3)\ ] & if\ T_3 < T \leq T_4 \\ 0 & if\ T > T_4 \end{cases}$$

where $T_1 = -28°C$, $T_2 = -12°C, T_3 = -1°C$ and $T_4 = +1°C$, and

$$M_{RH} = \begin{cases} 0 & if\ RH < RH_1 \\ \left(\frac{RH - RH_1}{(RH_2 - RH_1)}\right)^2 & if\ RH_1 < RH \leq RH_2 \\ 1 & if\ RH > RH_2 \end{cases}$$

where $RH_1 = 0.6$ and $RH_2 = 0.95$. The membership functions are shown in **Figure 3-6**. Given the input temperature and relative humidity is representative for 2 m above ground, the calculated icing potential is representative for 2 m as well, i.e. the variable is named "icing_potential_2m:idx". We choose 0-100 as scale for the SFIP in our comparative analysis.

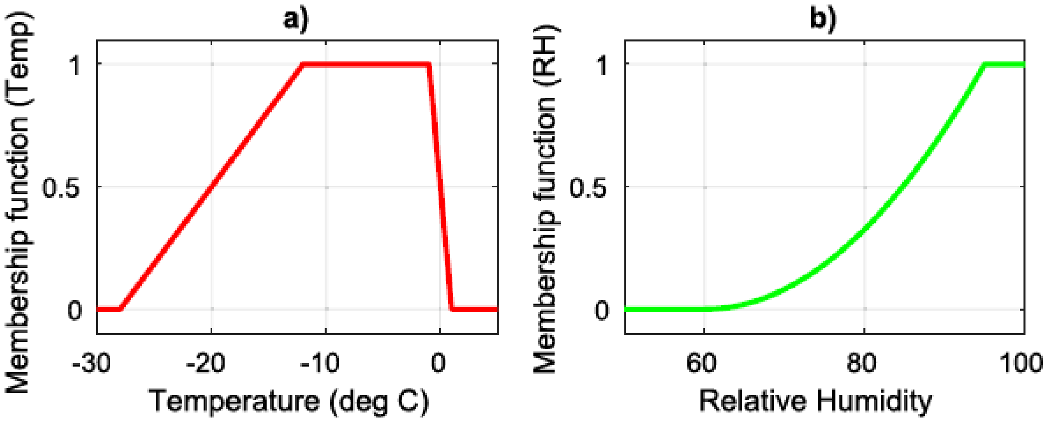


Figure 3-6 Membership functions for temperature T and relative humidity RH [9] used to estimate icing potential.

3.4. Snow indicator

Determining whether precipitation falls as snow depends largely on precipitation and air temperature but also other atmospheric conditions:

Temperature threshold: Snow typically forms when the air temperature is at or below 0 °C. However, snow can sometimes occur at slightly higher temperatures if the air is very dry.

Moisture: Adequate water vapor is necessary to form ice crystals through deposition (water vapor turning directly into ice).

Wet-Bulb Temperature: The combination of temperature and humidity indicate whether snow can form. If the wet-bulb temperature is below freezing, precipitation is more likely to fall as snow.

Ice Nuclei: Microscopic particles serve as surfaces for ice crystals to form.

Vertical temperature profile: The temperature of the atmosphere from the ground up is crucial. If the entire column of air is below freezing, precipitation will likely remain as snow. If there's a warm layer above freezing, the snow may melt into rain before reaching the ground.

Atmospheric Stability: Stable conditions or upward motion of air help maintain cloud formation and supercooled moisture.

Precipitation Intensity: Heavier precipitation can cool the air through evaporative cooling, which may allow snow to form even if the initial temperature is slightly above freezing.

Snow like rain require moisture and atmospheric processes like condensation and nucleation, but the temperature profile and cloud characteristics are key differences. Direct measurements of snow or identification of precipitation type is not common across stations. Without detailed information from near ground observations and lack of information in the vertical column, accurate snow predictions and comparative analysis of model vs observations is difficult. However, we may proclaim that if 1) precipitation is recorded/modelled and 2) the temperature at 2 m above ground is at or below 0 °C, the conditions (over the vertical column) are very likely favourable for water deposition in form of snow and can (with an acceptable degree of certainty) be used to assess the forecast capabilities to predict the risk for snowy conditions. Based on temperature and precipitation rates (PR) the associated snow rates (SR) may be estimated i.e. by applying the empirical relation [1]:

$$SR = a \cdot \left[1 + e^{\left(\frac{T-b}{c}\right)}\right]^{-1}$$

where coefficients are given (for 3-hour sampling intervals) as:

a = 18.8, b = 0.0811, c = 0.6508	for	1 mm ≤ PR < 2 mm,
a = 16.1, b = 0.2182, c = 0.5373	for	2 mm ≤ PR < 3 mm,
a = 14.9, b = 0.2295, c = 0.5174	for	3 mm ≤ PR < 4 mm,
a = 13.2, b = 0.2678, c = 0.5074	for	4 mm ≤ PR < 5 mm,
a = 11.9, b = 0.1524, c = 0.5174	for	PR ≥ 5 mm.

This excludes influences of i.e. wind. For other sample intervals the scaling factor *a* is adjusted accordingly, i.e. 1/3 for 1-hour sampling rate.

4. Results

The forecast model validation with met station measurements covers the entire country and an extensive time period – implying that relevant climate zones and seasons for drone operations are validated for.

4.1. Operational models: EURO1k vs MEPS 2.5 km

Table 4-1 shows the average amount of cases in the score matrix (N location x nn forecast times) where the EURO1k or MEPS 2.5 km forecast for the given variable is found convincingly most accurate. The method for calculating the score is described in Section 3.2 and illustrated by **Figure 3-3**.

Note that the precipitation hit rate (*) which is a binary evaluation rather than a score based on statistical estimators of values, i.e. an estimator of the ability to predict when there is precipitation or not in absolute terms.

Table 4-1 The number of cases in the score matrix (N location x nn forecast times) where the EURO1k or MEPS 2.5 km forecast is deemed most accurate for given variable.

Variable	**Average case (locations, ff) success rate**	
	EURO1k	**MEPS 2.5 km**
Wind speed 10 m a.g.	65.3 %	32.4 %
Wind direction 10 m a.g.	61.4 %	36.5 %
Air temperature 2 m a.g.	79.0 %	20.1 %
Relative humidity 2 m a.g.	63.1 %	35.2 %
Air pressure at msl	83.6 %	15.9 %
Precipitation hit rate*	76.5 %	24.3 %
Average	**71.5 %**	**27.4 %**

Figure 4-1 shows the number of forecast cases over N locations where the EURO1k or MEPS 2.5 km forecast is deemed most accurate for given variable.

PS: Not all variables are necessarily available for all N=249 locations and nn=65 forecast times.

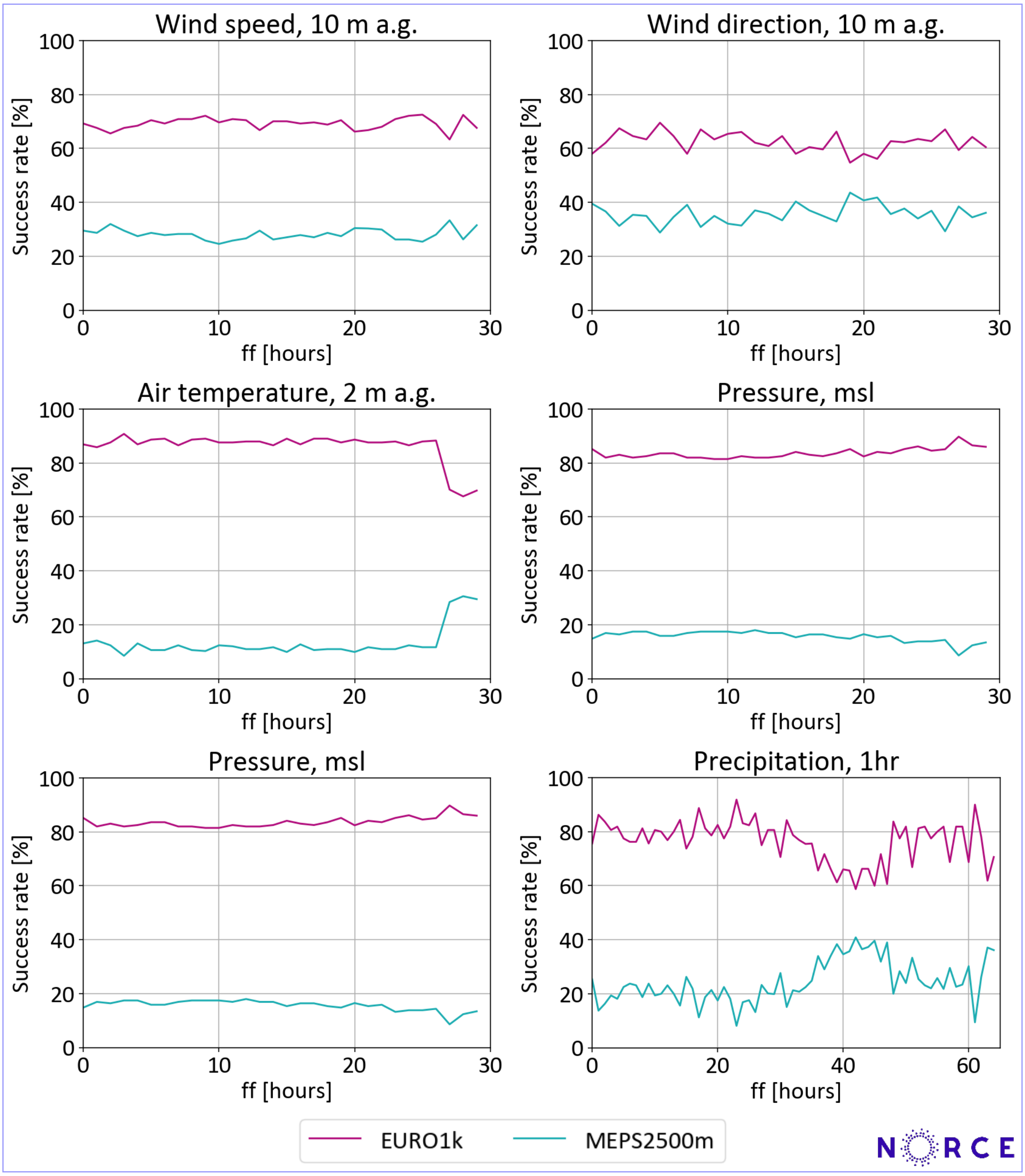


Figure 4-1 ***The number of forecast cases over N locations where the EURO1k or MEPS 2.5 km forecast is deemed most accurate for given variable.***

Table 4-2 shows the average amount of cases in the score matrix (N location x nn forecast times) where the EURO1k or the MEPS 2.5 km nowcast (i.e. historical ff000 forecast) for the given variable is found convincingly most accurate.

Table 4-2 The number of cases in the score matrix (N location x ff000) where the EURO1k or the MEPS 2.5 km historical ff000 forecast is deemed most accurate for given variable.

Variable	Average case (locations, ff) success rate	
	EURO1k	**MEPS 2.5 km**
Wind speed 10 m a.g.	50.0 %	50.0 %
Wind direction 10 m a.g.	71.9 %	25.0 %
Air temperature 2 m a.g.	54.5 %	33.3 %
Relative humidity 2 m a.g.	68.8 %	25.0 %
Air pressure at msl	76.0 %	24.0 %
Precipitation hit rate	100.0 %	0.0 %
Average	**70.2 %**	**26.2 %**

Figure 4-2 to **Figure 4-7** displays comparative statistics for the selected weather variables from the EURO1k and MEPS 2.5 km models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient (see Section 3.2. for description).

Figure 4-8 shows the precipitation hit rate for EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations. The hit-rate is a binary evaluation of the forecast model ability to predict whether there is precipitation or not in absolute terms rather than evaluation of amount

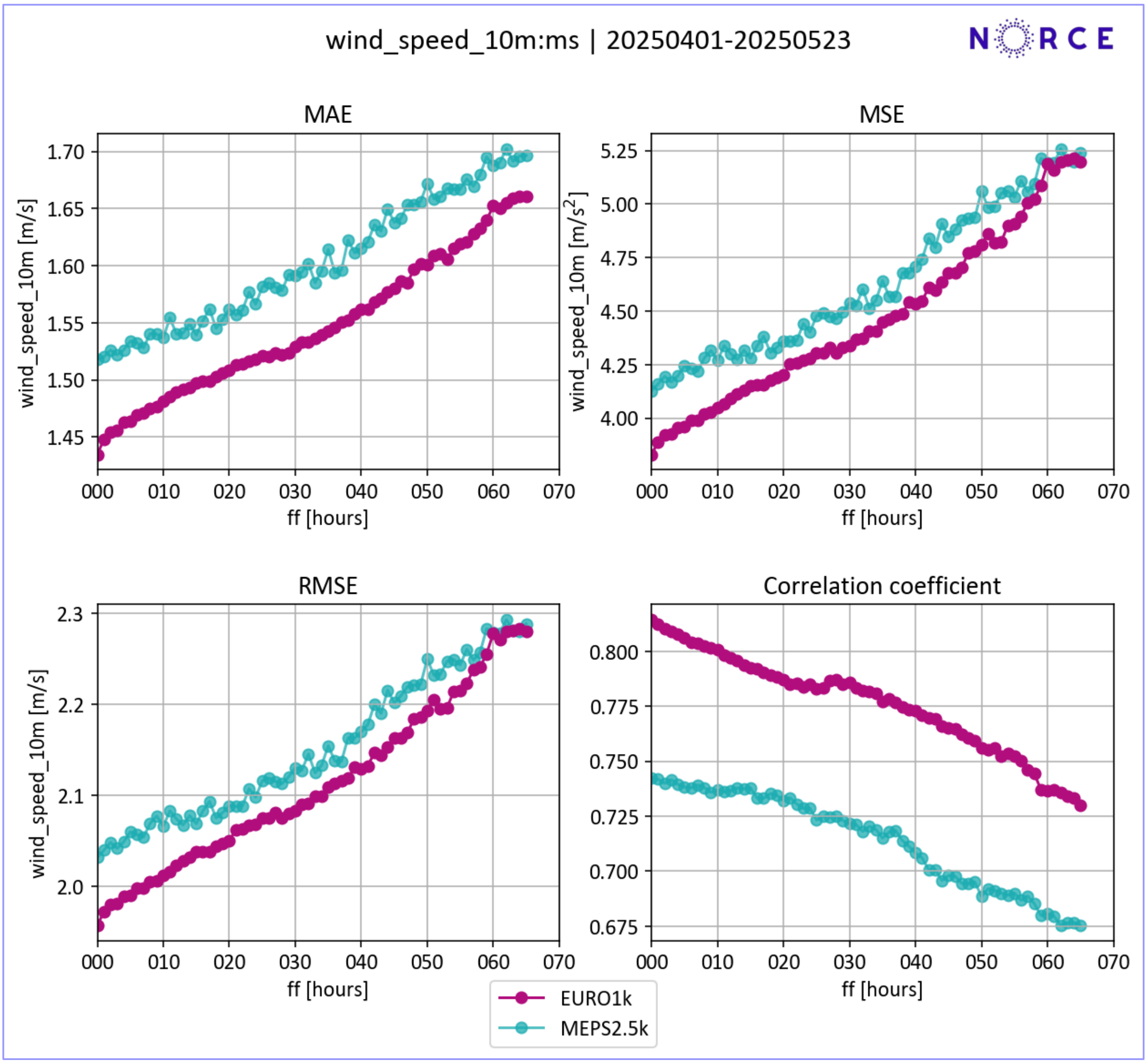


Figure 4-2 ***Comparative statistics for wind speed 10 m a.g. from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

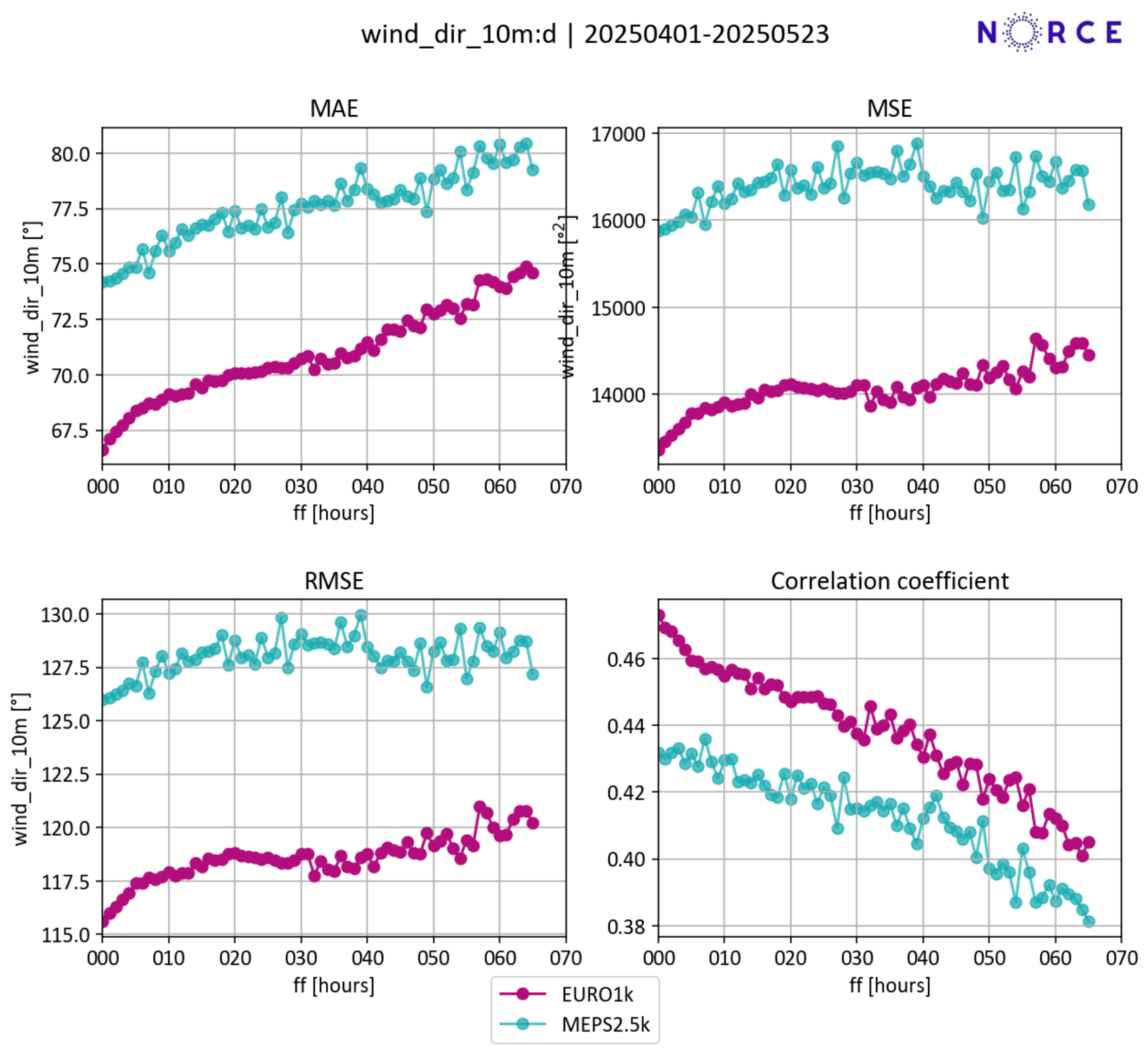


Figure 4-3 ***Comparative statistics for wind direction 10 m a.g. from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

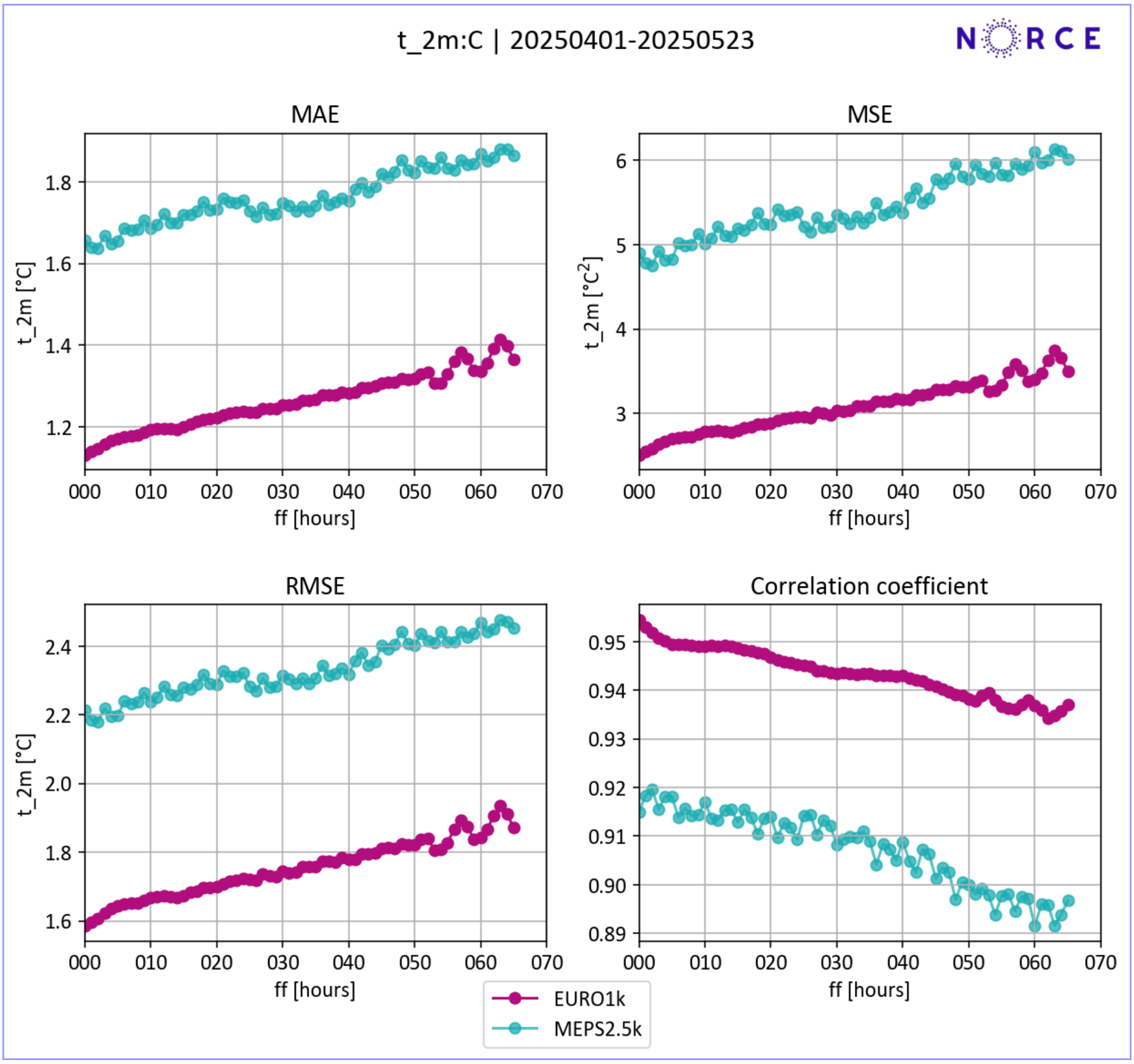


Figure 4-4 ***Comparative statistics for air temperature 2 m a.g. from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

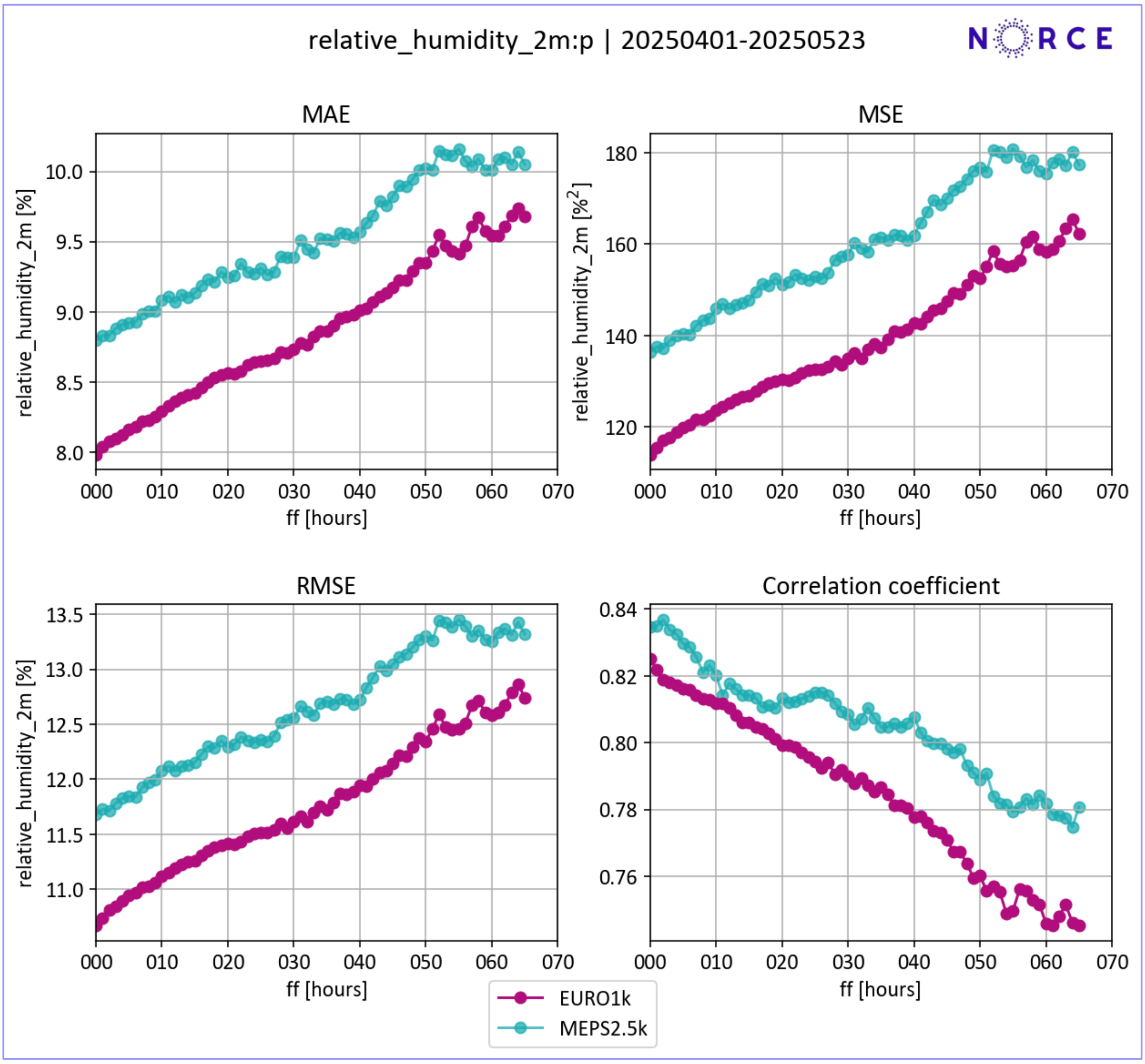


Figure 4-5 ***Comparative statistics for relative humidity 2 m a.g. from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

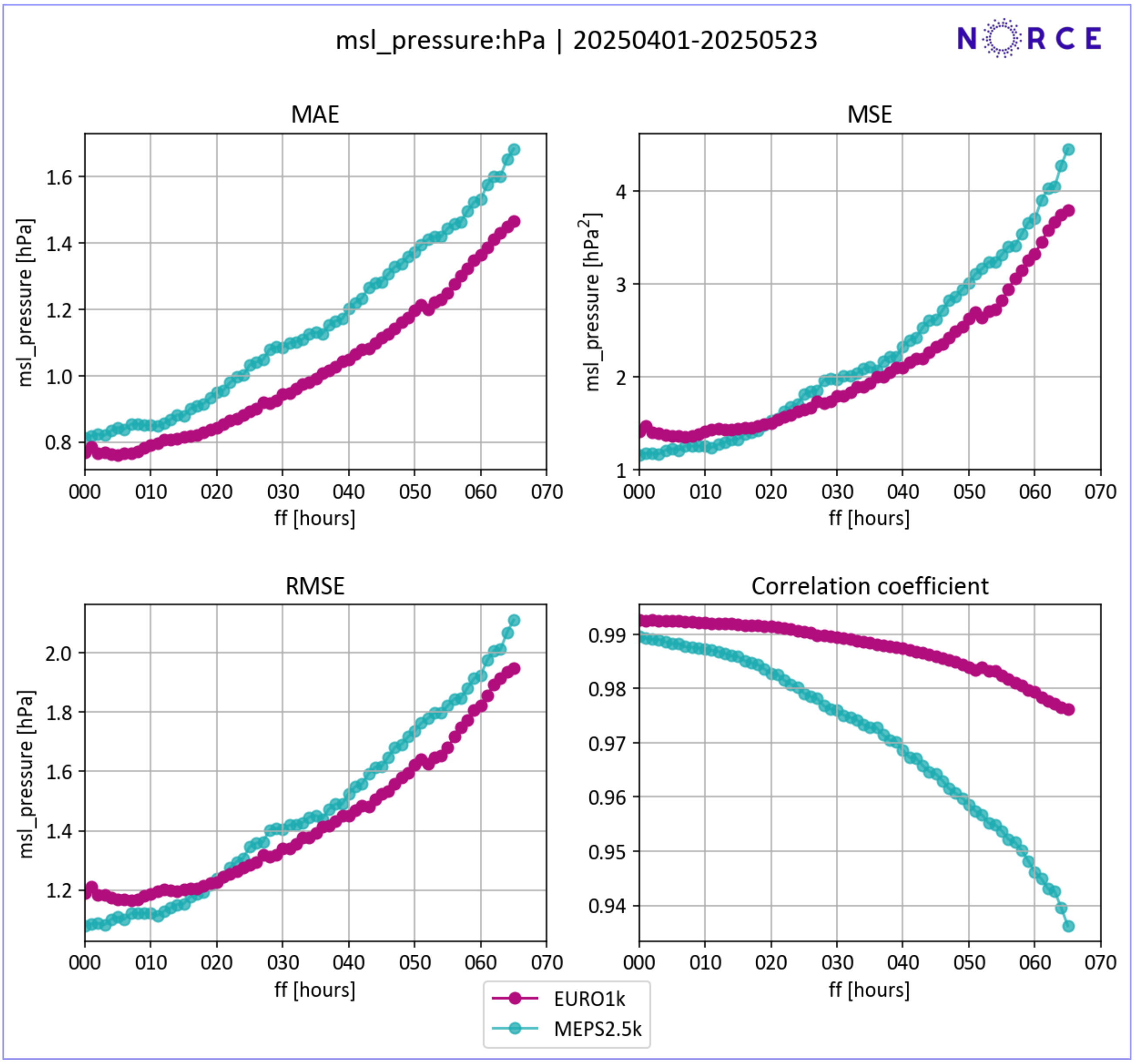


Figure 4-6 Comparative statistics for mean sea level pressure from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

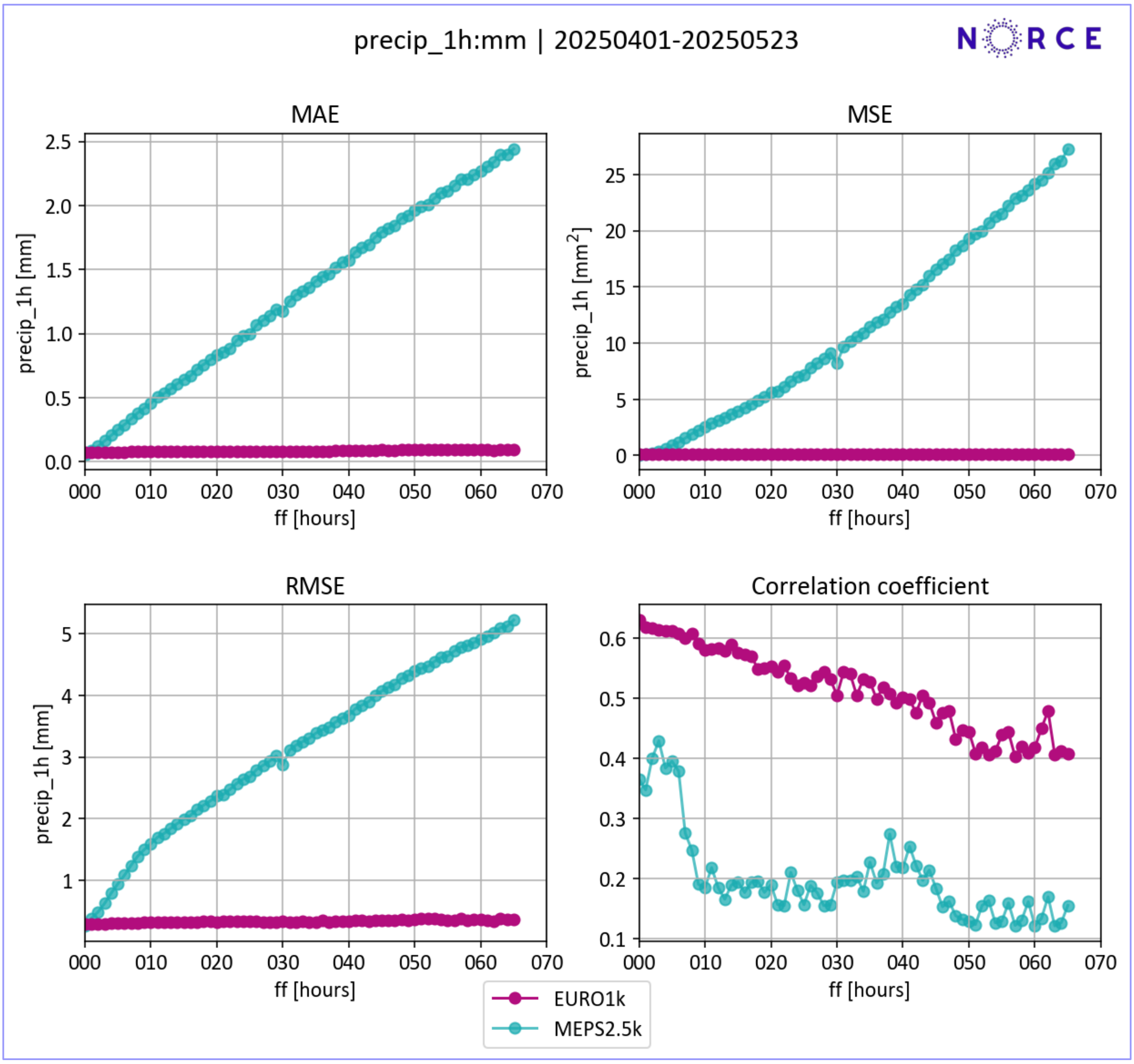


Figure 4-7 ***Comparative statistics for precipitation from the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

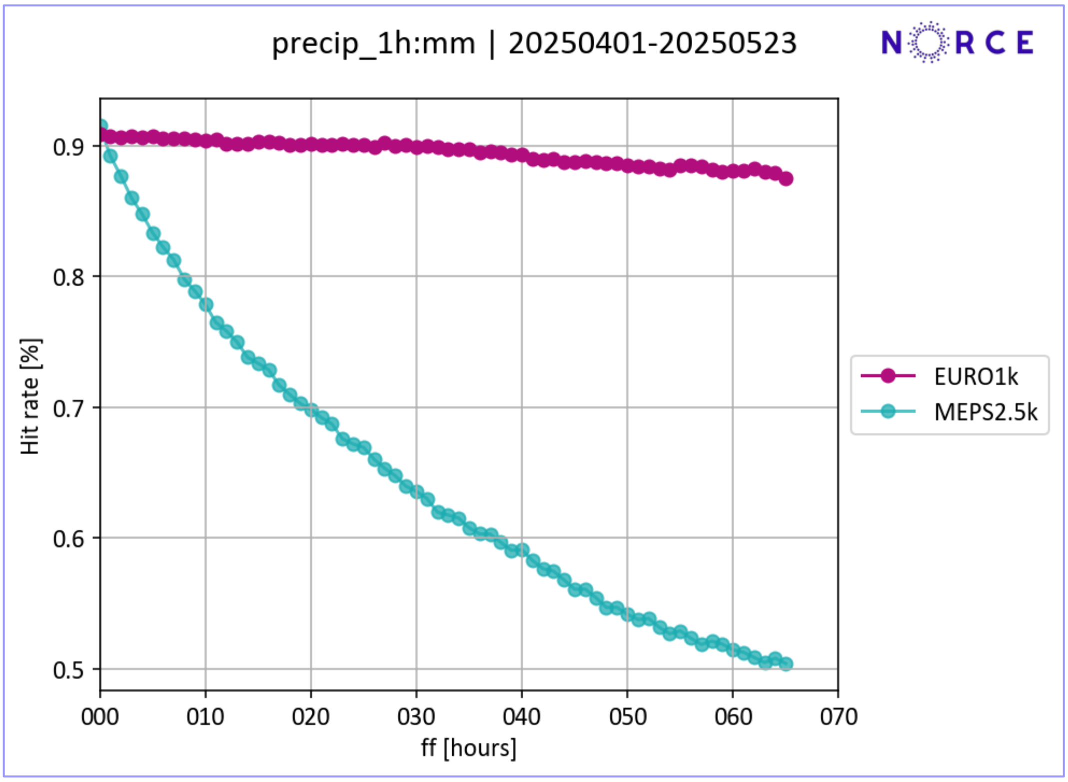


Figure 4-8 ***Precipitation hit rate for the EURO1k and MEPS 2.5 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The hit-rate is a binary evaluation of the forecast model ability to predict whether there is precipitation or not in absolute terms rather than evaluation of amount.***

4.2. Adjusted models: Calibrated EURO1k vs MEPS 1.0 km

The *calibrated EURO1*k forecast and *MEPS 1.0 km* reanalysis forecast differ from the “regular” EURO1k forecast and MEPS 2.5 km mainly by using assimilation a pool of nearby met station observations to nudge the model in the quest for making better weather predictions (consult Section 2.1 for further description of the respective forecast models). It should be reiterated that since *MEPS 1.0 km* weather data is strictly limited to near ground heights mirroring the standard height for weather measurements (i.e. 10 m wind, 2 m temperature and humidity, mean sea level pressure etc.) this product is not useful for later phases of the Gondul project, i.e. when Meteodrone data will be used to assess forecasts for the relevant drone operation altitudes. Another critical disadvantage is that the MEPS 1.0 km forecasts are issued from 4 hours ahead (ff004) to 62 hours ahead (ff062), which imply that that forecasts for the 3 first hours of, i.e. a military operation is not, are not available.

Table 4-3 shows the average amount of cases in the score matrix (N location x nn forecast times) where the calibrated EURO1k forecast or MEPS 1.0 km reanalysis for the given variable is found convincingly most accurate.

Table 4-3 ***The number of cases in the score matrix (N location x nn forecast times) where the EURO1k forecast or MEPS 1.0 km reanalysis is deemed most accurate for given variable.***

Variable	**Average case (locations, ff) success rate**	
	EURO1k	**MEPS 1.0 km**
Wind speed 10 m a.g.	65.6 %	31.1 %
Wind direction 10 m a.g.	60.3 %	37.5 %
Air temperature 2 m a.g.	76.3 %	22.4 %
Relative humidity 2 m a.g.	63.2 %	35.0 %
Air pressure at msl	81.7 %	17.9 %
Precipitation hit rate	54.1 %	44.2 %
Average	**66.9 %**	**31.3 %**

Figure 4-9 shows the number of forecast cases over N locations where the EURO1k forecast or the MEPS 1.0 km reanalysis is deemed most accurate as for given variable function of forecast time.

Figure 4-10 to **Figure 4-15** displays comparative statistics for the selected weather variables from the calibrated EURO1k and MEPS 1.0 km models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient (see Section 3.2. for description).

Figure 4-16 shows the precipitation hit rate for calibrated EURO1k and MEPS 1.0km forecast models versus observations as function of forecasting time ff across all 249 measurement locations. The hit-rate is a binary evaluation of the forecast model ability to predict whether there is precipitation or not in absolute terms rather than evaluation of amount

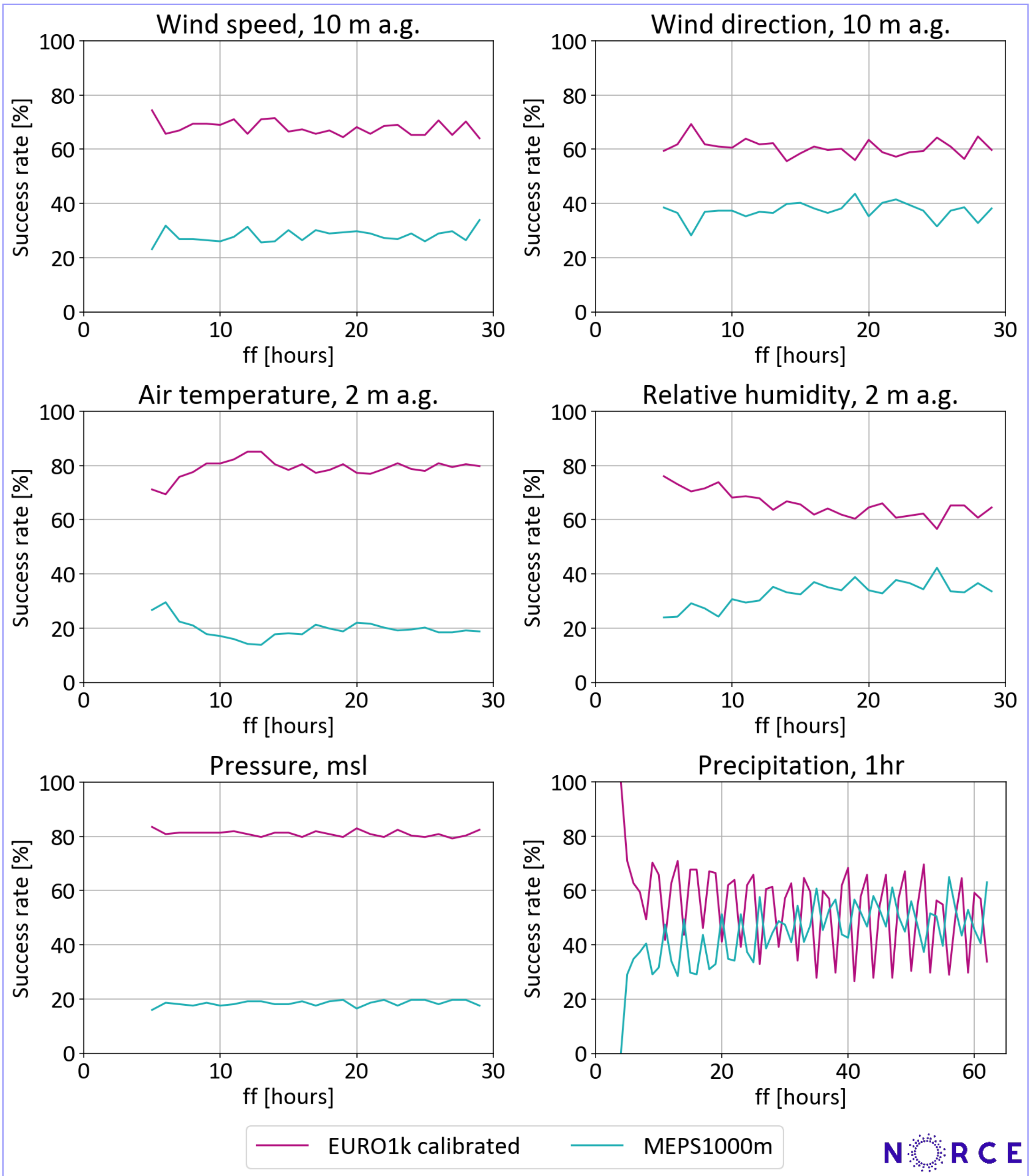


Figure 4-9 ***The number of forecast cases over N locations where the calibrated EURO1k or the MEPS 1.0 km forecast is deemed most accurate for given variable as function of forecast time ff.***

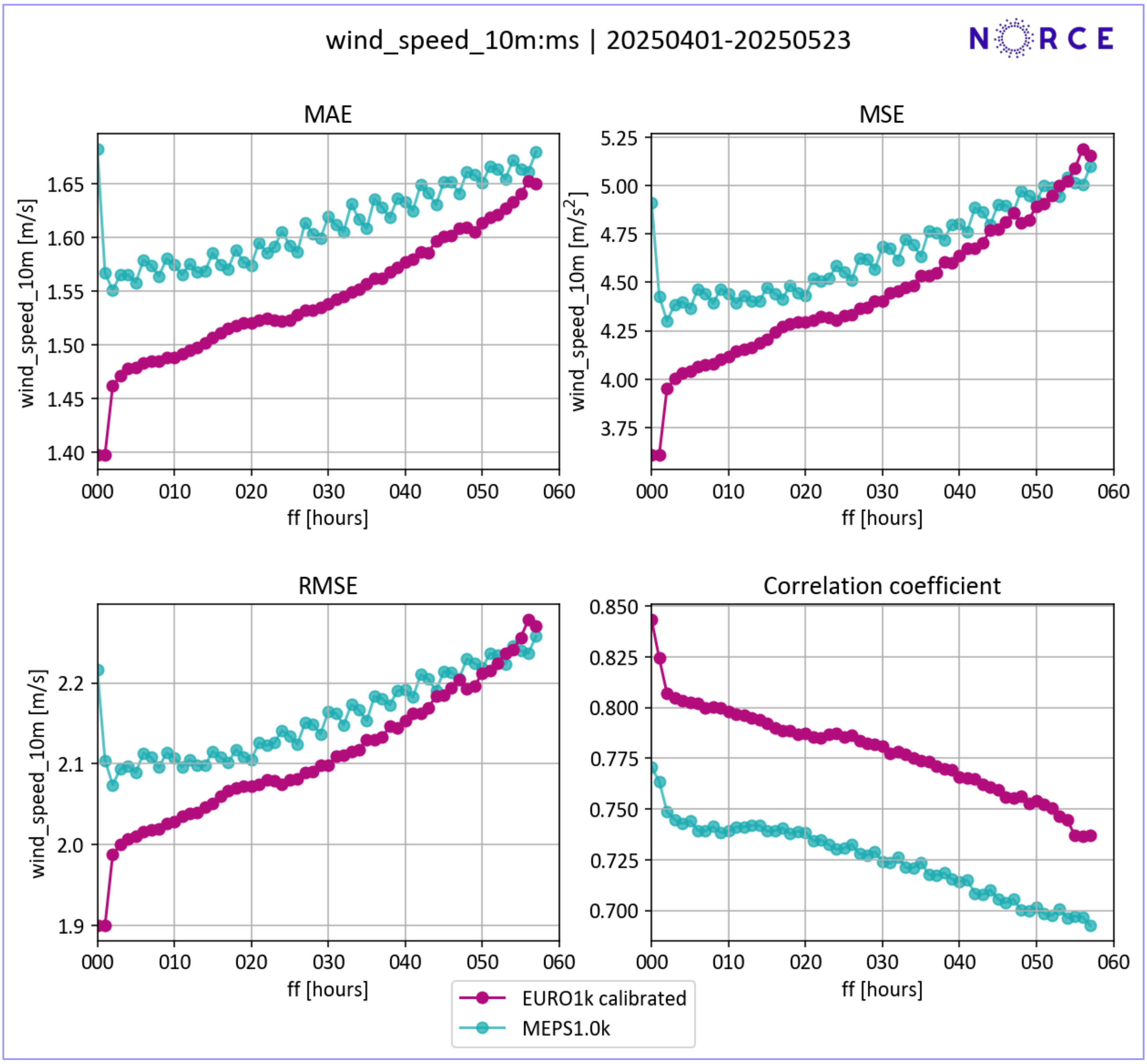


Figure 4-10 Comparative statistics for wind speed 10 m a.g. from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

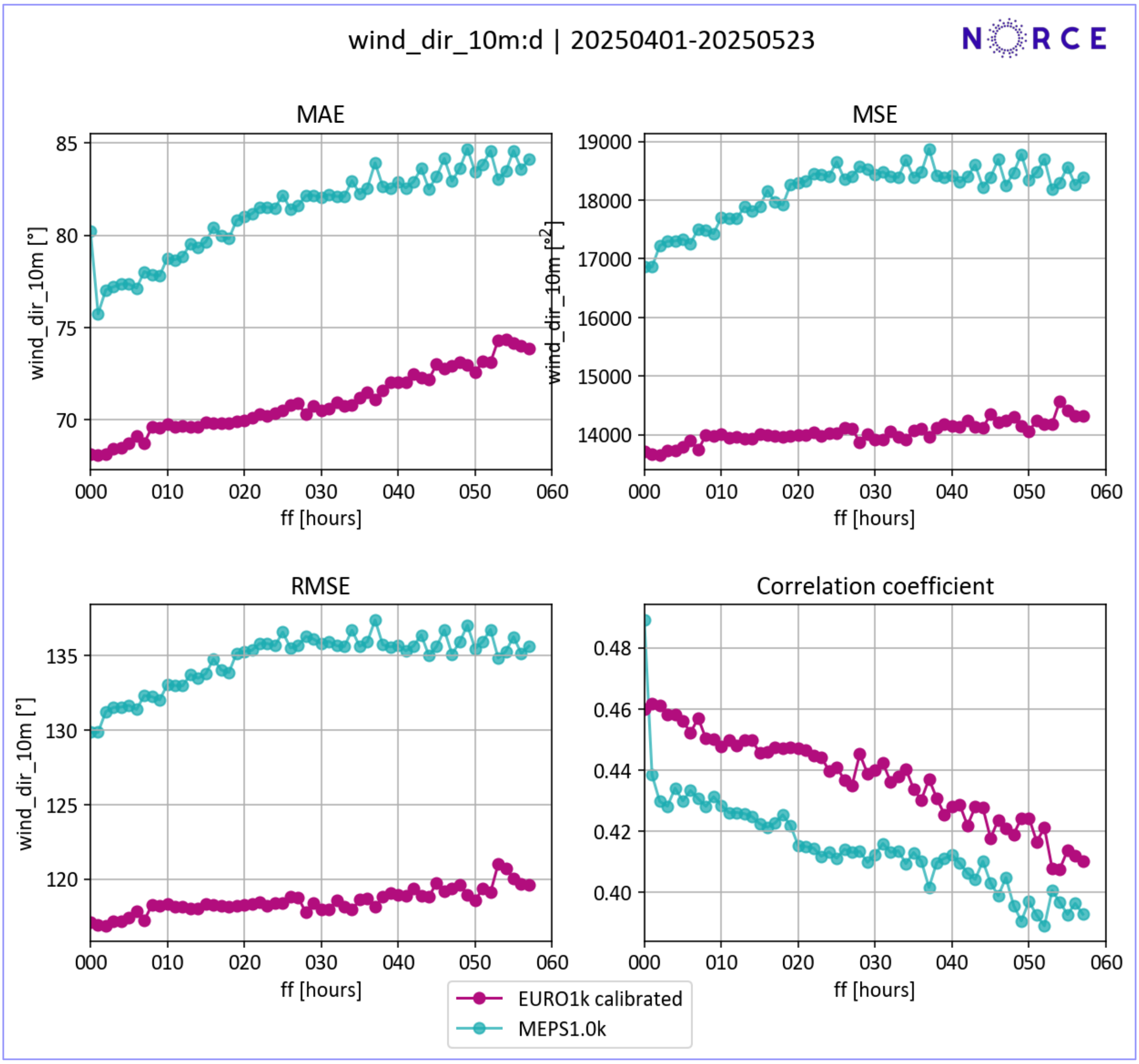


Figure 4-11 ***Comparative statistics for wind direction 10 m a.g. from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.***

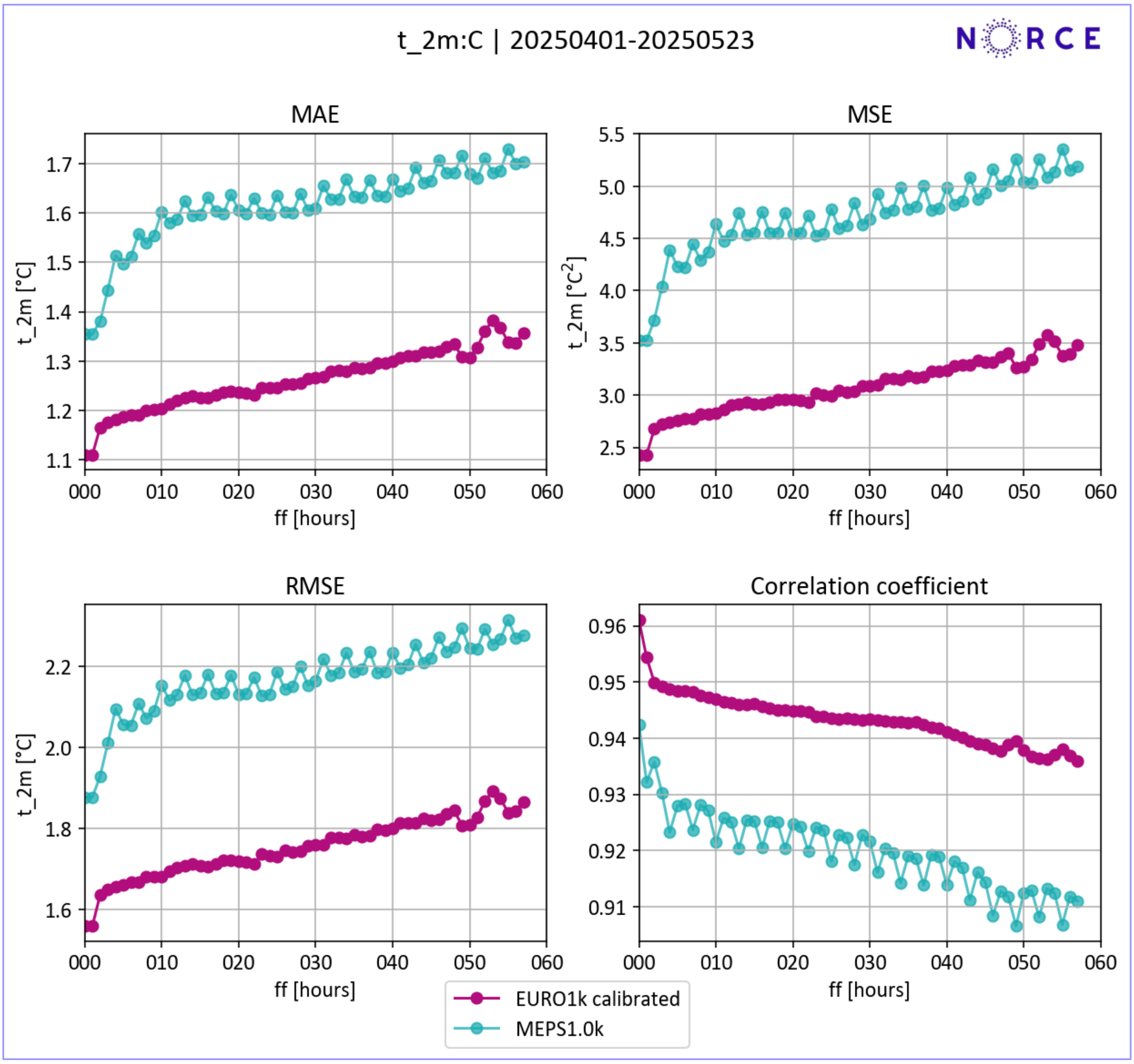


Figure 4-12 Comparative statistics for air temperature 2 m a.g. from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

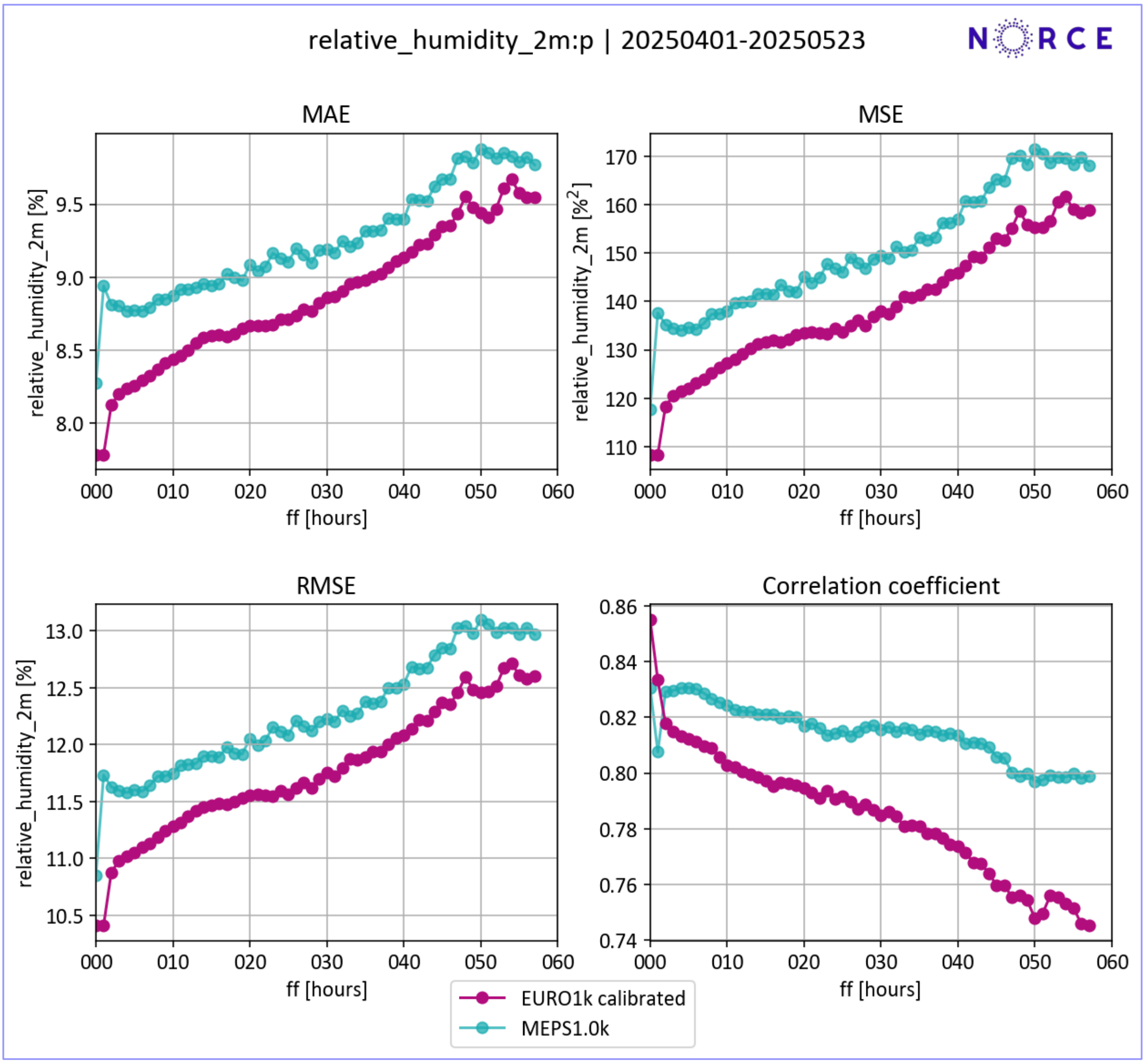


Figure 4-13 Comparative statistics for relative humidity 2 m a.g. from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

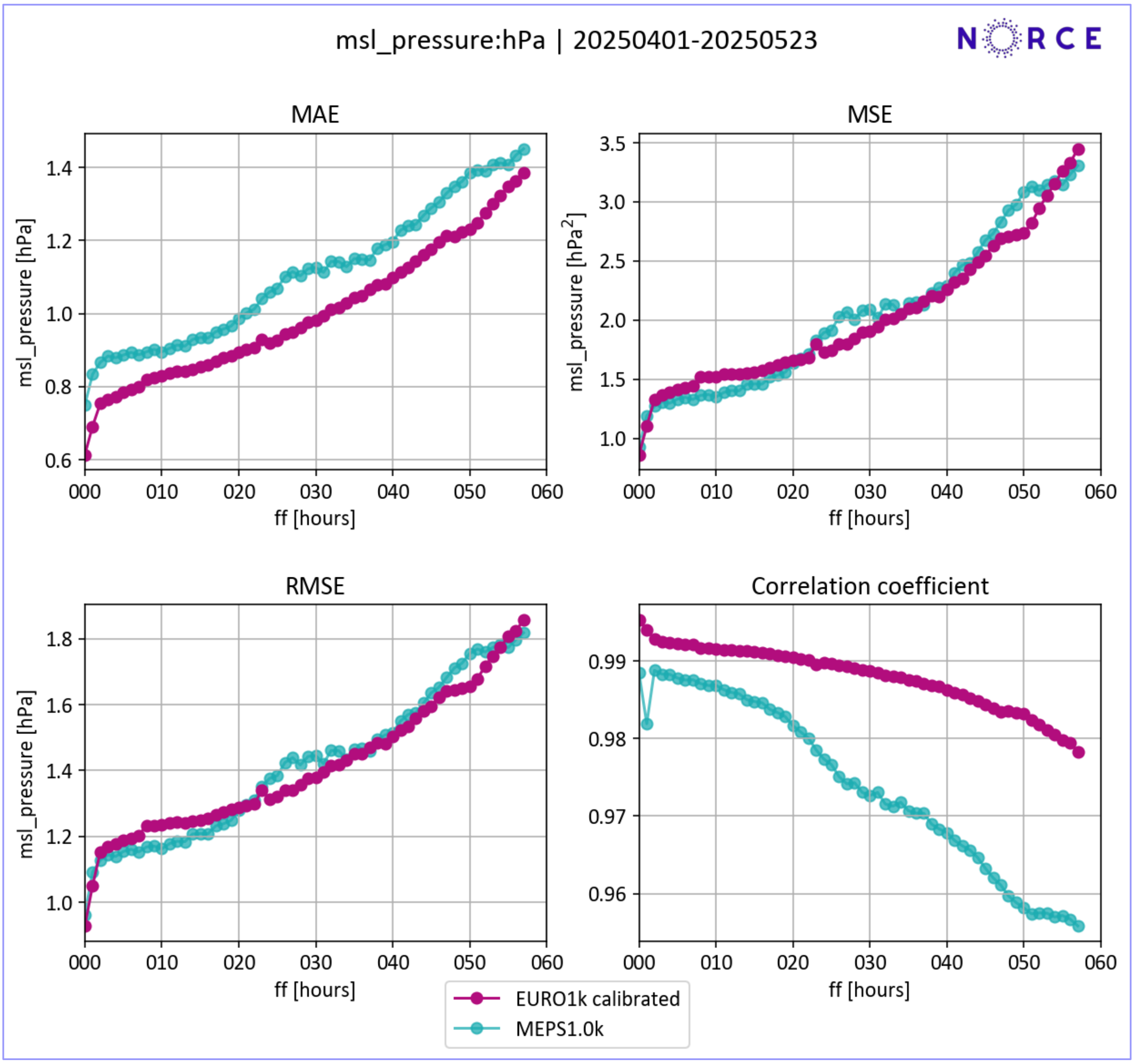


Figure 4-14 Comparative statistics for mean sea level pressure from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

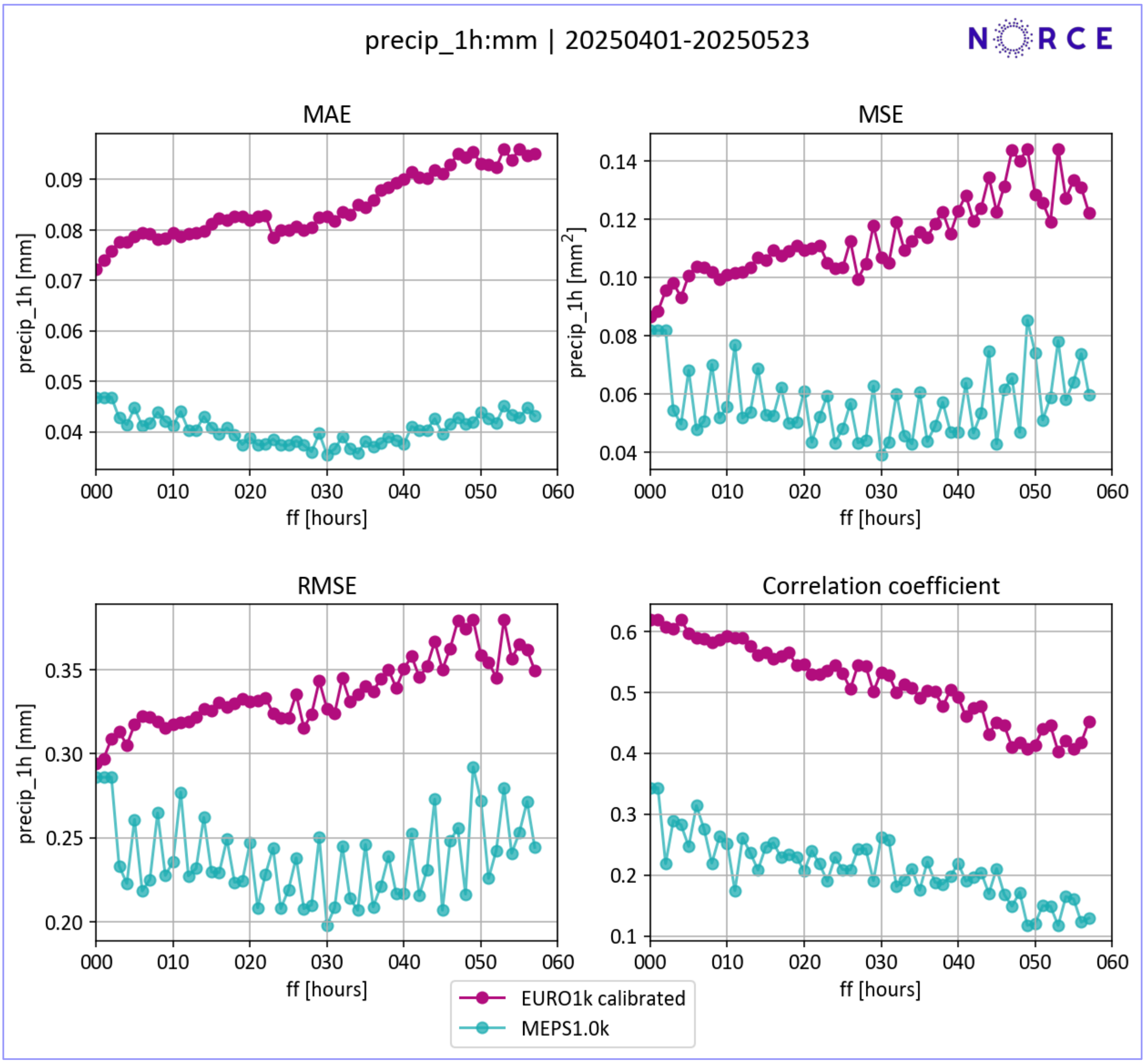


Figure 4-15 Comparative statistics for precipitation from the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The statistical estimators used are the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the Pearson correlation coefficient.

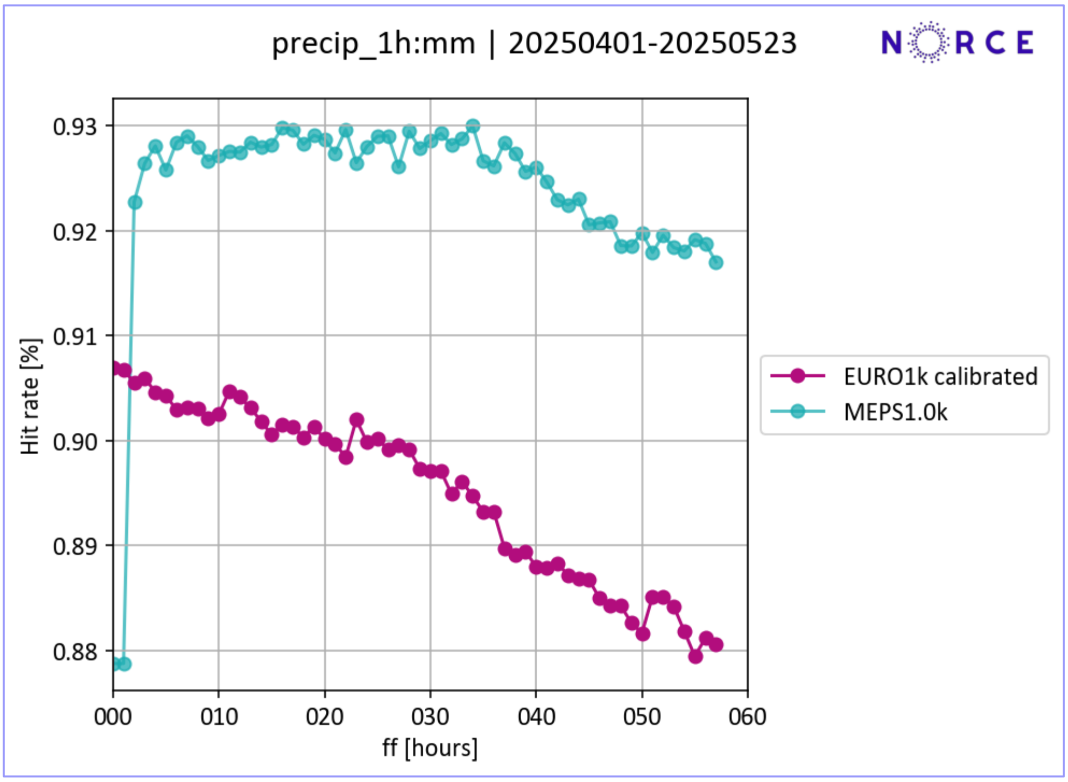


Figure 4-16 ***Precipitation hit rate for the calibrated EURO1k and MEPS 1.0 km forecast models versus observations as function of forecasting time ff across all 249 measurement locations for the period 20250401 to 20250523. The hit-rate is a binary evaluation of the forecast model ability to predict whether there is precipitation or not in absolute terms rather than evaluation of amount.***

4.3. Snow and icing conditions (pending)

More winter season forecast data is needed.

4.4. Continuous data collection and analysis

Note that the forecast data accumulation is still limited to a relatively short period in the spring of 2025 and is further restricted by the requirement of concurrent data for the datasets subject to comparative analysis. This is even more pertinent when it comes to the less frequent and seasonally contingent conditions considered adverse for drone operations, i.e. cold climate. For a more statistically robust assessment of forecast performance NORCE continues accumulation and analysis of forecast and observation data through 2025 and into the winter season of 2026.

The extended data timeseries surpassing the date of issue for this report will give a complete analysis and strengthened conclusions for:

- The specific adverse conditions – for which more winter season forecast data is needed.
- Forecast performance over longer

During this period the historical data archive will also be completed. As of time of writing the MEPS archive does not contain data for all 249 stations due to the low response time and frequent access/downtime issues on the THREDDS during March to May of 2025.

5. Conclusions

NORCE has performed a qualitative assessment and objective statistical comparison of the EURO1k forecast delivered by Meteomatics and MEPS forecast delivered by the Norwegian Meteorological Institute with observations from all 291 available official land-based weather stations. Score matrices obtained from the direct comparison which contain information on which of the two forecasts are most accurate for the control period, considering weather variables that are relevant for the Gondul project, i.e. military drone operations and planning: wind speed and direction, air temperature, relative humidity, air pressure and precipitation.

The analysis demonstrates that for both historical forecasts (ff000) ranging from 2023.01.01 to present, and accumulated forecasts (2025.03 to present) EURO1k outperforms MEPS 2.5 km on all selected weather variables. EURO1k provides, on average, more accurate predictions than MEPS 2.5 km in more than 70 % of the cases considering the selection of variables. Conversely, MEPS 2.5 km are deemed more accurate in approximately 27 % of the cases.

An assessment of the MEPS 1.0 km model is also conducted, using the *calibrated EURO1*k forecast as its antagonist. The *calibrated EURO1*k forecast and *MEPS 1.0 km* reanalysis forecast differ from the “regular” EURO1k forecast and MEPS 2.5 km mainly by using assimilation a pool of nearby met station observations to nudge the model in the quest for making better weather predictions (consult Section 2.1 for further description of the respective forecast models). There are some obvious limitations of use for the Gondul project: *MEPS 1.0 km* weather data is strictly limited to near ground heights mirroring the standard height for weather measurements (i.e. 10 m wind, 2 m temperature and humidity, mean sea level pressure etc), it’s forecasts are issued only from 4 hours ahead (ff004) of time, which imply that that forecasts for the 3 first hours of, i.e. highly relevant for military operations, are not available. Yet, their performance is tested and show that the calibrated EURO1k is, on average, provides more accurate predictions than MEPS 1.0 km ~67 % of the cases considering the selection of variables. Conversely, MEPS 2.5 km are mode accurate in ~ 31 % of the cases.

Next phase of the Gondul project will utilize weather observations collected over the vertical column by Meteodrones, towards which EURO1k and MEPS 2.5 km forecasts will be quantitatively compared and assessed on their forecasting capabilities, using the methodology developed for the analysis presented in the current report. Initiation of this work is scheduled for late spring / summer of 2025 for one test site (Andøya Air Station). The long-term ambition is to establish a network of 30 Meteodrones in Norway.

References

Byun, K., J. Yang, and T. Lee, 2008: A Snow-Ratio Equation and Its Application to Numerical Snowfall Prediction. *Wea. Forecasting*, **23**, 644–658, https://doi.org/10.1175/2007WAF2006080.1.

1. Byun, K., J. Yang, and T. Lee (2008), A Snow-Ratio Equation and Its Application to Numerical Snowfall Prediction, *Weather and Forecasting*, **23**, 644–658, URL: https://doi.org/10.1175/2007WAF2006080.1.
2. Frogner, I.-L., Singleton, A. T., Køltzow, Ø. K., and Andrae, U. (2019), Convection-permitting ensembles: Challenges related to their design and use, Quarterly Journal of the Royal Meteorological Society, Vol. 145, John Wiley & Sons Ltd.
3. Hann, Richard (2020), Atmospheric Ice Accretions, Aerodynamic Icing Penalties, and Ice Protection Systems on Unmanned Aerial Vehicles. NTNU. ISBN 978-82-326-4749-1.
4. Junker, W. (1990), Winter weather forecasting, presentation, NOAA, URL: https://www.wpc.ncep.noaa.gov/research/snow2a/snow2a.pdf
5. Meteomatics AG, EURO1k – The Fine-Scale Weather Model for Europe, URL: https://www.meteomatics.com/en/weather-model-europe/
6. Meteomatics AG, Weather API, URL: https://www.meteomatics.com/en/weather-api/
7. Meteomatics AG, Getting Started With Meteomatics Weather API, URL: https://www.meteomatics.com/en/weather-model-europe/
8. Meteomatics AG, Meteodrones Meteorological Data From the Atmospheric Boundary Layer, URL: https://www.meteomatics.com/en/Meteodrones-weather-drones/
9. Morcrette, C., K. Brown, R. Bowyer, P. Gill, and D. Suri (2019), Development and Evaluation of In-Flight Icing Index Forecast for Aviation. Wea. Forecasting, 34, 731–750, URL: https://doi.org/10.1175/WAF-D-18-0177.1
10. National Transportation Safety Board (1996), Aircraft accident report: In-flight icing encounter and loss of control, Simmons Airlines, D.B.A. American Eagle Flight 4184, PB96-91040I, NTSB/AAR-96/01, DCA95MA001.
11. Norwegian Meteorological Institute, What is Frost?, URL: https://frost.met.no/index.html
12. Norwegian Meteorological Institute, THREDDS Documentation, URL: api.met.no/product/THREDDS , https://THREDDS.met.no/THREDDS/catalog.html ,
13. Open Topo Data, Digital Elevation Model over Europe, EU-DEM, URL: https://www.opentopodata.org/datasets/eudem/
14. Pielke, Roger A. (2002). Mesoscale Meteorological Modeling. Academic Press. p. 65. ISBN 978-0-12-554766-6.
15. Wallace, J. M., and Hobbs, P. V. (1977), Atmospheric science: An introductory survey. Academic Press (San Diego), ISBM 0-12-732950-1, https://doi.org/10.1002/qj.49710444024.
16. World Meteorological Organization (WMO) (2025), Technical Regulations, Volume I – General Meteorological Standards and Recommended Practices, Basic Documents No. 2, WMO-No.49. URL: https://library.wmo.int/idurl/4/35722
17. World Meteorological Organization (WMO) (2008), Guide to Meteorological Instruments and Methods of Observation WMO-No. 8, Seventh edition URL: https://wmo.int/about-us/governance/technical-commissions/standards-and-recommended-practices

Appendix

Appendix 1 – Met station information

Appendix 2 – NMI THREDDS server operation status

Appendix 1 – Met station information

Information on the meteorological stations used in the EURO1k forecast evaluation is tabulated in **Table 0-1**. The list contains station name, station WMO number (a global ID number issued by the World Meteorological Organization), latitude and longitude, station height above sea level (asl), start time which is the time from which the station have been active and/or data are available, and type of climate.

Station height above sea level is found using Open Topo Data Digital Elevation Model over Europe, EU-DEM, with 25 m horizontal resolution [10], as shown in **Figure 0-1** . The stated vertical accuracy is ± 7m RMSE of other high resolution data sources. Open Topo Data can't interpolate elevations for locations very close to the coast and will return a value of NaN as can be seen for lighthouses ("Fyr" in Norwegian) and other seaside stations in **Table 0-1**.

To categorize the climate to which the stations pertain we use the differentiate between coastal "C", exposed coastal "Ce", inland "I", mountain "M" and fjord "F", the latter typically being inland mountainous regions connected to the sea via fjord systems.

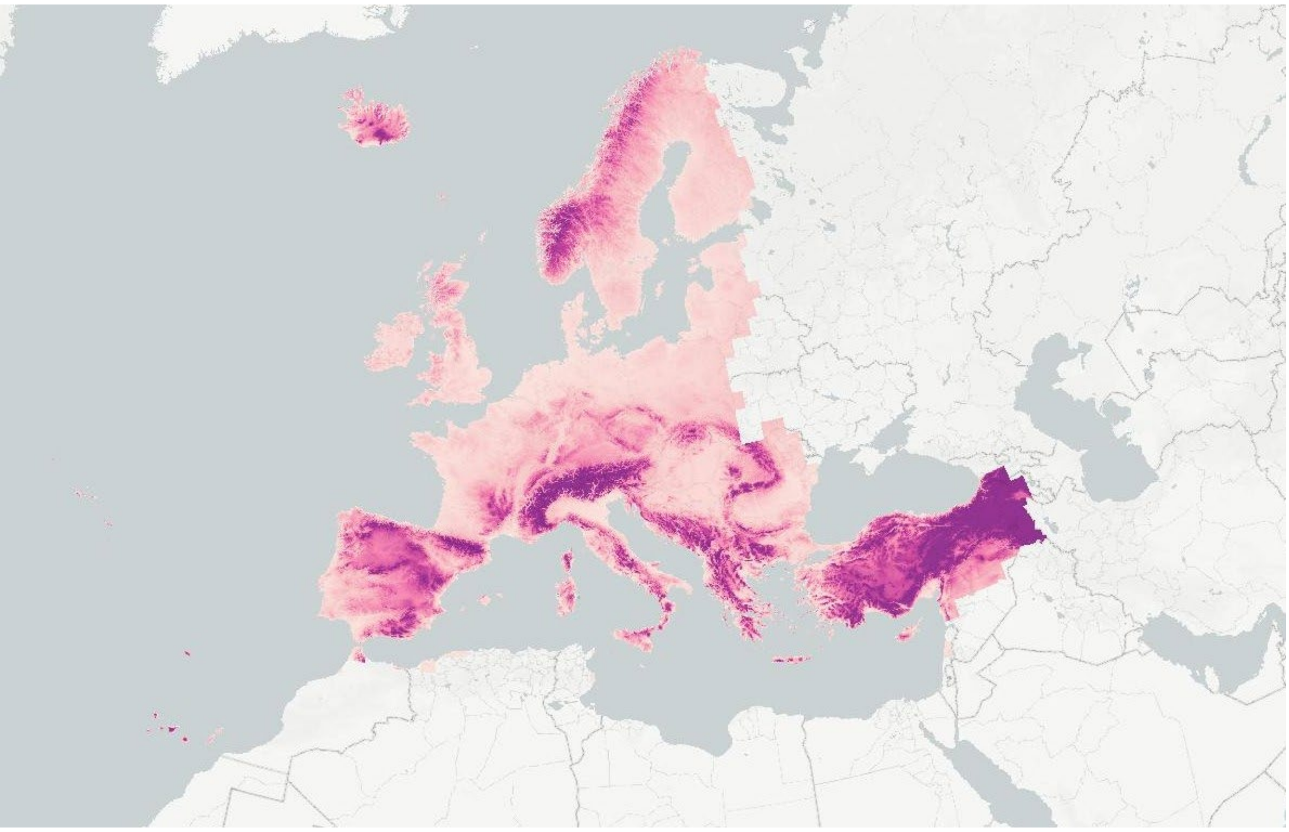


Figure 0-1 ***Render of elevation data from the Digital Elevation Model over Europe, EU-DEM, with 25 m horizontal resolution.***

Table 0-1 Information on the meteorological stations used in the EURO1k forecast evaluation.

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Filefjell	13640	61.1778	8.1125	958	2016-12-31T21:00:00Z	M
Namsos Høknesøra Airport	12900	64.4722	11.5786	2	2017-01-01T00:00:00Z	C
Midtstova	13460	60.6569	7.2769	1178	2017-01-01T00:00:00Z	M
Sula	12280	63.8500	8.4667	1	2017-01-01T00:00:00Z	C
Torungen Fyr	14650	58.4000	8.8000	NaN	2016-12-31T21:00:00Z	Ce
Røst Airport	11070	67.5278	12.1033	1	2016-12-31T21:00:00Z	Ce
Blasjo	14400	59.3428	6.8733	1101	2017-01-01T22:00:00Z	M
Storforshei	11480	66.3961	14.5306	105	2016-12-31T21:00:00Z	I
Andøya Airport	10100	69.2925	16.1442	5	2017-01-01T00:00:00Z	Ce
Rover	14140	59.4381	5.0781	21	2017-01-01T00:00:00Z	Ce
Aalesund	12240	62.4703	6.2106	17	2016-12-31T21:00:00Z	C
Sandhaug	13520	60.1839	7.4814	1250	2017-01-01T00:00:00Z	M
Eik Hove	14250	58.5006	6.5006	74	2016-12-31T21:00:00Z	I
Fjaerland-Bremuseet	13320	61.4333	6.7667	7	2016-12-31T21:00:00Z	F
Konnerud	14770	59.7128	10.1458	200	2016-12-31T21:00:00Z	I
Hovden-Lundane	14410	59.5833	7.3833	867	2016-12-31T21:00:00Z	M
Sørkjosen Airport	10460	69.7868	20.9594	0	2016-12-31T21:00:00Z	C
Selbu	12730	63.2333	11.0167	156	2016-12-31T21:00:00Z	I
Orkdal-Thamshamn	12340	63.3167	9.8500	NaN	2016-12-31T21:00:00Z	C
Klevavatnet	13450	60.7192	7.2086	999	2016-12-31T21:00:00Z	M
Roros	12880	62.5667	11.3833	623	2016-12-31T21:00:00Z	I
Evanger	13150	60.6469	6.1106	9	2016-12-31T21:00:00Z	I
Alta Airport	10490	69.9761	23.3717	3	2016-12-31T21:00:00Z	C
Apelsvoll	13810	60.7003	10.8683	271	2016-12-31T21:00:00Z	I
Hjartasen	11500	66.4992	14.9539	252	2016-12-31T21:00:00Z	I
Sauda	14240	59.6500	6.3667	16	2017-01-01T00:00:00Z	F
Kristiansand Airport	14520	58.2042	8.0854	13	2016-12-31T21:00:00Z	C
Mosjøen Airport (Kjærstad)	11220	65.7840	13.2149	49	2016-12-31T21:00:00Z	C
Laerdal-IV	13550	61.1000	7.5000	8	2016-12-31T21:00:00Z	F
Kristiansund Airport (Kvernberget)	12230	63.1118	7.8245	54	2017-01-01T00:00:00Z	C
Bardufoss Airport	10230	69.0558	18.5404	66	2016-12-31T21:00:00Z	I

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Bjornholt	14890	60.0514	10.6878	355	2017-01-01T00:00:00Z	I
Geilo-Oldebraten	13590	60.5333	8.2000	794	2016-12-31T21:00:00Z	M
Flisa II	13920	60.6167	12.0167	187	2016-12-31T21:00:00Z	I
Rekdal	12140	62.6511	6.7550	27	2017-01-01T00:00:00Z	C
Veggli II	14710	60.0500	9.1500	261	2016-12-31T21:00:00Z	I
Haugesund Airport	14080	59.3453	5.2084	21	2017-01-01T22:00:00Z	Ce
Byglandsfjord	14420	58.6667	7.8000	203	2016-12-31T21:00:00Z	I
Harstad	11800	68.8000	16.5333	60	2016-12-31T21:00:00Z	C
Solendet	12870	62.6833	11.8167	772	2016-12-31T21:00:00Z	I
Solvaer III	11210	66.3667	12.6167	0	2017-01-01T00:00:00Z	C
Venabu	13800	61.6500	10.1167	918	2016-12-31T21:00:00Z	M
Vaagsli	14340	59.7667	7.3667	825	2016-12-31T21:00:00Z	M
Bjorli	12300	62.2581	8.1997	569	2016-12-31T21:00:00Z	I
Tagdalen	12210	63.0500	9.0833	398	2016-12-31T21:00:00Z	I
Innerdalen	12270	62.7219	8.7753	411	2016-12-31T21:00:00Z	F
Fedje	13070	60.7500	4.7167	NaN	2017-01-01T00:00:00Z	Ce
Drevsjo	13930	61.8833	12.0500	665	2016-12-31T21:00:00Z	I
Ørsta-Volda Airport, Hovden	12090	62.1800	6.0741	80	2017-01-03T12:00:00Z	C
Kongsvinger	14680	60.1833	12.0000	191	2016-12-31T21:00:00Z	I
Myken	11150	66.7667	12.4833	1	2016-12-31T21:00:00Z	Ce
Asker	14860	59.8500	10.4333	132	2016-12-31T21:00:00Z	I
Fokstugu	12380	62.1167	9.2833	962	2016-12-31T21:00:00Z	M
Berlevåg Airport	10830	70.8714	29.0342	7	2017-01-01T00:00:00Z	Ce
Kirkenes Airport (Høybuktmoen)	10890	69.7258	29.8913	86	2017-01-01T00:00:00Z	C
Kjeller Airport	14660	59.9693	11.0361	106	2017-01-01T00:00:00Z	I
Kvitsoy-Nordbo	14110	59.0667	5.4167	7	2017-01-01T00:00:00Z	Ce
Pasvik	10840	69.4553	30.0411	32	2016-12-31T21:00:00Z	I
Bergen Airport Flesland	13110	60.2934	5.2181	40	2017-01-01T00:00:00Z	C
Majavatn V	11320	65.1661	13.3667	350	2016-12-31T21:00:00Z	I
Saerheim	14130	58.7606	5.6506	90	2016-12-31T21:00:00Z	C
Roldalsfjellet	14290	59.8314	6.7331	999	2016-12-31T21:00:00Z	M
Honefoss-Hoyby	14690	60.1667	10.2500	123	2016-12-31T21:00:00Z	I

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Aurskog	14840	59.9119	11.5800	131	2016-12-31T21:00:00Z	I
Slatteroy Fyr	14060	59.9167	5.0667	nan	2017-01-01T00:00:00Z	Ce
Laudal-Kleiven	14390	58.2758	7.4420	284	2016-12-31T21:00:00Z	I
Ferder Fyr	14820	59.0333	10.5333	nan	2017-01-01T00:00:00Z	Ce
Rena Ap	13890	61.1858	11.3706	254	2016-12-31T21:00:00Z	I
Gvarv	14700	59.3833	9.2000	73	2017-12-17T20:00:00Z	I
Skabu-Storslaen	13700	61.5167	9.3833	890	2016-12-31T21:00:00Z	M
Soknedal	12530	62.9533	10.1786	294	2016-12-31T21:00:00Z	I
Buholmrasa Fyr	12590	64.4000	10.4500	NaN	2017-01-04T16:00:00Z	I
Sarpsborg	14930	59.2833	11.1167	54	2016-12-31T21:00:00Z	I
Porsgrunn	14620	59.0872	9.6600	94	2016-12-31T21:00:00Z	I
Drag-Ajluokta	11430	68.0500	16.0833	NaN	2016-12-31T21:00:00Z	C
Bodø Airport	11520	67.2692	14.3653	15	2016-12-31T21:00:00Z	C
Mosstrand II	14500	59.8333	8.1833	943	2016-12-31T21:00:00Z	M
Sande-Galleberg	14850	59.6194	10.2150	61	2016-12-31T21:00:00Z	I
Brata	13600	61.9000	7.8667	565	2016-12-31T21:00:00Z	M
Kjobli i Snasa	11240	64.1667	12.4667	494	2016-12-31T21:00:00Z	I
Hekkingen Fyr	10150	69.6000	17.8333	6	2017-01-01T00:00:00Z	Ce
Lyngor Fyr	14670	58.6333	9.1500	NaN	2017-01-01T00:00:00Z	C
Liarvatn	14190	59.0508	6.1211	295	2016-12-31T21:00:00Z	I
Furuneset	13080	61.2928	5.0444	4	2016-12-31T21:00:00Z	C
Varntresk	11470	65.8264	14.1847	403	2016-12-31T21:00:00Z	I
Melsom	14810	59.2333	10.3500	38	2016-12-31T21:00:00Z	C
Grønneviksøren (Haukeland Sykehus) Heliport	13170	60.3799	5.3460	14	2016-12-31T21:00:00Z	C
Trondheim Airport Værnes	12710	63.4578	10.9240	5	2016-12-31T21:00:00Z	C
Harstad/Narvik Airport, Evenes	11830	68.4913	16.6781	20	2017-01-01T00:00:00Z	C
Sognefjell	13660	61.5667	8.0000	1447	2017-01-03T21:00:00Z	M
Finsevatn	13500	60.6000	7.5333	1300	2016-12-31T21:00:00Z	M
Svinoy Fyr	12050	62.3333	5.2667	NaN	2017-01-01T00:00:00Z	Ce
Ålesund Airport	12100	62.5625	6.1197	15	2017-01-01T00:00:00Z	Ce
Veiholmen	12250	63.5167	7.9500	NaN	2017-01-01T00:00:00Z	Ce
Nordstraum I Kvaenangen	10450	69.8333	21.8833	NaN	2016-12-31T21:00:00Z	C

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Mannen	12200	62.4556	7.7703	1253	2016-12-31T21:00:00Z	M
Sogndal Airport	13470	61.1561	7.1378	498	2017-01-01T00:00:00Z	F
Fruholmen Fyr	10550	71.1000	24.0000	NaN	2017-01-01T00:00:00Z	C
Kvamsoy	13290	60.3500	6.2667	NaN	2016-12-31T21:00:00Z	F
Mehamn Airport	10740	71.0297	27.8267	6	2017-01-01T00:00:00Z	C
Stafsberg Airport	13850	60.8181	11.0680	224	2016-12-31T21:00:00Z	I
Karasjok	10650	69.4667	25.5167	122	2016-12-31T21:00:00Z	I
Vossevangen	13370	60.6333	6.4333	62	2016-12-31T21:00:00Z	I
Tynset II	12650	62.2667	10.7667	495	2016-12-31T21:00:00Z	I
Makkaur Fyr	10920	70.7000	30.0833	27	2017-01-01T00:00:00Z	Ce
Hasvik Airport	10440	70.4867	22.1397	12	2017-01-01T00:00:00Z	C
Dagali Ap	13630	60.4188	8.5263	793	2017-01-01T00:00:00Z	M
Mjolfjell	13440	60.7019	6.9372	682	2016-12-31T21:00:00Z	M
Båtsfjord Airport	10860	70.6005	29.6914	143	2017-01-01T00:00:00Z	C
Sandefjord Airport, Torp	14830	59.1867	10.2586	85	2019-04-10T14:00:00Z	C
Tromsø Airport	10250	69.6833	18.9189	6	2016-12-31T21:00:00Z	C
Nyrud	10820	69.1469	29.2439	49	2016-12-31T21:00:00Z	I
Kotsoy	12540	62.9761	10.5606	126	2016-12-31T21:00:00Z	I
Oslo-Blindern	14920	59.9500	10.7167	130	2016-12-31T21:00:00Z	I
Setsa	11580	67.1656	15.4856	1	2016-12-31T21:00:00Z	C
Hjerkinn Ii	12390	62.2206	9.5422	1026	2016-12-31T21:00:00Z	M
Somna-Kvaloyfjellet	11360	65.2200	11.9928	279	2017-01-01T00:00:00Z	C
Hammerfest Airport	10520	70.6797	23.6686	79	2016-12-31T21:00:00Z	C
Nordoyan Fyr	12620	64.8000	10.5500	1	2017-01-01T00:00:00Z	Ce
Sihcajavri	11990	68.7500	23.5333	381	2016-12-31T21:00:00Z	I
Vardo	10980	70.3667	31.1000	1	2016-12-31T21:00:00Z	C
Fet I Eidfjord	13400	60.4167	7.2833	807	2016-12-31T21:00:00Z	F
Sandnessjøen Airport (Stokka)	11160	65.9568	12.4689	9	2017-01-01T00:00:00Z	C
Cuovddatmohkki	10570	69.3667	24.4333	286	2016-12-31T21:00:00Z	I
Tromso-Holt	10270	69.6522	18.9056	4	2016-12-31T21:00:00Z	C
As	14630	59.6606	10.7819	94	2016-12-31T21:00:00Z	I
Beitostolen Ii	13650	61.2506	8.9228	952	2016-12-31T21:00:00Z	M

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Lyngen Gjerdvassbu	10350	69.5589	20.0939	708	2017-01-01T00:00:00Z	M
Utsira Fyr	14030	59.3000	4.8833	25	2016-12-31T21:00:00Z	Ce
Krakenes	12030	62.0333	4.9833	NaN	2017-01-01T00:00:00Z	Ce
Grotli Iii	13610	62.0161	7.6636	876	2016-12-31T21:00:00Z	M
Gjerstad	14490	58.8700	9.0264	31	2016-12-31T21:00:00Z	I
Reipa	11140	66.9033	13.6458	5	2016-12-31T21:00:00Z	C
Oslo / Fornebu	14880	59.9000	10.6333	0	2017-01-02T09:00:00Z	C
Loken I Volbu	13710	61.1219	9.0631	539	2016-12-31T21:00:00Z	I
Banak Airport	10590	70.0688	24.9735	7	2017-01-01T00:00:00Z	C
Bulken	13360	60.6456	6.2219	331	2016-12-31T21:00:00Z	C
Fagernes	13670	60.9833	9.2333	351	2017-01-01T01:00:00Z	I
Fossmark	13140	60.5206	5.7247	46	2016-12-31T21:00:00Z	F
Stokmarknes Skagen Airport	11620	68.5788	15.0334	1	2017-01-01T00:00:00Z	C
Nesbyen-Todokk	13730	60.5667	9.1333	152	2016-12-31T21:00:00Z	I
Saltdal-Nordnes	11690	66.9372	15.3156	50	2016-12-31T21:00:00Z	I
Hemsedal Ii	13580	60.8547	8.5931	611	2017-01-01T00:00:00Z	M
Andoya-Trolltinden	10180	69.2414	16.0031	412	2017-01-01T00:00:00Z	Ce
Slettnes Lh	10780	71.0888	28.2170	9	2016-12-31T21:00:00Z	Ce
Værøy Heliport	11390	67.6546	12.7273	0	2017-01-01T00:00:00Z	Ce
Suolovuopmi Lulit	10580	69.5667	23.5333	403	2016-12-31T21:00:00Z	I
Torsvag Fyr	10330	70.2500	19.5000	NaN	2017-01-01T00:00:00Z	Ce
Lebergsfjellet	12290	62.5158	6.8717	610	2017-01-01T00:00:00Z	M
Oppdal-Bjorke	12450	62.6000	9.6833	579	2016-12-31T21:00:00Z	M
Moss Airport, Rygge	14940	59.3788	10.7854	48	2016-12-31T21:00:00Z	C
Juvvasshoe	13620	61.6778	8.3728	1881	2017-01-01T00:00:00Z	M
Gulsvik Ii	13760	60.3828	9.6050	152	2017-01-01T00:00:00Z	I
Straumsnes	11920	68.4319	17.6622	207	2016-12-31T21:00:00Z	C
Gullholmen	14600	59.4353	10.5781	7	2017-01-01T00:00:00Z	C
Svenner Lh	14780	58.9686	10.1478	NaN	2017-01-01T00:00:00Z	C
Marstein	12320	62.4450	7.8481	209	2016-12-31T21:00:00Z	F
Hoydalsmo II	14470	59.5000	8.2000	584	2016-12-31T21:00:00Z	I
Vardo Ap	10990	70.3544	31.0439	8	2017-01-01T00:00:00Z	C

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Afjord II	12420	63.9667	10.2167	17	2016-12-31T21:00:00Z	C
Lillehammer	13780	61.1000	10.4667	150	2016-12-31T21:00:00Z	I
Rotvaer	11050	68.3667	15.9500	NaN	2017-01-01T00:00:00Z	Ce
Florø Airport	13100	61.5836	5.0247	1	2017-01-01T00:00:00Z	C
Gaustatoppen	14610	59.8497	8.6561	1796	2017-01-01T00:00:00Z	M
Hasvik-Sluskfjellet	10420	70.6069	22.4428	404	2017-01-23T13:00:00Z	MC
Molde Airport	12170	62.7447	7.2625	3	2017-01-01T00:00:00Z	C
Folldal-Fredheim	12500	62.1281	9.9947	699	2017-01-01T00:00:00Z	I
Fagernes Airport, Leirin	13680	61.0156	9.2881	819	2017-01-01T00:00:00Z	I
Meraker-Egge	12930	63.4167	11.7333	116	2016-12-31T21:00:00Z	I
Haukelisaeter	14350	59.8167	7.2167	1041	2016-12-31T21:00:00Z	M
Ullensvang	13420	60.3186	6.6539	11	2016-12-31T21:00:00Z	F
Halten Fyr	12400	64.1667	9.4000	NaN	2017-01-01T00:00:00Z	Ce
Nelaug	14590	58.6500	8.6333	188	2017-01-01T06:00:00Z	I
Evenstad-Dih	13830	61.4253	11.0803	260	2017-01-01T00:00:00Z	I
Fister_Sigmundstad	14220	59.1667	6.0333	NaN	2016-12-31T21:00:00Z	C
Seljelia	11350	66.1317	13.5867	94	2016-12-31T21:00:00Z	I
Stryn	13210	61.9000	6.5500	610	2016-12-31T21:00:00Z	F
Iskoras Ii	10640	69.3000	25.3464	591	2017-01-01T00:00:00Z	I
Svolvær Helle Airport	11610	68.2433	14.6692	2	2017-01-01T00:00:00Z	C
Leknes Airport	11410	68.1525	13.6094	20	2017-01-01T00:00:00Z	C
Tveitsund	14550	59.0333	8.5167	276	2016-12-31T21:00:00Z	I
Valle	14440	59.2017	7.5328	304	2016-12-31T21:00:00Z	I
Losistua	10910	68.1906	17.7892	729	2017-01-01T00:00:00Z	M
Drammen Berstad	14800	59.7500	10.1333	8	2016-12-31T21:00:00Z	I
Stromtangen Fyr	14950	59.1500	10.8333	NaN	2017-01-01T00:00:00Z	C
Oksoy Fyr	14480	58.0667	8.0500	NaN	2017-01-01T00:00:00Z	C
Kvamskogen-Jonshogdi	13270	60.3833	5.9667	446	2016-12-31T21:00:00Z	I
Obrestad	14120	58.6500	5.5667	NaN	2016-12-31T21:00:00Z	Ce
Landvik	14640	58.3400	8.5225	10	2016-12-31T21:00:00Z	C
Takle	13190	61.0333	5.3833	NaN	2016-12-31T21:00:00Z	C
Nedre Vats	14170	59.4833	5.7500	51	2016-12-31T21:00:00Z	I

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Dividalen Ii	11980	68.7817	19.7017	202	2016-12-31T21:00:00Z	I
Skamdal	11460	66.2347	13.8967	6	2016-12-31T21:00:00Z	I
Mandal Iii	14300	58.0244	7.4517	3	2016-12-31T21:00:00Z	C
Helligvaer II	11440	67.4000	13.9000	17	2017-01-01T00:00:00Z	Ce
Hynnekleiv	14530	58.6006	8.4161	165	2016-12-31T21:00:00Z	I
Vest-Torpa II	13740	60.9333	10.0333	529	2016-12-31T21:00:00Z	I
Stavanger Airport Sola	14150	58.8767	5.6378	6	2016-12-31T21:00:00Z	C
Skrova Fyr	11600	68.1500	14.6500	NaN	2017-01-01T00:00:00Z	Ce
Tanabru	10760	70.2122	28.1586	21	2016-12-31T21:00:00Z	I
Vega-Vallsjo	11080	65.7000	11.8500	14	2017-01-01T00:00:00Z	Ce
Laksfors	11330	65.6214	13.2892	33	2016-12-31T21:00:00Z	I
Stavanger Vaaland	14160	58.9500	5.7333	32	2016-12-31T21:00:00Z	C
Hitra	12370	63.5192	9.1125	1	2016-12-31T21:00:00Z	C
Jomfruland Fyr	14760	58.8500	9.5500	NaN	2017-01-01T00:00:00Z	C
Frosta	12720	63.5656	10.6939	29	2016-12-31T21:00:00Z	C
Rognsundet	10430	70.4103	22.8194	4	2017-01-01T00:00:00Z	C
Austevoll	14180	60.0167	5.2058	34	2016-12-31T21:00:00Z	C
Sklinna Fyr	11020	65.2000	11.0000	NaN	2017-01-01T00:00:00Z	Ce
Gartland	12910	64.5308	12.3836	95	2016-12-31T21:00:00Z	I
Brønnøysund Airport	11120	65.4611	12.2175	1	2017-01-01T00:00:00Z	C
Ørland Airport	12410	63.6989	9.6040	8	2016-12-31T21:00:00Z	C
Lista Lh	14270	58.1097	6.5681	6	2016-12-31T21:00:00Z	C
Vadsø Airport	10880	70.0653	29.8447	23	2017-01-01T00:00:00Z	C
Mo i Rana Airport, Røssvoll	11510	66.3639	14.3014	66	2017-01-01T00:00:00Z	I
Modalen Iii	13260	60.8561	5.9731	106	2016-12-31T21:00:00Z	I
Sandane Airport (Anda)	13200	61.8300	6.1058	68	2017-01-01T00:00:00Z	F
Kongsberg/Brannstasjon	14730	59.6167	9.6333	170	2016-12-31T21:00:00Z	I
Namsskogan	12810	64.7419	12.8458	151	2016-12-31T21:00:00Z	I
Valan Airport	10680	71.0097	25.9836	5	2017-01-03T10:00:00Z	C
Eigeroya	14260	58.4353	5.8717	32	2017-01-01T00:00:00Z	Ce
Vangsnes	13380	61.1667	6.6500	90	2016-12-31T21:00:00Z	F
Hollekolten	13570	60.8706	8.5175	785	2017-01-01T00:00:00Z	I

Station name	WMO number	Lat [°N]	Lon [°E]	Height [m] asl	Start time	Climate type
Rørvik Airport, Ryum	12820	64.8383	11.1461	15	2017-01-01T00:00:00Z	C
Kvithamar	12700	63.4881	10.8794	33	2016-12-31T21:00:00Z	C
Tafjord	12180	62.2333	7.4167	0	2016-12-31T21:00:00Z	F
Skibotn 2	10370	69.3833	20.2667	4	2016-12-31T21:00:00Z	F
Tryvasshogda	14900	59.9833	10.6833	469	2017-01-01T00:00:00Z	I
Kise	13820	60.7733	10.8056	130	2016-12-31T21:00:00Z	I
Bo I Vesteralen	11560	68.6000	14.4333	NaN	2016-12-31T21:00:00Z	C
Kistefjell	10300	69.2897	18.1289	978	2017-01-01T00:00:00Z	M
Ona II	12120	62.8667	6.5333	NaN	2016-12-31T21:00:00Z	Ce
Tromsö	10260	69.6500	18.9333	84	2016-12-31T21:00:00Z	C
Hamar II	13860	60.8000	11.1000	140	2016-12-31T21:00:00Z	I
Ytteroyane Fyr	13040	61.5667	4.6833	NaN	2017-01-01T00:00:00Z	Ce
Favang	13870	61.4550	10.1856	181	2016-12-31T21:00:00Z	I
Dombaas	12330	62.0833	9.1167	593	2016-12-31T21:00:00Z	M
Lindesnes Fyr	14360	57.9833	7.0500	10	2016-12-31T21:00:00Z	C
Kvitfjell	13750	61.4647	10.1275	1006	2017-01-01T00:00:00Z	M
Trondheim/Voll	12570	63.4167	10.4500	99	2016-12-31T21:00:00Z	C
Sirdal-Haugen	14310	58.9333	6.9167	561	2016-12-31T21:00:00Z	M
Forde	13230	61.4000	5.7667	320	2017-01-01T00:00:00Z	F
Steinkjer	12770	64.0167	11.4500	21	2016-12-31T21:00:00Z	C
Kautokeino	10470	69.0000	23.0333	303	2016-12-31T21:00:00Z	I
Stord Airport	13330	59.7919	5.3409	49	1990-01-01T22:50:00Z	C
Røros Airport	12890	62.5784	11.3423	625	1990-01-01T09:50:00Z	I
Vardø Airport, Svartnes	10970	70.3554	31.0449	5	1993-02-09T09:50:00Z	C
Oslo Gardermoen Airport	13840	60.1939	11.1004	219	1989-12-31T23:50:00Z	I
Notodden Airport	13310	59.5657	9.2122	18	1990-10-19T06:50:00Z	I

Appendix 2 – NMI THREDDS server operation status

The Norwegian Meteorology Institute (NMI) issues status updates on their monitored systems and THREDDS server. THREDDS, is short for Thematic Real-time Environmental Distributed Data Services, which is a project which aims to offer coherent access to a large collection of real-time and archived environmental data used by NMI.

During any intermittent access issue and prolonged down-time on the server hosting MEPS forecast data, the forecasts are unavailable for download, which interrupts our data harvesting and infer loss of forecast data in the MEPS data set that we use for statistical comparison with observations and Meteomatics EURO1k forecast.

The status history can be reviewed in detail at https://status.met.no/history . Below follows a condensed overview of the error incidents in the period relevant for the GONDUL project: Error description and tabulated number of incidents (total and per category 1-4) in

1) **THREDDS.met.no - https down:**
   I.e "Our monitoring system has lost contact with THREDDS.met.no through https and you may also have problems connecting to the service. This seems like a real incident, and we are contacting our technical engineers in order to assess the situation and restore normal operations. We apologize for any inconvenience due to the unavailability of the service."

2) **Access issues for some datasets on THREDDS.met.no / Access problems on THREDDS.met.no / External network problems / THREDDS.met.no now running in degraded mode:**
   Anomalies and access issues for shorter or longer periods.

3) **[Scheduled] Hardware maintenance affecting data access on THREDDS.met.no:**
   I.e. " Monday April 7. between 10:45 and 13:00 CEST we will reduce access to certain archives due to a storage maintenance. Affected archives will be: MEPS, AROME Arctic and remote sensing. This only affects the long timeseries in the archives, operational weather forecasts are not affected."

4) **MEPS production (ensemble, deterministic and post processed deterministic):**
   I.e. "MEPS ensemble results from model run based on analysis of YYYY-MM-DD HH UTC is not yet published. Normally we would expect it by now. Please use an earlier forecast."

Table 0-2: ***Monthly number (as of 2025.10.15) of error incidents (total and per category 1-4) on THREDDS server and MEPS forecast production operated by the Norwegian Meteorological Institute.***

Period		Total number of incidents	1 THREDDS contact	2 THREDDS access	3 THREDDS maintenance	4 MEPS model production
2025	February	62	60		1	
	March	19	15	3		1
	April	34	21	1	3	9
	May	17	10	3		4
	June					
	July					
	August	62	60		1	
	September	19	15	3		1
	October	34	21	1	3	9
	November	17	10	3		4
	December					
2026	January					

NORCE Research AS
Postboks 22 Nygårdstangen
5838 Bergen, Norway

E-POST post@norceresearch.no
WEB norceresearch.no
TEL. +47 56 10 70 00
ORG NO 919 408 049