

Comparison of irradiance forecasts from operational NWP model and satellite-based estimates over Fennoscandia

Viivi Kallio-Myers¹  | Aku Riihelä¹  | David Schoenach¹ | Erik Gregow¹  | Thomas Carlund² | Anders V. Lindfors¹

¹Meteorological Research, Finnish Meteorological Institute, Helsinki, Finland

²Information & Statistics, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden

Correspondence

Viivi Kallio-Myers, Finnish Meteorological Institute, Helsinki, Finland.
Email: viivi.kallio-myers@fmi.fi

Funding information

The research conducted in this article has been partially funded by the Fortum and Neste Foundation (grant number 20190164).

Abstract

Accurate irradiance forecasts are needed for the growing solar energy industry also in Northern Europe. We have compared irradiance forecasts from an operational numerical weather prediction (NWP) model, a satellite-based model, and persistence models. We aim to determine whether operational NWP models are suitable for forecasting irradiance at the high latitudes, and how their accuracy compares to the satellite-based model. We have included all members and the ensemble average of the MetCoOp ensemble prediction system (MEPS), the MetCoOp-Nowcasting (MNWC) system, the satellite-based Solis-Heliosat model, and two persistence models. The comparison is made as a point comparison against in situ irradiance observations in Finland and Sweden, for intra-day forecasts with hourly and 15-min output and the full forecast of MEPS with hourly output. In addition, we show two energy market case studies. We find the operational NWP models to be very suitable for irradiance forecasting in the area, up to the full horizon of the forecasts. Solis-Heliosat errors grow with lead time, while the NWP model errors are largest in the beginning, settling to smaller values after the first hours. Solis-Heliosat has more accuracy for the first 2–3 h of the forecast, after which NWP models produce better forecasts. However, during morning periods Solis-Heliosat is found to have limited accuracy, while conversely, MNWC performs better in the morning than in the afternoon. The energy market case study highlights the same results: NWP models do well with forecasting irradiance in Fennoscandia, but the optimal selection of forecast model depends on the required forecast horizon and time.

KEYWORDS

Global Horizontal Irradiance (GHI), high latitudes, nowcasting, numerical weather prediction (NWP), satellite-based forecast, solar energy

1 | INTRODUCTION

To answer to the emissions reductions required to combat climate change, the energy industry is experiencing a global shift to renewable energy sources. This shift has been encouraged by global agreements like the Paris agreement (COP21), as well as policies by the European Union (EU), who have declared their aim to be the first climate-neutral continent by 2050 (European Commission, 2019). Solar energy has the highest relative growth rate of renewable energy sources in the EU, with an increase from 1% to 13% between 2008 and 2019 (Eurostat, Statics Explained, 2021). Meanwhile, the cost of solar energy production has significantly reduced in the past decade, resulting in solar energy-producing some of the lowest-cost electricity ever seen in some countries (IEA, 2020; Vartiainen et al., 2020).

This increase is also present in Finland, where solar energy connected to the grid increased 64% in 2019 (Energy Authority, 2021), and in Sweden, with a 65% increase in 2015–2016 (Landelius et al., 2018). Both Finland and Sweden are aiming at carbon neutrality, by 2035 and 2045, respectively (Bonde et al., 2020; Ministry of the Environment, 2021). Despite the dark winters, the solar resource in Fennoscandia is good: the resource in Finland is similar to that of Germany (Hakkarainen et al., 2015; Huld et al., 2008), one of the largest solar energy producer in the EU (Madsen & Hansen, 2019).

The large-scale use of solar energy brings forth challenges: due to the natural fluctuations in Global Horizontal Irradiance (GHI, or irradiance here onwards), mainly caused by clouds, photovoltaic (PV) power production is very variable (Raza et al., 2016). Varying power production, particularly, in large-scale, can cause technical issues with grid integration, management, stability and reliability (Ahmed et al., 2020). These issues are mitigated by forecasting PV power or irradiance (Antonanzas et al., 2016; Raza et al., 2016).

Various forecast methods have been developed for various forecast time scales. Usually, forecasts are divided by time scale into short-term, medium-term and long-term forecasts (Wan et al., 2015), or intra-hour, intra-day and day-ahead forecasts (Ahmed et al., 2020), to better respond to the energy industry needs. Models include statistical methods, which rely on historical data, as well as physical methods, for example, numerical weather prediction (NWP) models, which attempt to solve the state and development of the atmosphere (Inman et al., 2013; Yang et al., 2018). Various reviews describe the different methods in more detail (Diagne et al., 2013; Inman et al., 2013; Wan et al., 2015; Yang et al., 2018).

Forecast methods based on satellite imagery have been found suitable for time scales of approximately 1–6 h (Diagne et al., 2013; Kühnert et al., 2013), after which

cloud development reduces forecast accuracy. Usually, satellite-based methods use consecutive images from geostationary satellites to derive a cloud index and cloud motion, after which the Heliosat method (Cano et al., 1986; Rigollier et al., 2004) and Clear Sky (CS) models are used to estimate the irradiance from the cloud index (Arbizu-Barrena et al., 2017; Wang et al., 2019). Satellite-based methods have also been studied in high latitudes (Kallio-Myers et al., 2020), showing them to be a viable option despite the high viewing angles of geostationary satellite instruments in the area.

NWP models have been found to be best for day-ahead forecasting (Larson, 2013; Yang et al., 2018). NWP models have received much attention in the recent past, with research and computing advances leading to an increasing resolution and better forecasts. Various studies have been made for solar forecasting with NWP models, including on regional mesoscale models such as the Australian Community Climate and Earth-System Simulator (ACCESS) (Huang & Thatcher, 2017; Joshi et al., 2019) and Weather Research and Forecasting Solar model (WRF-Solar) (Jimenez et al., 2016; Lee et al., 2017; Razagui et al., 2021), as well as global area models such as the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS) (Huang et al., 2018; Lopes et al., 2018; Perez et al., 2013; Tuononen et al., 2019). Perez et al. (2013) and Huang et al. (2018) found the global ECMWF model IFS to have better GHI forecasts than mesoscale models despite the lower horizontal resolution, while Huang and Thatcher (2017) found the mesoscale ACCESS to perform better than the Global Forecast System (GFS). In a comparison focusing on Sweden, Landelius et al. (2018) found the operationally run regional model HARMONIE-AROME to achieve better accuracy for GHI forecasts than the ECMWF IFS.

In this study, we use the operational mesoscale model of Fennoscandia, the MetCoOp ensemble prediction system (MEPS), which is based on HARMONIE-AROME. Landelius et al. (2018) showed HARMONIE-AROME to do well with GHI forecasting, but the ensemble system MEPS has not been extensively studied specifically with solar forecasting. On the other hand, satellite-based methods have been found to be suitable for high latitudes (Kallio-Myers et al., 2020), and to provide better forecasts than NWP models for the first hours of the forecast (Wang et al., 2019). Our aim for this study is thus two-fold: first, to find to what extent MEPS can be used to forecast GHI in Fennoscandia, and second to study the relative abilities of MEPS and satellite-based forecasts in the high latitude location. In addition, we have looked into specific energy market forecasting scenarios from a case study basis, to better understand the value of each

method in a more real-life situation, as recommended by Yang (2020).

The paper is structured as follows. In Section 2, we introduce the models, observations and the locations used in the study, and in Section 3, the methods to produce the comparisons. In Section 4, results are shown for intra-day forecasts and the full forecast of MEPS, as well as the energy market case studies for intra-day and day-ahead forecasts. In Sections 5 and 6, the paper ends with discussion and conclusions.

2 | DATA

2.1 | MetCoOp ensemble prediction system

The MEPS is the main weather forecasting system of the Meteorological Cooperation on Operational (MetCoOp) NWP and includes the national weather services of Estonia, Finland, Norway and Sweden. It is an implementation of the ensemble version HarmonEPS (Frogner et al., 2019) of the convection-permitting NWP model

HARMONIE-AROME (Bengtsson et al., 2017). The MEPS version running at the time of the comparison uses HARMONIE-cy40h.1.2—a detailed description is available in Frogner et al. (2019).

The forecast domain is resolved horizontally in a 900x960 large grid and in the vertical in 65 hybrid levels where the lowest level is at around 12 m and the highest level at 10 hPa. The domain has a horizontal resolution of 2.5 km and spans around Fennoscandia, including several countries in Northern Europe (see Figure 1). The forecast model is currently integrated up until 54–66 h into the future with non-hydrostatic dynamics, a semi-Lagrangian advection scheme and a 75 s time step. Model output is provided hourly. The upper-air data assimilation uses a 3D-Variational minimization to get the model initial conditions, utilizing various conventional observations, satellite radiances, as well as radar reflectivities. The surface assimilation is done with the surface model SURFEX (Masson et al., 2013), which uses conventional observations in an optimal interpolation minimization. Surface and upper-air assimilation are currently performed independent from each other and are, therefore, uncoupled.

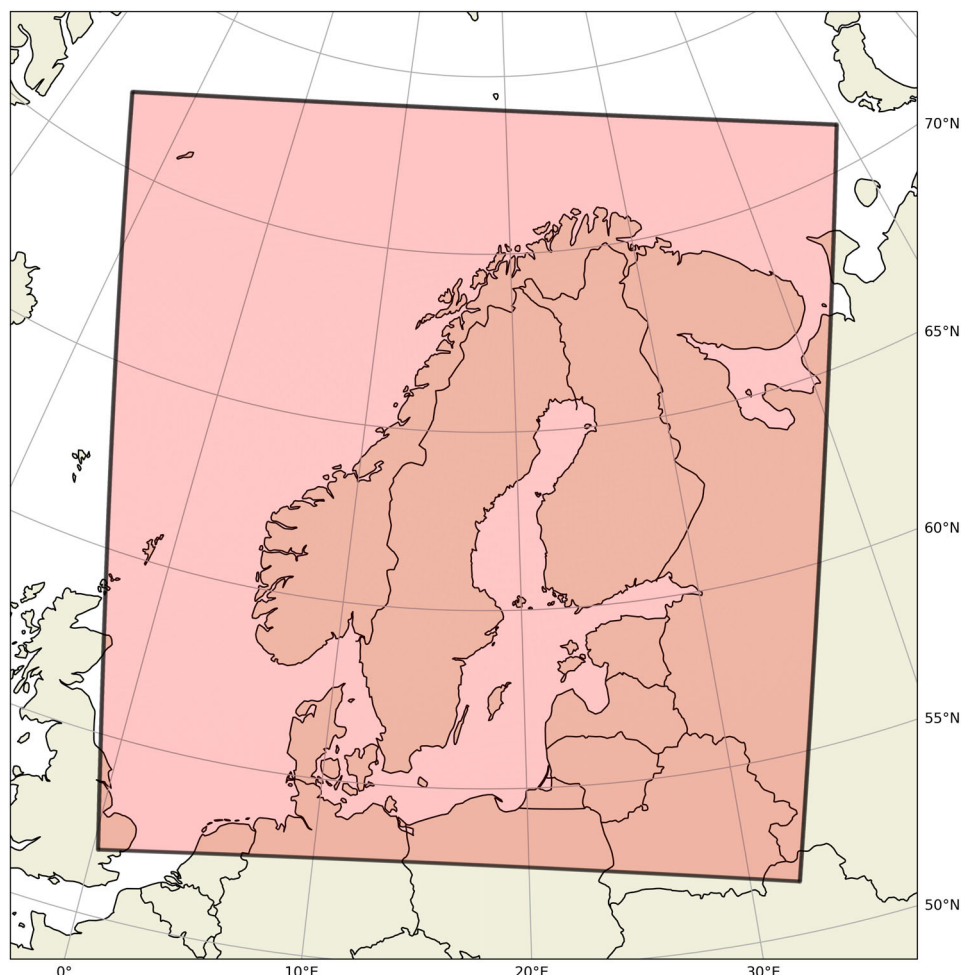


FIGURE 1 MEPS domain in 2019

The HARMONIE-AROME has two radiation parameterization schemes, the short-wave using 6 spectral intervals and long-wave using 16 spectral bands, as described in documents of ECMWF (2016) and the mesoscale research model Meso-NH (Mascart & Bougeault, 2011). In addition, an improved cloud liquid optical property scheme (Gleeson et al., 2015; Nielsen et al., 2014), which is based on detailed Mie theory computations, is used in the HARMONIE-AROME setup.

MEPS is a Limited Area Model (LAM), and therefore, needs lateral boundary conditions from an NWP model with a larger (or global) domain to solve the forecast integrations. For this, MEPS uses the ECMWF IFS HRES hourly data.

During the comparison period of this study in 2019, MEPS is run in a 6 h cycle (forecasts at 00, 06, 12 and 18 UTC), each cycle producing the unperturbed control run (Deterministic run, hereafter MEPS Deterministic), and 9 perturbed members to form the ensemble. The MEPS Deterministic and two other members are run-up to a forecast horizon of 66 h, and the remaining 7 members up to 54 h.

2.2 | MetCoOp-Nowcasting rapid refresh cycling model

The MetCoOp-Nowcasting (MNWC) system is a version of the aforementioned MEPS control member with an emphasis on nowcasting and very short-range forecasting. In nowcasting, a quicker delivery time of about 60 min compared to MEPS' 125 min is mainly achieved by shortening the cut-off time of MEPS' 75 min to 25 min and by having a shorter forecast lead time. MNWC uses the same model and domain specifications as MEPS, but is run in a rapid refresh mode. This means that a new 9-h forecast is initiated every hour, and the forecast is delivered with a higher temporal resolution of 15 min.

After the data assimilation and before the forecast integration, MNWC applies an initialization method to the humidity and temperature fields of the upper-air levels to account for cloud observations from satellite (Gregow et al., 2020) and ground-based observations. Gregow et al. (2020) has shown that this cloud-initialization is beneficial in terms of the cloud cover and cloud base. On the other hand, the cloud-initialization causes an undesirable precipitation spin-up, which is why MNWC does not use its own forecasts in updating the cycle, but forecasts from previous runs of the MEPS control member.

2.3 | Satellite-based Solis-Heliosat model

The satellite-based forecast used in the comparison is produced with the Solis-Heliosat method developed by Kallio-

Myers et al. (2020). Solis-Heliosat uses imagery from the Meteosat Second Generation (MSG) Spinning Enhanced Visible and InfraRed Imager (SEVIRI) and the Heliosat method (Cano et al., 1986; Rigollier et al., 2004), and it has been validated for the high latitude area of Finland.

Solis-Heliosat is initiated with CS GHI estimates produced with a CS model; Pylib-python (Holmgren et al., 2018) is used here with default configuration. The CS GHI estimates are then adjusted for the attenuation caused by clouds. The attenuation caused by clouds is provided using the Cloud Albedo (CAL), retrieved from SEVIRI imagery. CAL is retrieved from reflectance measurements with the Heliosat method, with both VIS006 and VIS008 channel reflectances combined following the Cros et al. (2006) method. CS index (CSI) is calculated from CAL in the same manner as in Mueller et al. (2012), with specifications found in Kallio-Myers et al. (2020). Irradiances are calculated by combining the CSI and CS estimate. GHI forecasts are then obtained by extrapolation of cloud motion based on optical flow calculations on successive SEVIRI images. For further detail on the forecast method, please refer to Kallio-Myers et al. (2020).

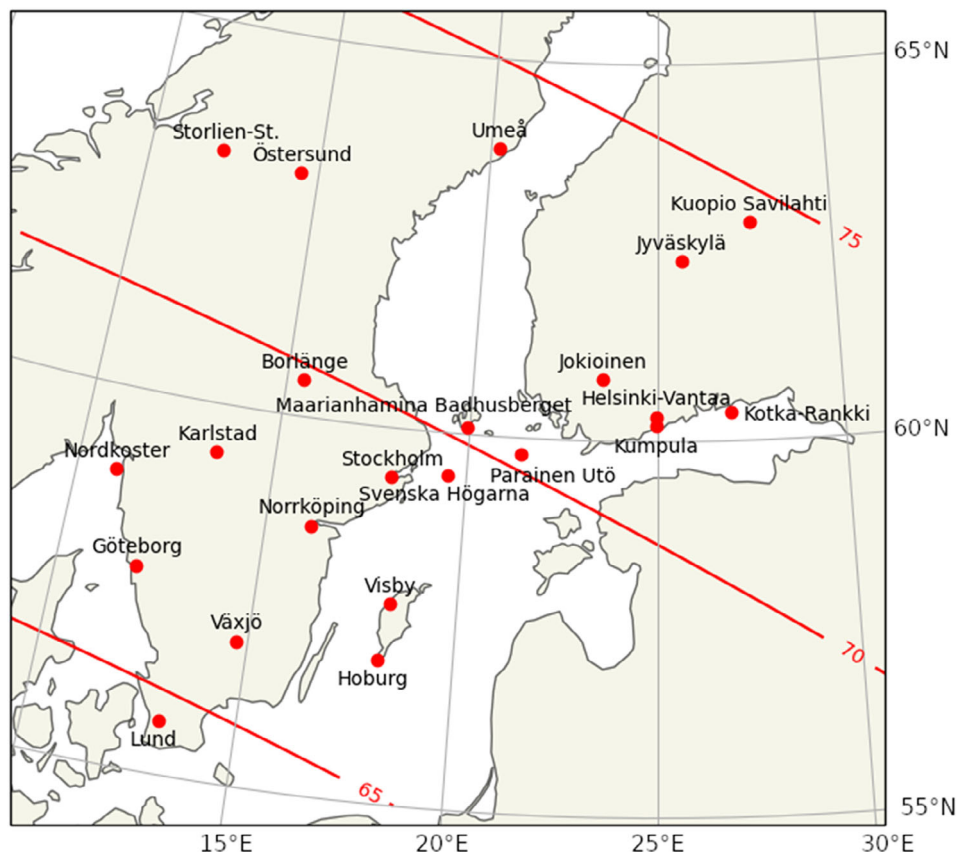
For the purposes of this study, Solis-Heliosat forecasts were calculated for the period of 16.7.2019–31.8.2019 with forecasts starting every 15 min. The forecast is only run at times with a Sun Zenith Angle (SZA) below 80°. Output is also produced every 15 min. While Solis-Heliosat forecasts cover in principle the entire SEVIRI imaging area, with the high viewing angles of SEVIRI in Fennoscandia, the forecast area used is limited to viewing angles below 75°, as shown in Figure 2.

2.4 | Reference observations

In situ GHI measurements are available from 8 stations in southern and central Finland, and from 14 stations in southern and central Sweden. Climatologically, the stations represent coastal, marine and inland conditions. All stations are within the valid area for Solis-Heliosat forecasts, as shown in Figure 2. The figure shows both the locations of the stations and the SEVIRI viewing angles. Additional information on the station locations is found in Table 1.

The measurement stations are equipped with Kipp and Zonen CM11 pyranometers in Finland and with Kipp and Zonen CM21 pyranometers in Sweden. The pyranometers are all ventilated and regularly maintained. The measurements are automatically quality controlled, with manual checks made for suspicious measurements. The stations provide 1 min means of GHI measurements. The pyranometers in both national networks have been calibrated through comparison to a standard

FIGURE 2 Measurement station locations (red dots) and SEVIRI viewing angles (red lines)



pyrheliometer for the direct solar irradiance and a calibrated shaded pyranometer for the diffuse sky irradiance according to World Meteorological Organization (WMO) recommendations. Both FMI and SMHI operate absolute pyrheliometers, which provide the traceability to World Radiometric Reference (WRR) through international or regional pyrheliometer comparisons (Carlund, 2013; Finsterle, 2016).

For high-frequency data, for example, 1-min means there exist significant uncertainties in the pyranometer measurements and the uncertainties vary with the measurement conditions. This study is limited to summer months and also situations when the SZA is below 80°, limiting measurement uncertainties. Based on results from the Baltic Region Pyrheliometer Comparison (BPRC) in 2012 held in Norrköping, Sweden (Carlund, 2013), it is estimated that 2 sigma measurement uncertainties for GHI are within ± 30 Wm⁻² for the 1-min averages. Uncertainties for 15-min and hourly means decrease slightly with increasing averaging time, and they are estimated to be of the order of 2–5% (Wang et al., 2012).

3 | METHODS

In this study, forecast horizon refers to the length of the forecast, that is, the time period between the first and last

forecast times. Output or step refers to the forecast time-resolution or step-size, and forecast runs refer to the times of producing a forecast. Lead time is used for the time between forecast run and the forecast time, that is, the valid time of the forecast.

3.1 | CS index

The CSI describes the cloudiness of a situation by comparing the observed GHI to the GHI value of a cloudless case at the same time:

$$CSI = GHI_{OBS} / GHI_{CS}$$

CSI can also be calculated for an estimated situation, by using the GHI estimate (GHI_{EST}) instead of observed GHI (GHI_{OBS}). To produce GHI_{CS} , we use the Pvlip-python (Holmgren et al., 2018) model Pvlip Solis with default settings (Ineichen, 2008). In this study, CSI is used particularly in forming the persistence forecasts.

3.2 | Persistence forecasts

Persistence forecasts are a commonly used benchmark in irradiance forecast validations (Inman et al., 2013;

TABLE 1 Details on measurement station location and station average GHI for the comparison period of 16.7.2019–31.8.2019

Station name	Country	Lat (°)	Lon (°)	Average GHI (W/m ² , SZA < 80°)
Helsinki-Vantaa	FI	60.33	24.96	376.0
Jokioinen	FI	60.81	23.50	377.0
Jyväskylä	FI	62.40	25.67	352.1
Kumpula	FI	60.20	24.96	387.6
Parainen Utö	FI	59.78	21.37	419.7
Kotka-Rankki	FI	60.38	26.96	369.2
Kuopio Savilahti	FI	62.89	27.63	327.5
Maarianhamina Badhusberget	FI	60.10	19.93	403.7
Norrköping	SWE	58.58	16.15	353.8
Visby	SWE	57.67	18.35	404.8
Umeå	SWE	63.81	20.24	337.9
Svenska Högarna	SWE	59.44	19.50	425.2
Växjö	SWE	56.93	14.73	341.7
Storlien-St.	SWE	63.30	12.12	324.7
Östersund	SWE	63.20	14.48	344.5
Borlänge	SWE	60.49	15.43	336.6
Karlstad	SWE	59.36	13.47	352.1
Stockholm	SWE	59.35	18.06	361.4
Nordkoster	SWE	58.89	11.00	357.0
Göteborg	SWE	57.69	11.98	331.0
Hoburg	SWE	56.92	18.15	411.2
Lund	SWE	55.71	13.21	368.8
<i>All stations</i>				365.2

Note: The average GHI includes only times with SZA below 80°.

Yang et al., 2020). Persistence forecasts essentially assume a situation to continue as it is. In solar forecasting, it is recommended to use a persistence forecast where the diurnal variation is accounted for by assuming the effect of clouds, rather than irradiance itself, to remain constant throughout the forecast (Yang et al., 2020). Here we use two such persistence forecasts, one short-term forecast with two different steps for intra-day forecasts and one with focus on the next day.

The intra-day persistence forecast is calculated using the observed CSI at the start of the forecast for each forecast step, combining them with the clear-sky irradiance (GHI_{CS}) estimate of the forecast time. The short-term persistence (persistence 15 min) is run every 15 min for a forecast horizon of 12 h, with 15-min forecast step. In addition, for a better comparison to the hourly accumulated model output, we form an hourly average from the 15 min persistence output using four consecutive steps. The hourly persistence (persistence 1 h) is, therefore, not a separate forecast, but only an averaged output of the 15 min forecast.

For next day, or day-ahead, persistence we use the –48 h persistence (persistence 48 h), as defined in Yang (2019). This uses the observed 1 h CSI of the t-48 h, where t is the forecast start time. The CSI is combined with the forecast time GHI_{CS} estimate as with the intra-day persistence forecast. Persistence 48 h produces hourly estimates as a time series for the whole period.

3.3 | Error parameters

Various error parameters are used in solar forecasting validations. With varying climatologies, resolutions and forecast horizons, different parameters may give very different apparent ability in model performance. The diurnal dependence of irradiance also brings challenges. Attempts have been made (e.g., Yang, 2019; Yang et al., 2020) to unify and standardize the use of metrics in solar forecasting and promote more thorough analysis of methods, as well as better comparison between different forecasting models and

locations. We follow mainly the analysis recommended in Yang et al. (2020), with some variations.

We use Mean Bias Error (MBE) and Root Mean Square Error (RMSE) and their relative counterparts (rMBE, rRMSE) to assess the general forecast performance, and the relative performance of the methods:

$$\text{MBE} = \frac{1}{N} \sum_{i=1}^N (\text{GHI}_{\text{EST},i} - \text{GHI}_{\text{REF},i})$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\text{GHI}_{\text{EST},i} - \text{GHI}_{\text{REF},i})^2}$$

In addition, we use the forecast skill score to enable comparison to other models validated at different locations. In forming the skill score s , we use only the persistence forecast and not climatology, mainly as the focus is on intra-day forecasts. According to Yang (2019):

$$s = 1 - \frac{\text{RMSE}_{\text{EST}}}{\text{RMSE}_{\text{REF}}}$$

For RMSE_{REF} , we use the persistence forecast RMSE. The normalization for rMBE and rRMSE is made using the average observed GHI for each station (Table 1).

3.4 | Comparison

We have made the comparison for MEPS, MNWC and Solis-Heliosat, using persistence forecasts as a reference. The comparisons are made separately for intra-day forecasts, and the full forecast horizon of MEPS. For the NWP models, the nearest grid point values are used, and for Solis-Heliosat, the nearest pixel value, to compare to the measurement station irradiance. All the comparisons are made for the time period 16.7.2019–31.8.2019. The time period was selected based on data availability and the length of the daylight time in the study area.

In the comparison, we have used all members of MEPS, with emphasis on the MEPS Deterministic member. We have also included an ensemble average (EA), which is simply the average GHI of all the MEPS members. With MNWC, we use both 15-min and hourly estimates, and for both NWP-methods, all runs are included.

To facilitate analysis between the 15-min and hourly accumulated estimates and Solis-Heliosat and GHI measurements, we have converted the NWP output of accumulated GHI into an average irradiance by calculating the average GHI for the accumulation period. These values do not represent instantaneous GHI, but the

accumulating period. This conversion enables comparing the performance of the 15-min and hourly forecasts in the same range, and it is made for both MEPS and MNWC output.

The Solis-Heliosat forecasts are run only when the SZA is below 80° , to exclude forecasts based on low-quality estimates made during high solar zenith angles. All other forecast runs are used in the comparison. The same restriction applies to the persistence forecasts, which rely on the GHI measurement at the start of the forecast. For all forecasts, including all of the models, the evaluated times are restricted to times when SZA is below 80° . This restricts also NWP model data, even though the runs produced at night are included for the NWP-methods.

The 1-min observations for both Finland and Sweden were averaged over 15-min and 1-h, to provide the comparison for both time scales. As the NWP values represent the past 15-min or hour, the observations were averaged for the same time. Solis-Heliosat, however, represents the SEVIRI image retrieval time. Therefore, Solis-Heliosat is compared to observations averaged over 15-min around the retrieval time, for example, 12:53–13:07 for the 13:00 retrieval. The persistence forecast is made using the observed CSI from the past 15-min and the comparison is to the same average as with NWP.

For Solis-Heliosat, an hourly output is also made, using 4 consecutive 15-min steps. This is compared to an hourly observation average, with the same 7-min shift as for the 15-min step comparison to ensure the observations being centred on the 4 SEVIRI retrieval times. Only even lead time hours are included, except for the energy comparison (see Section 3.5).

In producing the observation averages, 15-min averages are only kept for times with the minimum of 10 1-min observations, and for hourly the minimum of 30 1-min observations.

In the intra-day comparison, all forecasts are cut to the maximum forecast horizon of 12 h. In the full MEPS forecast comparison, the 54 h forecast is included for the 54-h MEPS members, while the 66 h runs for the three longer MEPS members are cut to 54 h to provide a uniform forecast horizon. The full comparison includes all members of MEPS, as well as the EA. No persistence forecast is included in the full MEPS comparison; persistence forecasts are only produced during the daylight hours, resulting in an unrealistic wave pattern in continuous multi-day forecasts.

3.5 | Case studies for energy markets

We have made an additional comparison for specific forecasting situations on a case study basis. The comparison is made for intra-day and day-ahead forecasts separately.

TABLE 2 The three forecasted hours in the energy market case study, with model runtimes and the latest possible run for forecasting each hour

Forecasted time	Trading closure	Forecast at user	MEPS	MNWC 1 h	MWNC 15 min	Satellite	Persistence
7–8	6:00	5:00	0:00	3:00	3:00	4:30	4:30
10–11	9:00	8:00	0:00	6:00	6:00	7:30	7:30
13–14	12:00	11:00	6:00	9:00	9:00	10:30	10:30
Runtimes			2 h 20 min	1 h 5 min	1 h 5 min	15–30 min	15–30 min

Note: All hours are in UTC.

TABLE 3 The day-ahead requirements and the selected forecast runs for the day-ahead energy market case study

Forecasted time	Trading closure	Forecast at user	MEPS	Persistence	Persistence-48 h
Next day (D)	D-1 10:00	D-1 9:00	D-1 6:00	D-1 8:30	D-2 (48 h)

Note: All hours are in UTC.

For the intra-day study, we select an hour of focus, for which a forecast is made at a specific time. We then evaluate the performance of those model runs, which are available at the required time, in forecasting the GHI for the hour of focus. Setting these constraints better highlights how the different models perform in energy forecasting situations, compared to the overall evaluation. The hours have been selected to represent morning, noon and the afternoon within high SZA conditions.

The selected hours for the intra-day study are listed in Table 2 along with further information on the case study setup. According to Nord Pool (2021), trading closes an hour prior to delivery for across border trading in the Nordic and Baltic regions, excepting the Finnish and Estonian border, where trading closes 30 min before delivery. For local trading, trading can happen up to 30 to even 0 min prior to the start of delivery (Fingrid, 2021). For this case study, we use the closure time of 1 h before delivery.

We assume a user to require an hour to look at the forecast, meaning that the forecast should be at the user 2 h prior to the start of the hour of focus. The models have varying runtimes (see Table 2); for each model, we have selected the latest run, which will be available by the required time. Therefore, we compare differing runtimes, but the validated hour remains the same for all models. The runtimes vary slightly from the runtime of the models, due to time taken by post-processing procedures and data logistics.

We note that for Solis-Heliosat and Persistence 1 h the 15–30 min runtime means forecasting an hour with uneven lead time. Therefore, for this case study, we have averaged the hourly Solis-Heliosat and Persistence 1 h over the hour of focus, rather than by lead time hours.

For the day-ahead market, the hours of focus are all hours of the next day with SZA below 80°. During summer time, the trading for the following day closes at 10 UTC for the Nordic and Baltic regions (Nord Pool, 2021). Again, we assume the user to need an hour with the forecast. The details for the timings of the used models in the day-ahead comparison are found in Table 3.

In the day-ahead energy market case study, we include MEPS with all members and EA, as well as two persistence forecasts: Persistence 1 h, and persistence 48 h. The forecast runs start at different times, therefore, the lead times vary between models. Nevertheless, the hours for which the forecast is produced, remain the same. For the persistence 48 h there is no single run time, but each forecast step has its own origin at 48 h earlier.

4 | RESULTS

4.1 | Intra-day comparison

Figure 3 shows rMBE, rRMSE and forecast skill (s) by forecast lead time for all models. The forecasts are restricted to a lead time of 12 h, so that only the first 12 h of the forecasts are included. Solis-Heliosat and the persistence models are only run when SZA is below 80°, which means that the short lead times include starts from the whole day, while the 10–12 h lead times only include very late afternoons or evenings, when the forecast has started early in the morning. The NWP models are run also at night, and therefore, have more variety of (start) times for any lead time.

Generally, the errors for the 15 min step are larger for all models, as the averaging process reduces the

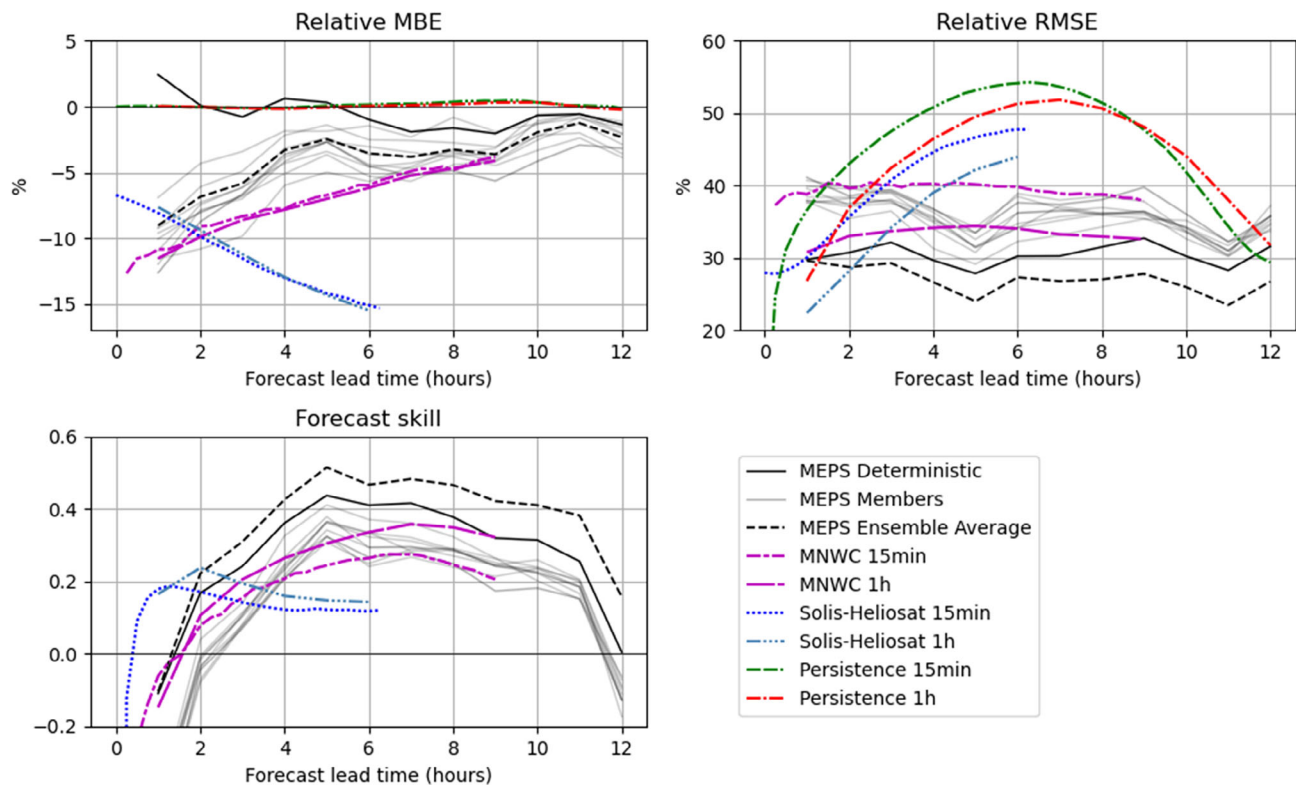


FIGURE 3 rMBE, rRMSE and forecast skill (s) by forecast lead time for all models, for both hourly and 15 min step. MEPS forecasts are restricted to a lead time of 12 h. Only times with SZA below 80° are included, and for Solis-Heliosat and Persistence only forecasts with a start time SZA below 80° . Forecast skill calculated relative to persistence forecast

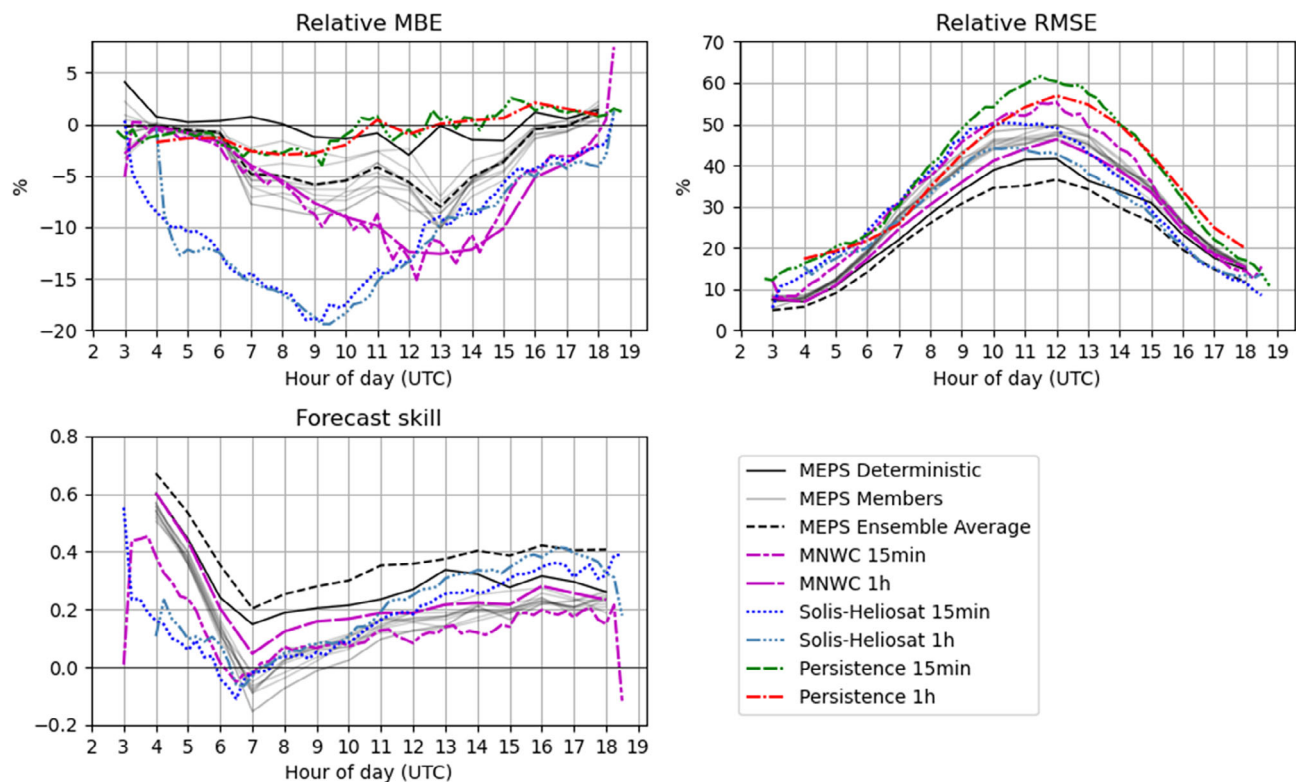


FIGURE 4 rMBE, rRMSE and forecast skill by hour of day for all models, for both hourly and 15 min step. MEPS forecasts are restricted to a lead time of 12 h. Only times with SZA below 80° are included, and for Solis-Heliosat and Persistence only forecasts with a start time SZA below 80° . Forecast skill calculated relative to persistence forecast

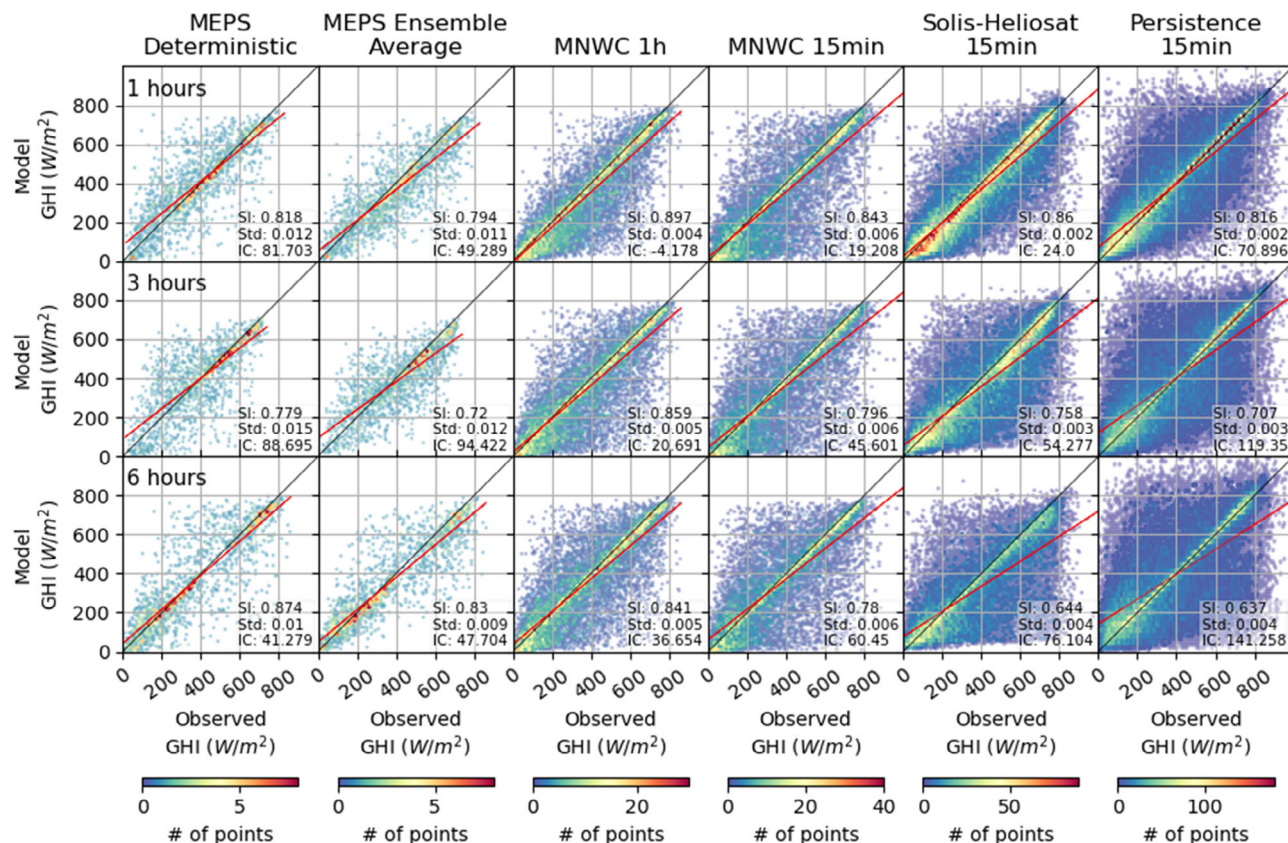


FIGURE 5 Scatter plots between the 1, 3 and 6 h lead time GHI forecasts and GHI observations for all models, with 1:1 line (black line) and linear regression (red line). SI = slope, Std = standard deviation, IC=intercept. Bins with fewer than 5 points are plotted with increased transparency

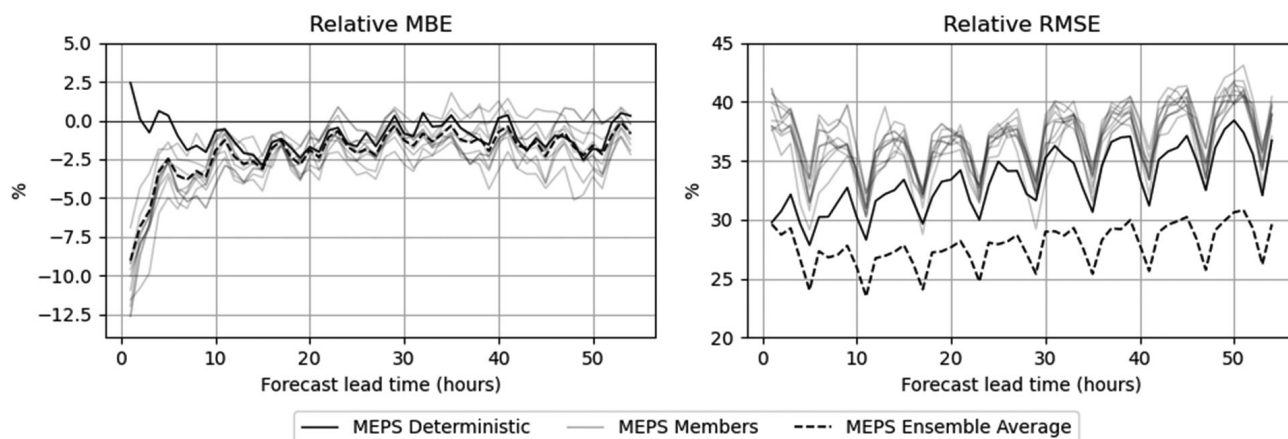


FIGURE 6 rMBE and rRMSE by forecast lead time for the full 54 h forecast of MEPS. Only times with SZA below 80° are included

errors for the hourly output. The persistence forecasts have very low rMBE, but very quickly growing rRMSE, as expected from earlier studies (e.g., Antonanzas et al., 2016; Pedro et al., 2019). The decrease of rRMSE at the end of the forecast is caused by the lack of night

runs, as the end of the forecast only includes times with low irradiance.

For Solis-Heliosat the reducing error growth can also be somewhat seen at the end of the forecast, due to the same reason as with the persistence models. Solis-Heliosat

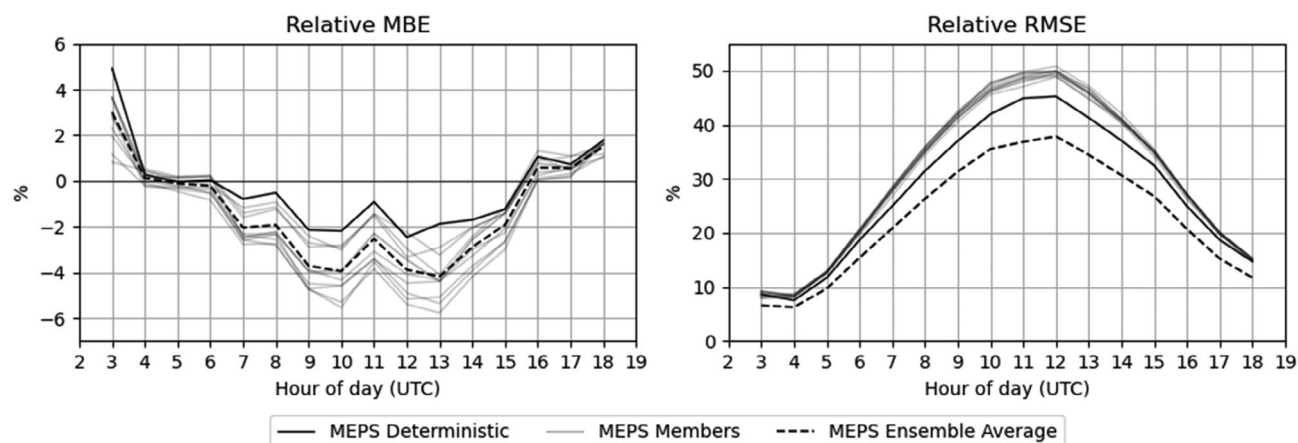


FIGURE 7 rMBE and rRMSE by hour of day for the full 54 h forecast of MEPS. Only times with SZA below 80° are included

TABLE 4 Relative MBE for the 3 h of focus for all compared methods

rMBE	Time	MEPS Det.	Ensemble average	MNWC 1 h	MNWC 15 min	Solis-Heliosat 1 h	Solis-Heliosat 15 min	Persistence 1 h	Persistence 15 min
7–8 SET	07:15:00				−5.16		−28.29		−5.24
	07:30:00				−6.60		−29.82		−5.72
	07:45:00				−5.94		−32.31		−6.00
	08:00:00	−1.07	−2.56	−5.98	−6.21	−31.25	−34.58	−5.83	−6.29
10–11 SET	10:15:00				−10.12		−12.25		1.54
	10:30:00				−9.37		−12.26		2.64
	10:45:00				−10.29		−12.06		2.41
	11:00:00	−1.46	−3.03	−9.61	−8.13	−12.22	−12.11	2.28	2.71
13–14 SET	13:15:00				−12.95		−9.23		0.18
	13:30:00				−14.30		−8.93		−0.94
	13:45:00				−12.83		−7.48		0.11
	14:00:00	−2.17	−3.95	−12.97	−11.74	−8.71	−9.20	−0.13	0.11

Note: For the hourly step, the time refers to the past hour, while for the 15-min step the time refers to the past 15 min. All times are in UTC.

has an increasing negative rMBE: it under predicts irradiance. To an extent, this can be associated with the essentially linear cloud motion scheme and the challenges in determining the cloudy-to-clear transition in the forecast (Kallio-Myers et al., 2020). Nevertheless, Solis-Heliosat has distinctly lower rRMSE than the persistence 15 min after the first 15 min, and from the first hour for persistence 1 h. Solis-Heliosat also outperforms MNWC in both time steps for the first 2–3 h, and MEPS for the first 1–3 h.

MNWC under predicts GHI in the beginning, but improves throughout the forecast. Particularly, the 15 min step of MNWC is superior compared to Solis-Heliosat after 2–3 h and persistence 15 min after 1–2 h. The errors of the hourly step of MNWC are larger than for MEPS Deterministic or EA.

The under prediction of irradiance in MNWC is potentially caused by the addition of too thick clouds

with the cloud-ingest method that MNWC uses (Gregow et al., 2020). In such a method as the cloud-ingest of MNWC, it is fundamentally more difficult to add clouds than remove them: when removing clouds, it is clear that the cloud optical depth should become zero, while when adding clouds, it is non-trivial to reach the correct optical depth.

The MEPS Deterministic has a small positive rMBE, whereas the other MEPS members have a larger negative rMBE. The rRMSE of MEPS Deterministic is also distinctly lower. In the ensemble scheme, the Deterministic member is the “best guess”, while the other members are formed with perturbed initial conditions—although cloudiness is not a directly perturbed feature in the MEPS ensemble. While the expectation of the Deterministic member having initial conditions closest to reality seems to be confirmed by the low initial errors, the impact of the

TABLE 5 Relative RMSE for the 3 h of focus for all compared methods

rRMSE	Time	MEPS Det.	Ensemble average	MNWC 1 h	MNWC 15 min	Solis- Heliosat 1 h	Solis-Heliosat 15 min	Persistence 1 h	Persistence 15 min
7–8 SET	07:15:00				34.28		46.36		40.68
	07:30:00				36.21		50.16		45.30
	07:45:00				37.86		53.06		47.38
	08:00:00	28.74	24.67	32.45	38.49	48.29	56.16	42.97	50.73
10–11 SET	10:15:00				52.80		46.32		53.76
	10:30:00				54.48		46.93		56.76
	10:45:00				53.23		48.04		58.56
	11:00:00	41.93	34.70	45.79	53.33	41.04	49.25	52.43	60.74
13–14 SET	13:15:00				49.03		39.89		52.31
	13:30:00				48.17		40.07		50.89
	13:45:00				46.97		39.58		49.45
	14:00:00	33.98	29.14	40.23	44.88	33.55	39.35	45.36	46.61

Note: For the hourly step, the time refers to the past hour, while for the 15-min step the time refers to the past 15 min. All times are in UTC.

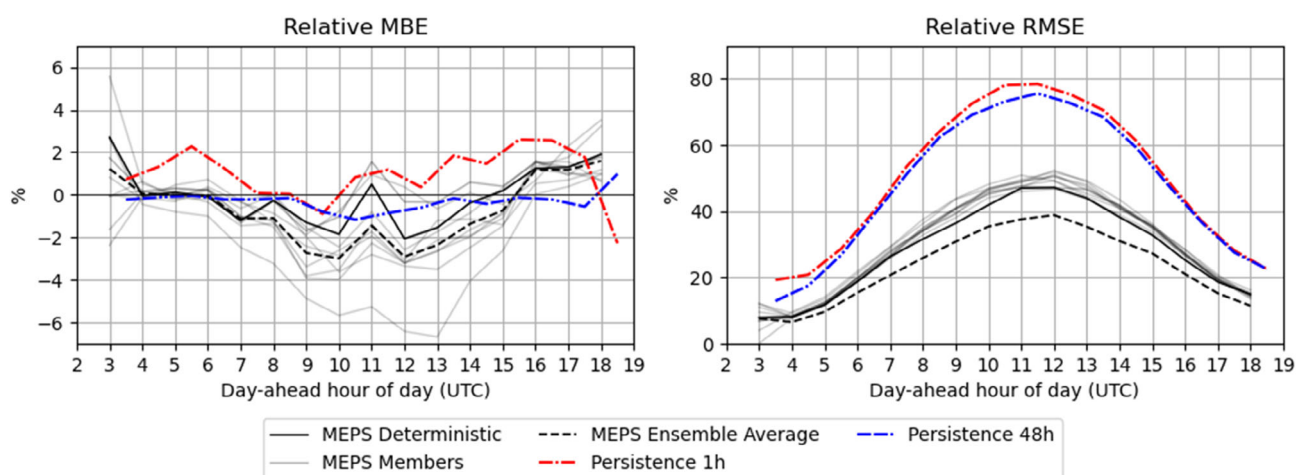


FIGURE 8 rMBE and rRMSE by hour of day for the day-ahead forecast case study. The runtimes of the models are listed in Table 3, while for all models the forecasted times of the next day are the same. Only times with SZA below 80° are included

better initial conditions is seen to disappear with increasing lead time as the MEPS members' errors converge.

The under prediction of the other members may potentially be caused by the model behaviour with clouds, particularly, with the increase of cloudiness in the perturbations of the ensemble members. As clouds are often present in conditions close to saturated humidity, atmospheric moisture-influencing perturbations in those conditions may often lead to moisture condensation and thus increased cloudiness. However, in cloud-free conditions, humidity adjustments (decreases) will likely have a much smaller impact on model cloudiness. It can be noted, further that the latest MEPS version (cy43) does not show this behaviour persistently, so the

root cause may be some feature specific to this MEPS setup (Fortelius, n.d., personal communication).

The EA follows the MEPS members with negative rMBE, while the rRMSE is very low and below the MEPS Deterministic member throughout the forecast. Solis-Heliosat has lower rRMSE for only the first 2 h.

The forecast skill shows the same results as the rMBE and rRMSE. Compared to the persistence 1 h rRMSE, Solis-Heliosat improves most in the beginning, with MEPS Deterministic and the EA performing best shortly after. For the 15 min step, Solis-Heliosat performs well in the beginning and MNWC much better after 3 h. The negative initial forecast skill is a result of the very low initial rRMSE of the persistence models.

Figure 4 contains rMBE, rRMSE and the forecast skill (s) by time of day for all models. Again, only the first 12 h of the forecasts are included. Each hour may now contain various lead times. However, Solis-Heliosat and the persistence forecasts again only contain shorter lead times for the morning hours. This is caused by the running restriction of SZA below 80°. The afternoon hours contain more varying lead times, as do all the hours of the NWP models.

The persistence forecasts follow the expected pattern of low rMBE and high rRMSE, while Solis-Heliosat has very large negative rMBE in the morning hours. This is caused by a large part of the morning forecasts starting at times of high SZA, which result in poor forecast quality for a method relying on satellite imagery from visible light channels. The same result was calculated with restricting the Solis-Heliosat to only include runs started at below 60° SZA (see Supplementary Figures S1 and S2). With such a restriction, the Solis-Heliosat rMBE is in a very similar range to the rest of the models for the morning hours.

The rRMSE for Solis-Heliosat is also high during the morning, but in the afternoon, the errors for the hourly step are in the same range as MEPS Deterministic, while the 15 min step outperforms the 15 min step of MNWC. Generally, all models have slightly higher errors in the afternoon than the morning, potentially related to the higher prevalence of local convective clouds.

MNWC tends to overall under predict irradiance. It performs relatively better in the morning than in the afternoon, and between 3 and 7 am MNWC rMBE is on par with the MEPS members and EA. By noon MNWC rMBE decreases to larger negative values. The same effect can be seen in the rRMSE, with better performance in the morning than afternoon for both time steps.

The rMBE of the Deterministic member of MEPS is closer to zero than for the rest of the members and the EA, which under predict irradiance more. The MEPS Deterministic and particularly the EA have low rRMSE throughout the day, with a slight increase in the late afternoon.

The forecast skill highlights the same behaviour: the EA provides a large improvement to the persistence 1 h with MEPS Deterministic close behind. MNWC does well in the morning, but in the afternoon Solis-Heliosat improves the forecast even above MEPS Deterministic.

Figure 5 shows the scatter plots between the forecast and observed irradiance, for lead times of 1, 3 and 6 h. All models are included, but only with their original time step (Solis-Heliosat and Persistence are shown for 15 min step). The linear regression and 1:1 lines are also included, with slope, standard deviation and intercept given for each line. Bins with less than 5 points have been plotted with higher

transparency. For MEPS there are fewer runs than for other models, hence the lower number of points.

For MEPS Deterministic and EA the slope gets closer to 1 with increasing lead time, while for MNWC, Solis-Heliosat and Persistence, the slope decreases. As expected, the decrease is largest for persistence 15 min, but also significant for Solis-Heliosat. MNWC does better for short lead times, but does not deteriorate much with the lead time. Interestingly for the 1 h lead time the worst correlation is found for the EA. This is consistent with the under prediction of the MEPS members seen for the beginning of the forecast for the lead time errors.

For a basic statistical test on the equality in predictive performance, we applied the modified Diebold-Mariano test (Harvey et al., 1997) to forecast pairs, which could feasibly express equal performance, these being MEPS Deterministic versus persistence, and combinations of Solis-Heliosat, MNWC and EA. One hour mean GHI MBE was the tested variable, with test metrics calculated for all valid data with forecast lead times of 1 to 4 h. Among these tests, only the MEPS Deterministic versus persistence showed equivalent performance (as defined with this statistic) at the 2 h forecast lead time step. Note that the Diebold-Mariano test does not indicate which forecast is better, only if their performance is highly similar in the statistical sense when tested sample populations are large.

4.2 | Full MEPS forecast comparison

The rMBE and rRMSE by lead time are shown in Figure 6 for the full 54 h forecast of MEPS, including all members and the EA. The rMBE is very good for all members and the EA after 10 h, before which the effect of the beginning spin-up can still be seen. The MEPS Deterministic and EA have very similar rMBE from 10 h onwards, with the other members showing a little more variability. A slight under prediction is present for the full forecast for all members.

A distinct wave pattern is visible in the rRMSE by lead time for all members. This is caused by the MEPS runs starting every 6 h: if the runs started every hour, this wave would disappear. The highest irradiance times close to midday accumulate at certain hours, while at others the late evening and early morning hours dominate, causing dips in the rRMSE. Generally, the MEPS members, including Deterministic, show a slight increase in rRMSE with lead time. MEPS Deterministic has again lowest rRMSE in the beginning, with other members taking some hours to recover and reach their minimum rRMSE. The EA has very low rRMSE throughout, with over 5% difference to the MEPS Deterministic.

Figure 7 shows the rMBE and rRMSE by time of day for the full forecast of MEPS. The behaviour of both errors is

similar to the first 12 h of the forecast. With less emphasis on the beginning of the forecast, a slight improvement can be seen in rMBE through the day. Largest negative rMBE is again found during midday. rRMSE is overall slightly higher than for the first 12 h, with the MEPS Deterministic and the EA slightly closer to the rRMSE of the other members.

4.3 | Intra-day energy market case study

Tables 4 and 5 contain the rMBE and rRMSE, respectively, for the comparison of the intra-day energy forecasting hours. The three sets refer to the hours of focus, that is, the hour that is forecasted. The hourly step represent the full past hour, while the 15 min step represents the past 15 min.

Similar results to the lead time and time of day comparison can be seen in this case study. Solis-Heliosat has high errors for the first set, due to the high start time SZA. For the afternoon, however, Solis-Heliosat improves. For the last set, the rRMSE is comparable to that of MEPS.

MNWC has good performance in the first set, but much higher errors for the last. Particularly the MNWC 15 min step errors of the first set are very good compared to Solis-Heliosat and Persistence 15 min.

MEPS Deterministic and the EA have the lowest errors for almost all sets. MEPS has earlier run times due to the less frequent runs, but with the spin-up effect, the slightly longer lead rather improves the errors.

The persistence forecasts under predict irradiance for the first set, but while rMBE improves for the latter sets, the rRMSE somewhat increases. All the models do generally well compared to persistence 15 min and persistence 1 h.

4.4 | Day-ahead energy market case study

Figure 8 shows the rMBE and rRMSE for the day-ahead forecasts of the energy market case study. Note that the lead time is different for the different models, but the forecasted hour is the same.

Both persistence 1 h and persistence 48 h have relatively low rMBE, and very high rRMSE. The long lead time increases the rRMSE much over the 12 h forecasts. Persistence 1 h has slightly more varying rMBE than the persistence 48 h.

MEPS performs well with the next day, the rMBE is only slightly larger than for the persistence models, and the rRMSE is very low compared to the persistence models. The EA continues to do well, while MEPS Deterministic is closer, but has lower rRMSE than the other members.

5 | DISCUSSION

The comparisons in this article are made by comparing single model grid point values and satellite pixel values to in situ point observations. The MEPS and MNWC horizontal resolution are 2.5 km, while the SEVIRI image pixels in high latitudes could reach a diameter of around 8 km (Kwiatkowska et al., 2016). Neither the grid point nor the satellite pixel, therefore, represent only the measurement point, leading to potentially higher errors.

The operational models we compared have various good qualities; however, operational NWP data is not always easily available. Open access solutions have progressed in past years, but only parts of MEPS data are openly available to the public. The huge data quantities that operational NWP models produce do not ease the issue of availability and usability.

Due to continuous development, a new version of MEPS has been released since the comparison period of this study. In addition to various updates in the model, the members are currently run in sets of 5 per hour, over 6 run cycles, to produce an ensemble of 30 members. The Deterministic member is also run every 3 h instead of 6. This may somewhat change the behaviour of the MEPS members, as well as the performance of MEPS in the energy market case study, although with MEPS a short lead time was not quite as necessary as with, for example, Solis-Heliosat. The MNWC has also been updated at the same time as MEPS. Particularly the effect of too thick clouds has been reduced, potentially improving the under prediction of irradiance in the newer version.

The EA was included in the comparison, and it has very low errors. However, whereas the MEPS members represent different potential states of the atmosphere, the EA does not. The EA performs well when evaluated over many cases with the used error metrics, but a single forecast is not necessarily physically realistic. It may then perform well by avoiding large errors by falling closer to climatology. On the other hand, this may not be an issue in a use case in which avoiding large errors would bring most profit.

Solis-Heliosat was found to under predict irradiance, which may be related to the cloud movement scheme explained in Kallio-Myers et al. (2020). With a more sophisticated cloud movement scheme, this issue could be solved. In addition, the high rMBE of runs started at high SZA is related to the use of the visible channels of SEVIRI. The sensitivity to SZA is a weakness of using these channels, rather than the method. With the addition or use of other (infrared waveband) SEVIRI channels, Solis-Heliosat could perform better in the early morning hours. Overall, Solis-Heliosat performance in this study is very similar to that observed in an earlier

study with a longer evaluation period (Kallio-Myers et al., 2020).

In the energy market case studies, we have assumed the user to require an hour to study the forecast, and the trading to end an hour prior to delivery. However, some of the trading happens up to delivery, and the users may need less time. This could change the schedule by up to 2 h, which would have an effect on particularly Solis-Heliosat and the persistence. In addition, with Solis-Heliosat and the persistence, the user would have the option of seeing multiple forecast runs within an hour of decision-making.

6 | CONCLUSIONS

In this article, we have made a comparison of GHI forecasts, based on NWP model data and satellite imagery. We have included NWP data from the operationally run MetCoOp model MEPS, and its nowcasting version MNWC, using the full forecast and all forecast runs for a period of 16.7.2019–31.8.2019. All MEPS members, as well as an EA, have been included, with an hourly time step. For MNWC, both hourly and 15 min output have been compared. The satellite-based model, Solis-Heliosat, was included with 15 min and average hourly output. As a reference forecast, two persistence models were used, with an hourly and a 15 min step. The comparison has been made between the NWP grid points or satellite pixel values, and in situ observed GHI, for 22 stations in Finland and Sweden.

The comparison was separated into an intra-day study, covering the first 12 h of the forecasts, and a study with the full 54 h of the MEPS forecast. In addition, two case studies for energy market situations were made for intra-day and day-ahead forecasts.

All of the compared models were mostly found to under predict irradiance. The NWP models had large initial rMBE, which moves closer to zero with lead time. With Solis-Heliosat, rMBE grows throughout the forecast. For the hourly step, Solis-Heliosat does well for up to 2 h lead time, with the MEPS Deterministic member and the EA performing best after. With 15 min step, Solis-Heliosat performs best initially, and MNWC after 2–3 h. Solis-Heliosat is found to have very large errors for the morning, for runs starting at high SZA, and very low errors toward the evening. MNWC, on the other hand, performs much better in the morning than afternoon. The EA is found to perform best overall, with the MEPS Deterministic showing similar accuracy.

The full forecast comparison of MEPS showed very good accuracy for the longer lead times, with small, negative rMBE for all members and the EA after the first hours of the forecast. The EA does overall best, with the

Deterministic member having lowest errors among the MEPS members.

The energy market case studies highlight the same characteristics of Solis-Heliosat performing well in the evening and poorly in the morning hours, MNWC performing better in the morning, and MEPS Deterministic and the EA being overall best.

The results show NWP based forecasts to be very suitable for forecasting irradiance in Fennoscandia. Both MEPS with hourly step and MNWC with 15 min step perform well, MEPS showing good accuracy even up to 54 h of the forecast. Nevertheless, Solis-Heliosat has high accuracy and value as a forecast method for short lead times of up to 2–3 h. In energy trading situations using more than one model, depending on the desired time and temporal frequency, would guarantee optimal accuracy of irradiance forecasts.

ACKNOWLEDGEMENTS

Carl Fortelius and Karoliina Hämäläinen at FMI are thanked for enlightening discussions on MEPS ensemble design.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

Viivi Kallio-Myers: Conceptualization (equal); formal analysis (lead); funding acquisition (lead); investigation (equal); methodology (lead); software (lead); validation (lead); visualization (lead); writing – original draft (lead). **Aku Riihelä:** Conceptualization (equal); funding acquisition (supporting); project administration (equal); supervision (equal); writing – original draft (equal); writing – review and editing (lead). **David Schoenach:** Data curation (equal); resources (equal); writing – original draft (equal); writing – review and editing (equal). **Erik Gregow:** Data curation (equal); methodology (supporting); resources (equal); writing – original draft (equal); writing – review and editing (equal). **Thomas Carlund:** Data curation (equal); resources (equal); writing – original draft (equal); writing – review and editing (equal). **Anders Lindfors:** Conceptualization (equal); funding acquisition (supporting); methodology (supporting); project administration (equal); supervision (equal); writing – original draft (equal); writing – review and editing (equal).

ORCID

Viivi Kallio-Myers  <https://orcid.org/0000-0002-8984-1628>

Aku Riihelä  <https://orcid.org/0000-0001-6581-8792>

Erik Gregow  <https://orcid.org/0000-0002-6017-5094>

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How to cite this article: Kallio-Myers, V., Riihelä, A., Schoenach, D., Gregow, E., Carlund, T., & Lindfors, A. V. (2022). Comparison of irradiance forecasts from operational NWP model and satellite-based estimates over Fennoscandia. *Meteorological Applications*, 29(2), e2051. <https://doi.org/10.1002/met.2051>