

RESEARCH ARTICLE

Enhancing severe convection forecasts with microwave radiance assimilation in limited-area models

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Abstract

Accurate representation of atmospheric humidity in convection-scale data assimilation is essential for forecasting severe precipitation. Satellite radiances, especially from microwave water-vapour channels, provide valuable information on tropospheric moisture globally, yet remain largely underused in convection-permitting limited-area models (LAMs). This study demonstrates the benefit of assimilating such radiances in LAMs for intense convection forecasting. We use the ICOSahedral Non-hydrostatic model over Italy at 2.2-km resolution (ICON-2I), coupled to the local ensemble transform Kalman filter, following the operational configuration of Arpa Emilia-Romagna and ItaliaMeteo. The severe convective event of September 15, 2022 in the Marche region, Central Italy, serves as a case study; this produced over 400 mm rainfall, substantially underestimated by the operational forecast assimilating only conventional and radar data. We introduce the assimilation of clear-sky microwave water-vapour channels from the polar-orbiting Microwave Humidity Sounder (MHS) as main focus, complemented by all-sky infrared radiances from the geostationary Spinning Enhanced Visible and InfraRed Imager (SEVIRI) following the German Weather Service operational configuration. Each instrument alone improves the Marche event precipitation forecast, but their joint assimilation yields the best performance, indicating positive synergy between microwave and infrared water-vapour channels. Inspection of forecast initial conditions shows that joint MHS+SEVIRI assimilation introduces consistent modifications to the pre-convective atmospheric state, with increased low- to mid-tropospheric humidity favouring deep convection. The relative contribution of each platform is assessed with the partial analysis increments algorithm, highlighting the complementary impact of the two satellites throughout the troposphere. Extended verification over five days confirms overall improvement in root-mean-square error (RMSE) and bias for temperature, humidity, and wind at surface and upper levels, particularly in the mid-troposphere. The fractions skill score and dichotomous scores also show benefit for intense rainfall forecasts from MHS assimilation. These results motivate the operational introduction of satellite radiances in the Arpa Emilia-Romagna and ItaliaMeteo systems.

KEYWORDS

convective-scale, ensemble data assimilation, satellite data assimilation, water-vapour channels

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1 | INTRODUCTION

Satellite data assimilation (DA) is widely recognized as one of the most significant contributors to the improvements in numerical weather prediction (NWP) over the last few decades. Global NWP has benefited the most from satellite DA, especially over areas that are largely covered by ocean, like the Southern Hemisphere (Bauer *et al.*, 2015). Satellite observations offer a more uniform coverage of the atmosphere and Earth surface in space and time than in situ measurements, providing valuable observations over data-sparse regions. However, these benefits come with certain limitations: onboard sensors typically have relatively low vertical resolution, and it is challenging to account properly for the effects of clouds, precipitation, and surface influences (Bauer *et al.*, 2011; Thépaut, 2003).

Polar-orbiting microwave sounders have proven to be the most impactful source of data in global DA systems (Chambon *et al.*, 2023; Cucurull & Anthes, 2014), also compared with infrared radiances. Microwave frequencies can penetrate non-precipitating clouds that are opaque to infrared radiation. Among the different available channels on passive microwave instruments, water-vapour absorption bands are particularly relevant to enhance representation of atmospheric humidity, a crucial quantity driving the development of precipitation and deep convection. The free-troposphere humidity field is generally largely undersampled in conventional observations (primarily radiosondes and aircraft), with observational limitations and vertical gaps in humidity measurements (Ferreira *et al.*, 2019). The information coming from water-vapour absorption channels is therefore crucial to infer the humidity field far from the surface. Nevertheless, the importance of water-vapour sounding channels is not limited to humidity representation: because humidity structures in the free troposphere are driven largely by the wind field, another key objective and the potential advantage of assimilating humidity observations is to constrain and improve the wind analysis. In the absence of clouds and precipitation, and in a free troposphere, atmospheric humidity behaves as a tracer, the evolution of which follows a continuity equation. This property enables a “wind-tracing” capability that contributes to better dynamical initial conditions and consequently improves forecast accuracy (Geer *et al.*, 2018). Originally, this mechanism has been demonstrated to provide great benefit to medium-range forecasts in 4D-Var, by inferring wind increments through the adjoint of the forecast model equation (Peubey & McNally, 2009). More recent studies have shown that ensemble DA (EnDA: Carrassi *et al.*, 2018) is also capable of generating wind tracing (Bonavita *et al.*, 2020). In particular, EnDA leverages the ensemble-based correlation to infer wind increments from

tracer observations of humidity (Allen *et al.*, 2015), clouds, and precipitation (Lien *et al.*, 2016).

Although the data coverage of polar-orbiting satellites in limited-area models (LAMs) is inevitably limited, the significant impact of microwave radiance DA in global models has encouraged a recent stream of efforts toward their use in LAM DA. Microwave radiances have shown positive impact on analyses and forecasts in LAMs at high resolution using a three-dimensional variational (3DVar) scheme in the Arctic region (Randriamampianina *et al.*, 2019, 2021) and Northern Europe (Lindskog *et al.*, 2018). Schwartz *et al.* (2012) have been the first to assimilate microwave radiances successfully with regional EnDA, with a positive impact on tropical cyclone forecasts. Within high-resolution LAMs, the assimilation of microwave channels has mainly been applied to tropical cyclone case studies (Christophersen *et al.*, 2021; Wu *et al.*, 2019). In a recent work on a severe convection case study, Zhang *et al.* (2024) demonstrated the benefit of all-sky assimilation of microwave channels from different platforms, in addition to infrared all-sky radiances. The main challenges of all-sky radiances come from their connection to cloud microphysics, which potentially implies multiple and simultaneous nonlinear and non-Gaussian processes that are difficult to discriminate between for their use in DA; this is particularly the case for infrared radiances (Geer *et al.*, 2019). Moreover, the definition of the observation errors (Tandeo *et al.*, 2020), expected to be larger in the presence of clouds and precipitation, is particularly subtle, because representation errors (Janjić *et al.*, 2018) become the dominant error source for all-sky observations (Geer, 2019).

Variational DA leverages a tangent linear and adjoint forward model to compute increments in the control variables, which is a well-established and powerful approach; however, it can become challenging in the presence of the strong nonlinearities, discontinuities, and sharp gradients that characterize precipitation processes. EnDA, by contrast, requires only the full nonlinear forward operator, thereby avoiding the explicit construction of tangent linear and adjoint models (Evensen, 2003; Schomburg *et al.*, 2026). This advantage is especially relevant in all-sky satellite DA, where a highly nonlinear radiative transfer model is employed as the forward operator. It should be mentioned that an implicit linear approximation is applied anyway in ensemble-based DA methods like the local ensemble transform Kalman filter (LETKF: Hunt *et al.*, 2007), without the need to linearize the forward operator explicitly. This implicit linearization is performed in the ensemble space about the background ensemble mean, and it can be considered a valid approximation when the spread of the background ensemble is not too large.

A key challenge of assimilating all-sky radiances is establishing the relationship between variations in the observed radiance and changes in the atmospheric physical fields, for example, temperature, wind, humidity, and hydrometeors. Given that an accurate radiative transfer model is available to compute observation model equivalents, ensemble-based approaches address this problem implicitly by using ensemble-derived covariances (Geer *et al.*, 2018). These characteristics have supported the advancement of all-sky assimilation with ensemble-based methods significantly. Since November 2023, at the German Weather Service (DWD) the first all-sky assimilation of infrared water-vapour channels in an operational NWP system has been active (Schomburg *et al.*, 2026), using the LETKF. It is expected that microwave radiances can provide complementary information to IR all-sky radiances when they are assimilated simultaneously, due to their different cloud penetration capability (Zhang *et al.*, 2024).

Despite these encouraging results, satellite observations, especially at microwave frequencies, are still largely under-used within operational high-resolution LAMs at convection-permitting scales, where deep convection is often resolved explicitly rather than parameterized ($\sim 1\text{--}4$ km horizontal resolution). At convection scale, DA faces significant challenges due to the stronger influence of nonlinear dynamics, flow imbalances, and moist physical processes (Gustafsson *et al.*, 2018; Pagé *et al.*, 2007; Yano *et al.*, 2018). In addition, convective events are typically intermittent (Barone *et al.*, 2025), spatially localized, and characterized by non-Gaussian behaviour. Traditional DA approaches typically assume approximate linearity and near-Gaussian error statistics (Ruiz *et al.*, 2021).

Enhancing DA of microwave radiances in operational LAM is desirable, especially for areas lacking sufficient in situ observations. The Italian domain is a valuable example: approximately 40% is covered by the sea, where almost no data are available. To address this point, in this work the operational system of the National Agency for Meteorology and Climatology (ItaliaMeteo) and the Regional Agency for Prevention, Environment and Energy of Emilia-Romagna (Arpa Emilia-Romagna) is employed. As members of the COnsortium for Small-scale MOdelling (COSMO), the ICOSahedral Non-hydrostatic (ICON) model and the LETKF data assimilation system are run operationally. No satellite radiances have been assimilated so far in the operational setup, leaving vast areas of the domain almost completely lacking in observations. ICON is run in LAM mode over Italy (ICON-2I domain) at convection-permitting scale, with 2.2-km horizontal resolution.

This study presents results from satellite DA experiments starting from a poorly predicted severe convection case study that occurred in the Marche region, Central

Italy, in September 2022. The primary focus is evaluating the impact of the direct assimilation of clear-sky microwave radiances in water-vapour channels from the Microwave Humidity Sounder (MHS) satellite instrument. In addition, infrared all-sky radiances in water-vapour channels from the SEVIRI geostationary instrument are assimilated using the operational DWD configuration (Schomburg *et al.*, 2026), in order to evaluate the potential complementary information coming from the joint assimilation of microwave and infrared radiances. These two sources of satellite data are assimilated on top of the conventional observations and radar volumes of reflectivity and radial velocity currently assimilated in the operational ICON-2I setup. Latent heat nudging (LHN) is also applied, using surface rainfall intensity (SRI) fields estimated from the Italian radar network data. To the authors' knowledge, the assimilation in a convection-permitting scale LAM of such a rich dataset, consisting of microwave satellite radiances, all-sky infrared radiances, radar volumes, and conventional data, has still not been documented in the literature. The quantification of the relative impact of each observation type on the analysis is evaluated using the partial analysis increments (PAI) algorithm by Diefenbach *et al.* (2023). This study is intended as a starting point and a basis for future, longer experiments prior to operational use: the aim is to demonstrate and characterize physically the impact of these new satellite observations on a high-impact benchmark event, rather than to provide an extended, multi-season verification required for an operational implementation.

The synoptic and mesoscale configuration of the severe convection event analysed in this work is presented in Section 2. In Section 3, the NWP system is presented, providing details about the ICON model and the LETKF scheme. The observation dataset, setup of the DA experiments, and verification scores are also described, including the technical details concerning the implementation of satellite microwave radiance assimilation. The results of the experiments are presented in Section 4, first focusing just on a single deterministic forecast for the day of the convective event, then extending the forecast verification to a five-day evaluation period to collect more robust statistics on the impact of satellite DA. A summary and future outlook are given in Section 5.

2 | OUR CASE STUDY: SEPTEMBER 15, 2022, MARCHE REGION, ITALY

The impact and importance of satellite observations is studied here, with a focus on a severe convection-driven extreme event that occurred on September 15, 2022 in the Marche region, Central Italy. Hereafter, the event will be

referred to as the *Marche2022* convective storm. A detailed analysis of the synoptic and mesoscale meteorological configuration can be found in previous studies (Gentilucci *et al.*, 2023; Grenzi, 2025; Tartaglione, 2025; Torcasio *et al.*, 2023). The event originated from the residual circulation of Hurricane *Danielle*, which formed as a tropical depression on September 1, 2022 in the central North Atlantic (38°N, 45°W). It rapidly intensified to Category 1 status, aided by sea-surface temperatures 2–3°C above average, before transitioning into an extratropical cyclone by September 8. Interaction with a low-pressure system from Atlantic Canada sustained the system for several days across the North Atlantic Ocean. The cyclonic circulation dissipated gradually during the night between September 15 and 16, after approaching the Iberian Peninsula and impacting the weather in the Western Mediterranean.

At synoptic scale (Figure 1a), the September 14–15 period was characterized by the coexistence of the decaying *Danielle* over the eastern Atlantic, a secondary low-pressure system over Scandinavia, and a ridge over the central Mediterranean. *Danielle* acted as conveyor of warm, moist subtropical air towards the Mediterranean basin and the Italian Peninsula. Analyses of mid-tropospheric humidity show consistent transport of moisture toward northern Europe and subsequent redirection of it southward as the Scandinavian trough deepened (Torcasio *et al.*, 2023). This significant amount of atmospheric moisture was a crucial ingredient for convective storm development: moisture advection, together with strong southwesterly flow aloft, favoured the development of long-lived, stationary convection.

During the morning of September 15, a southwesterly flow associated with a thick cloud band moved across Italy. Orographic lifting along the Apennines repeatedly triggered deep convection as the moist southwesterly flow impinged on the terrain. During the early afternoon (1400–1500 UTC) of September 15, satellite imagery from *Meteosat Second Generation* showed one convective system evolving into a quasi-stationary, self-regenerating structure (the *Marche2022* storm, Figure 1b). A persistent low-level moisture convergence line crossing the Apennines range in a west–east direction, together with orographic lifting, played a crucial role in the process of convection initiation (Grenzi, 2025). Infrared observations revealed a pronounced V-shaped signature (Figure 1b), indicative of intense updrafts reaching the tropopause and strong upper-level winds advecting the anvil cloud downstream. In this configuration, downdraft outflows repeatedly initiated new cells upwind (known as the back-building process), anchoring the system to the orography for several hours. The system reached maximum intensity around 1700 UTC, with rainfall rates exceeding 100 mm · h⁻¹ locally. The largest accumulations were recorded near Cantiano, close to Mount Catria (the highest peak in the area), where total precipitation reached 419 mm. The convective system weakened after 2100–2200 UTC as the low-level inflow diminished and synoptic forcing shifted eastward. Despite its limited temporal extent, the exceptional rainfall intensity over steep, small catchments triggered destructive flash floods and landslides, causing 13 fatalities and economic losses of the order of 2 billion euros (Bendia *et al.*, 2026).

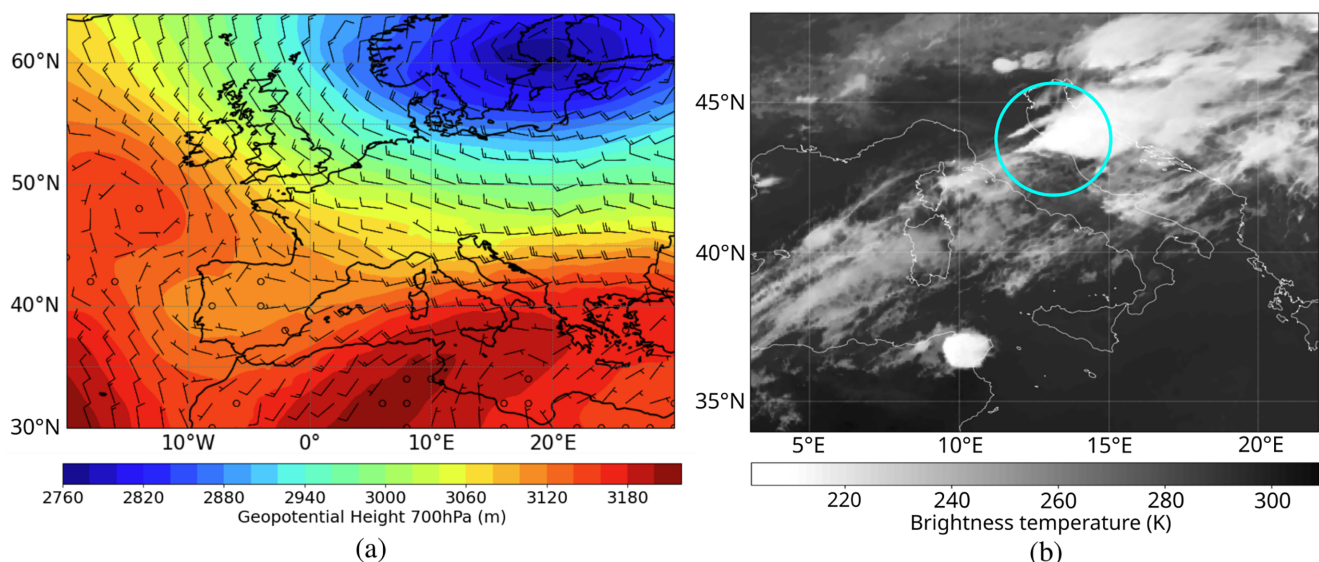


FIGURE 1 (a) Geopotential height (contours) and wind vectors at 700 hPa on September 15, 2022 at 1700 UTC, taken from ERA5 reanalysis. (b) Satellite image over Italy from *Meteosat Second Generation* SEVIRI instrument in the window channel at 10.8 μm at 1712 UTC, sensitive to surface and cloud-top thermal emission. The circle indicates the location of the convective storm. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70256)]

Global and limited-area operational models severely underestimated rainfall and misplaced the convective system core. At that time, Arpa Emilia-Romagna produced operational forecasts over the Italian domain with the COSMO limited-area model (Baldauf *et al.*, 2011), nowadays superseded by the ICON model. Previous studies showed substantially improved performance of the ICON model over COSMO in capturing the *Marche2022* storm development, even though a consistent underestimation of precipitation still persisted (Grenzi, 2025). This makes the *Marche2022* event an ideal test ground of the impact of satellite radiances in water-vapour absorption channels, thus sensitive to moisture content in the troposphere. Will these radiances bring improvement in the forecast rainfall?

3 | METHODOLOGY

This section illustrates first the technical details of the operational numerical model and ensemble DA system used in this work. The observations employed in the assimilation cycle and in the forecast verification are then presented, with particular focus on satellite radiances, which are of primary interest in the study. Afterwards, the experimental setup is described, including the verification metrics used to evaluate the impact of satellite DA.

3.1 | Numerical model

The non-hydrostatic atmospheric model ICON (Zängl *et al.*, 2015) employs an unstructured icosahedral mesh composed of triangular elements arranged according to an Arakawa C-grid staggering. In this work, we use

the regional configuration ICON-2I, operated at Arpa Emilia-Romagna in collaboration with the ItaliaMeteo Agency, as a limited-area model covering the Italian domain (Figure 2). The model integration is performed with a horizontal grid spacing of 2.2 km, 65 hybrid vertical levels, and the upper boundary of the computational domain located at 22-km altitude. For deterministic forecasts, boundary conditions are taken from the High-Resolution Integrated Forecasting System (IFS HRES) run by the European Centre for Medium-Range Weather Forecasts (ECMWF).

The model solves the fully compressible non-hydrostatic set of governing equations, advancing prognostic variables that include the horizontal velocity component normal to cell edges, vertical velocity, air density, virtual potential temperature, and the specific contents of water vapour, cloud liquid, cloud ice, rain, snow, and graupel. At this convection-permitting scale, deep convective motions are represented explicitly, whereas shallow convection is parameterized using the Tiedtke–Bechtold scheme (Bechtold *et al.*, 2008; Tiedtke, 1989). Radiative transfer is treated with the ecRad parameterization (Hogan & Bozzo, 2018); to reduce computational cost, radiative calculations are performed on a coarser grid with halved spatial resolution (~ 4.4 km) and with a longer radiation time step. Cloud microphysical processes are represented through a single-moment microphysics scheme (Seifert, 2008).

3.2 | Data assimilation system

The DA scheme relies on a LETKF approach (Hunt *et al.*, 2007), in which then analysis ensemble mean and

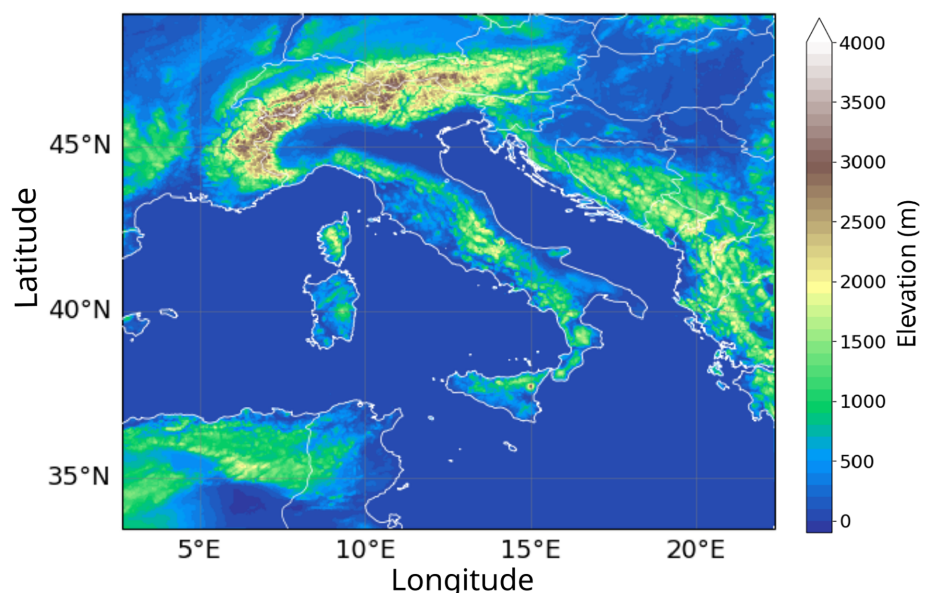


FIGURE 2 ICON-2I domain used in this work and employed operationally at Arpa Emilia-Romagna and ItaliaMeteo Agency. Surface orography is shown. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

error covariance are computed via a linear deterministic transformation in the space of the ensemble (the analysis is affine to that space). The LETKF algorithm is embedded in the Kilometre-scale ENsemble Data Assimilation (KENDA: Schraff *et al.*, 2016) framework, following the operational implementation adopted by Arpa Emilia-Romagna and the ItaliaMeteo Agency. The system employs a 40-member ensemble at the same spatial resolution as the deterministic forecast, while lateral boundary conditions are derived from the ensemble prediction system of ECMWF IFS. The updated variables in the control vector are specifically horizontal components of the wind field, temperature, pressure, specific humidity, and mixing ratios of cloud water, cloud ice, rain water, graupel, and snow ($u, v, t, p, q, clwmr, climr, rwmr, qg, qs$, respectively). Model equivalents, that is, the application of the forward observational operator transforming the model variables in the observation variables (then used to evaluate the innovations), are computed at the exact time of each observation inside the assimilation window, rather than exclusively at the nominal analysis times. In this implementation, the LETKF is a truly four-dimensional DA scheme, referred to as 4D-LETKF in Hunt *et al.* (2007) and implemented in KENDA.

The KENDA system determines the analysis weights in ensemble space on a reduced-resolution grid (Yang *et al.*, 2009) defined on 30 pressure levels and with a horizontal coarsening factor equal to 3 (resulting in approximately 6.5-km resolution). The computation is carried out independently at each grid point in ensemble space. These weights are subsequently interpolated back to the native high-resolution grid to generate analysis increments in model space, a strategy that yields substantial computational savings while affecting the quality of the analysis only marginally.

As in other ensemble Kalman filter schemes, the background-error covariance is estimated from the ensemble, enabling a flow-dependent representation. Nevertheless, the finite ensemble size and an imperfect description of model error generally lead to an underestimation of ensemble spread in both forecast and analysis states (Anderson, 2009; Scheffler *et al.*, 2022), which can ultimately result in filter divergence. This issue is mitigated through multiplicative covariance inflation implemented here via relaxation to prior spread (RTPS: Whitaker & Hamill, 2012). In RTPS, the posterior ensemble standard deviation is relaxed toward the prior spread, according to a scalar factor $\alpha = 0.95$. To limit the influence of spurious long-range correlations arising from sampling error, the analysis is performed locally at each grid point of the coarsened grid using observational localization. A Gaspari-Cohn function (Gaspari & Cohn, 1999) modulates the contribution of observations according to

their distance from the analysis location, with horizontal localization radii tailored to the specific observation being assimilated. In the vertical, the localization scale is height-dependent, increasing from 0.075 to 0.5 in logarithmic pressure coordinates between 1000 hPa and the model top near 22-km altitude. Observation error is assumed to be uncorrelated spatially and among observations, making the observation-error covariance matrix, $\mathbf{R}$, diagonal. To mitigate the effect of neglecting observation-error correlations and to reduce computational cost, data reduction techniques like superobbing and thinning are applied (Duncan *et al.*, 2024).

3.3 | Observing system

A multi-platform dataset is used in this study, combining conventional, radar, and satellite observations. In the following sections we describe them in detail.

3.3.1 | Conventional data

The observational dataset assimilated in this study is the operational configuration used at Arpa Emilia-Romagna and ItaliaMeteo. Specifically, conventional (CONV) observations of 10-m wind and surface pressure from ground stations (SYNOP) are employed, together with temperature, horizontal wind, and humidity information from aircraft observations (AIREP) and radiosonde soundings (TEMP). It should be noted that humidity measurements from AIREP are rather sparse and limited. While TEMP

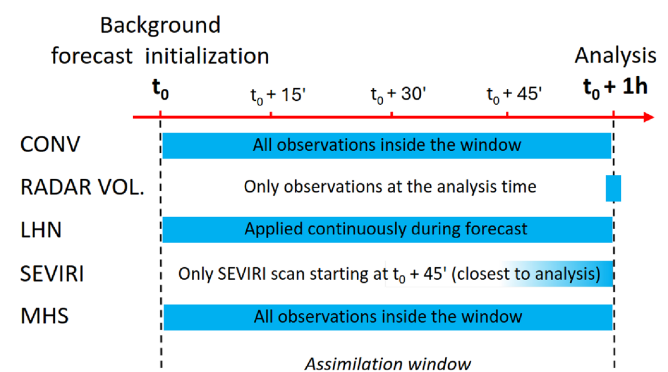


FIGURE 3 Scheme showing a generic assimilation window of 1 h, starting at time t_0 . The assimilation strategy is described for the different observation types contributing to the LETKF analysis at time $t_0 + 1$ h. CONV and MHS data are used whenever available within the window, while for SEVIRI only the scan starting at $t_0 + 45$ min is considered. Radar volumes are used at the proper analysis time. LHN is applied continuously during the model run. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

data are usually available only once or twice per day, SYNOP and, to a lesser extent, AIREP are available at higher temporal frequency (hourly). In our DA setup, CONV observations are given an adaptive horizontal localization length scale between 50 and 100 km and observational errors are specified as in Schraff *et al.* (2016). Each hourly KENDA cycle, all the CONV data inside the 1-h assimilation window are assimilated by the 4D-LETKF, computing model equivalents at the exact times of each observation (Figure 3).

Concerning forecast verification, 2-m temperature, 2-m relative humidity, 2-m dew-point temperature, and 10-m wind are considered at the surface; temperature, relative humidity, and wind velocity horizontal components at upper levels. All the conventional observations are monitored through a quality-control procedure, before being used for any purpose.

3.3.2 | Radar data

The radar observations assimilated include three-dimensional volumes of reflectivity and radial velocity collected by the Italian radar network. A map showing the locations of these radars is given in Gastaldo *et al.* (2021). Before being assimilated, these data are subjected to a dedicated quality-control procedure designed to mitigate the effects of non-meteorological echoes, beam blocking, and signal attenuation. A more detailed description of the radar preprocessing and quality-control methodology is provided in Gastaldo *et al.* (2021). The assimilation of radar measurements is performed through the Efficient Modular Volume RADarOperator (EMVORADO: Bick *et al.*, 2016; Zeng *et al.*, 2016), which generates model-equivalent synthetic radar observations from the prognostic variables of the ICON model. Within the DA framework, radar volumes are associated with a horizontal localization length scale of 16 km. Observation errors for reflectivity are prescribed uniformly as 10 dBZ; for radial velocity, the error is set to $2.5 \text{ m} \cdot \text{s}^{-1}$ for reflectivity $\geq 10 \text{ dBZ}$, $25 \text{ m} \cdot \text{s}^{-1}$ for reflectivity $\leq 0 \text{ dBZ}$, and varies linearly between these thresholds. Considering the very high spatial resolution of radar measurements, a superobbing procedure is applied to both observations and corresponding model background fields, obtaining super-observations and corresponding model equivalents at an effective resolution of 10 km, following Bick *et al.* (2016). Although radar data from the Italian network have a 5-min temporal resolution, the radar acquisition is assimilated only every hour at the analysis time (Figure 3). Reflectivity values $< 5 \text{ dBZ}$ are set to 5 dBZ in both observations and first guess before assimilation, following the approach by Gastaldo *et al.* (2021), to avoid non-meteorological factors such as

the presence of aerosols, birds, or the incomplete removal of clutter by the quality-control procedure.

In addition to their use in DA, radar observations contribute to the generation of the Italian radar composite. The product of accumulated precipitation is subsequently adjusted using rain-gauge measurements and employed for precipitation verification. More details about this procedure are provided in Section 3.5.1. Additionally, the SRI product obtained from the Italian Civil Protection Department (DPC) at 1-km resolution is assimilated into each LETKF ensemble member using a LHN approach (Jones & Macpherson, 1997; Stephan *et al.*, 2008). Raw radar reflectivity volumes used for SRI estimation undergo a separate quality-control procedure (Rinollo *et al.*, 2013) that accounts for beam blockage, range effects, beam height, and attenuation. Composite SRI fields are derived following the approach by Vulpiani *et al.* (2012). These SRI products are available at 5-min temporal intervals but are then assimilated at 10-min temporal and 1-km spatial resolution. Prior to their use in LHN, SRI products undergo a quality-control procedure rejecting low-quality data and are then interpolated onto the model grid. The LHN approach is based on the assumption that vertically integrated latent heat release is approximately proportional to precipitation. It is applied continuously throughout the DA cycle, modifying the model thermodynamic state by adjusting humidity and consequently temperature profiles in regions affected by precipitation.

3.3.3 | Satellite data

Two different passive satellite instruments are used for assimilation: (1) the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) and (2) MHS, in the infrared and microwave portions of the electromagnetic spectrum, respectively. The model equivalents for all satellite observations are computed by the fast radiative transfer model for TIROS Operational Vertical Sounder (RTTOV) version 13.2 (Saunders *et al.*, 2018), implemented as observation operator for satellite DA in KENDA and widely used in several national meteorological services.

Spinning Enhanced Visible and InfraRed Imager (SEVIRI)

Level 1.5 radiances at full resolution from SEVIRI on board the *Meteosat Second Generation (msg)* satellite (Schmetz *et al.*, 2002) are preprocessed by DWD and then received in Network Common Data Form (netCDF) format, ready to be tested within our ICON-KENDA system. SEVIRI is a geostationary instrument providing observations in the visible and thermal infrared portion of the spectrum, at

high spatial and temporal resolution. In particular, SEVIRI from *Meteosat-11* is used in this article.

The all-sky assimilation of SEVIRI radiances has been operational at DWD since November 2023 (Schomburg *et al.*, 2026) and our setup for SEVIRI assimilation largely follows their approach. During the preprocessing step from the DWD side, some basic procedures are carried out, such as conversion from radiances to brightness temperatures through inversion of the Planck function, the definition of necessary metadata for assimilation in ICON/KENDA, basic quality checks (filter out corrupted and double data), channel selection, and computing topography information. In the present study, only the two SEVIRI water-vapour absorption channels are considered in all-sky conditions: channel 5 at $6.25\ \mu\text{m}$, peaking near the tropopause, and channel 6 at $7.35\ \mu\text{m}$, peaking in the mid-troposphere (Table 1). In the thermal infrared spectral range considered here, cloud layers are opaque; consequently, the measured radiances primarily convey information about the cloud top under cloudy conditions. Although the SEVIRI instrument provides radiances at 15-min intervals, in the DA cycle data are ingested only once per hour. Specifically, we assimilate the SEVIRI scan initiated 15 min before the full hour, which is the closest one to the analysis time, as explained in Schomburg *et al.* (2026) (Figure 3). The spatial sampling of these observations corresponds to an approximate footprint of $3\times 3\ \text{km}^2$ at the Equator, increasing to about $3\times 5\ \text{km}^2$ over the ICON-2I domain as a result of the Earth's curvature with increasing latitude and longitude.

A critical step in satellite ensemble DA is the definition of vertical localization of satellite radiances and particularly the height assignment, which might be particularly challenging, since radiances correspond to an integrated signal over the entire atmospheric column, being an example of non-local observations (Hutt *et al.*, 2021). Instead of analysing the Jacobians of the forward operator with respect to temperature and humidity, which is a common but computationally expensive strategy to identify the atmospheric level of maximum influence

(Hutt *et al.*, 2020), we adopt the methodology described in Schomburg *et al.* (2026), which makes direct use of the all-sky transmission calculated internally by RTTOV. The height assignment of a radiance observation is then defined as the altitude at which the transmission decreases to 0.5, and this level is taken as the centre of the Gaspari–Cohn localization function. The associated vertical localization length scale is prescribed as 0.3 in logarithmic pressure coordinates. Horizontal localization is set to 25 km and thinning to $12\times 12\ \text{km}^2$ for both channels is used.

Concerning observation error, the cloud-dependent error model described in Schomburg *et al.* (2026) is used for all-sky SEVIRI brightness temperatures, neglecting interchannel correlations, as in the DWD operational setup. This approach is based on a polynomial fit of the standard deviation of the first-guess departures, with the cloud impact parameter defined in Okamoto *et al.* (2014) used as predictor. Lastly, satellite observations are not assimilated in high orography regions, defined as grid-point altitude $>1000\ \text{m}$. High and complex topography introduces a number of surface effects like variable emissivity, skin temperature variations, and terrain-induced radiative distortions. These can lead to less accurate radiative transfer computations and large observation-minus-background departures in radiance data; for this reason, observations over mountain areas are filtered out before being ingested by the DA system.

Given that cloud representation in numerical models is often associated with significant uncertainties, a quality-control procedure is applied to screen out radiances with large departures from the background state. The default first-guess check implemented in KENDA is applied to SEVIRI radiances. Precisely, a radiance observation is rejected if the departure from the background state is $\geq 3\sqrt{\sigma_o^2 + \sigma_f^2}$, where σ_o and σ_f are the observation-error and first-guess ensemble spread, respectively.

Running RTTOV requires temperature and humidity profiles, surface pressure, skin temperature, 2-m temperature, 10-m wind, orography, and land/sea-ice mask

TABLE 1 Technical details of the satellite channels assimilated from SEVIRI and MHS instruments.

Instrument	Chan. no.	Frequency/wavelength	WF peak	Sensitivity	Condition
SEVIRI	5	$6.25\ \mu\text{m}$	$\sim 300\ \text{hPa}$	WV	all-sky
SEVIRI	6	$7.35\ \mu\text{m}$	$\sim 500\ \text{hPa}$	WV	all-sky
MHS	3	$183.3 \pm 1.0\ \text{GHz}$	$\sim 350\ \text{hPa}$	WV	clear-sky
MHS	4	$183.3 \pm 3.0\ \text{GHz}$	$\sim 500\ \text{hPa}$	WV	clear-sky
MHS	5	$190.3\ \text{GHz}$	$\sim 700\ \text{hPa}$	WV and surface emission	clear-sky

Abbreviation: WF, weighting functions; WV, water vapour.

taken from the ICON model first guess. In addition, for all-sky IR assimilation, the input variables from ICON include

- layer cloud fraction: ICON diagnostic cloud cover;
- liquid water content: ICON diagnostic total (grid-scale + subgrid) specific cloud liquid water;
- ice water content: ICON diagnostic total (grid-scale + subgrid) specific cloud ice.

The KENDA suite interpolates the ICON profiles onto the RTTOV coefficient levels, using the method by Rochon *et al.* (2007). Coefficients from the RTTOV v13 predictor files on 54 levels are employed. For all-sky IR scattering a Chou-scaling solver is used, described by Tang *et al.* (2018), while aerosol scattering is not included. Cloud optical properties are taken from the RTTOV coefficient files, using the particle effective diameter (Deff) for liquid clouds and ice cloud properties from Baum *et al.* (2011). The sea-surface emissivity is computed with the InfraRed EMISsivity model (Saunders *et al.*, 2017), while over land RTTOV default constant emissivity (0.98) is used. We point out here that SEVIRI water-vapour channels peak in the mid to upper troposphere. The atmosphere is largely opaque at these wavelengths, due to strong water-vapour absorption, meaning the surface emission contribution to the top-of-atmosphere radiance is rather small under most conditions.

Microwave Humidity Sounder (MHS)

In addition to SEVIRI, the second satellite data type considered in this study comprises level 1.5 radiances at full resolution from the MHS instrument. MHS is a five-channel passive, cross-scanning microwave sounder, assimilated operationally in the global ICON model at DWD. The instantaneous field of view is approximately $16 \times 16 \text{ km}^2$ at nadir, then the footprint increases with increasing scanning angle.

Nevertheless, MHS data are still not assimilated in the limited-area model ICON-D2 at DWD nor in ICON-2I at Arpa Emilia-Romagna and Italia Meteo. At the time of the *Marche2022* event, MHS was on board three satellites: *Metop-B* and *Metop-C* managed by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) in continental Europe, and *NOAA-19* managed by the National Oceanic and Atmospheric Administration (NOAA) in USA. These are all polar sun-synchronous satellites, which pass close to each other over the ICON-2I domain twice per day, in the morning (0600–1000 UTC) and in the evening (1800–2200 UTC). Each KENDA cycle, all MHS observations available over the ICON-2I domain within the 1-h assimilation window are used at their exact time (Figure 3),

exploiting the four-dimensional implementation of the LETKF.

MHS observations undergo the same preprocessing step as SEVIRI at DWD, after which we receive the netCDF files ready to be used. Three water-vapour MHS absorption channels are considered (numbers 3, 4, and 5), the same used for assimilation in the global ICON model. Importantly, and in contrast to what is done for SEVIRI, only clear-sky conditions are considered. This is due to the current unavailability in KENDA of the RTTOV-SCATT package (Bauer *et al.*, 2006; Saunders *et al.*, 2018) for computing scattering from hydrometeors in the microwave spectrum, necessary in all-sky assimilation. However, compared with infrared radiances, which are almost completely opaque to any cloud type, making clear-sky assimilation in the infrared spectrum very restrictive, the clear-sky assimilation of microwave channels removes only precipitating clouds, while retaining all the cloudy and non-precipitating pixels where scattering from hydrometeors is not significant. Details of the MHS assimilated channels are found in Table 1. The channels peak at different tropospheric levels, going from the upper to the lower troposphere. In particular, channel 5 is also sensitive to surface emission, which is particularly relevant over land, where it can suffer from small biases in the NWP model (in this case, ICON) that may affect the accuracy of the RTTOV computations. For this reason, MHS channel 5 is assimilated only over the sea. Concerning channels 3 and 4, the influence of the surface is much reduced compared with channel 5; however, surface emissivity must be taken into account anyway in radiative transfer computations, particularly over the land, where the emissivity is much higher and less uniform compared with the sea. Therefore, to improve the assimilation of MHS channels 3 and 4 over non-ocean surfaces, dynamic emissivity retrieval (Baordo & Geer, 2016; Karbou *et al.*, 2006) is used in this work.

The clear-sky assimilation requires the activation of a cloud detection scheme for microwave radiances to filter out thick or precipitating clouds, where scattering processes cannot be neglected. The method adopted in this article is based on a modified version of Buehler *et al.* (2007), a cloud filtering method for mid and upper tropospheric humidity. The method combines two approaches: (1) thresholding brightness temperature observations from MHS channel 3, T_{ch3} , and (2) defining a threshold on the brightness-temperature difference between the low- and high-peaking MHS channels, that is, channels 5 and 3, respectively:

$$thresh_{\text{ch5-ch3}} = A + BT_{\text{ch3}} \cdot B, \quad (1)$$

with the coefficients A and B depending on the latitude and satellite viewing angle. We used the values tuned for the

global ICON model. The cloud detection is not symmetric, that is, it only aims to remove cloudy observations and not cloudy model points, assuming that the clear-sky simulation for a cloudy model field of view is a good enough approximation to still make use of observations.

None of the channels is assimilated over high orography, similarly to what is done for SEVIRI. Both vertical and horizontal localization radii are as for SEVIRI, as well as the vertical height assignment based on the transmissivity explained before. Thinning is not applied to MHS, because the native spatial resolution of microwave radiances is sufficiently coarse compared with the ICON grid spacing, making data reduction unnecessary. Observation error is set to the default used for global ICON assimilation, 2 K for all three channels considered. Different tests have been performed on our ICON-2I configuration (not shown), changing the observation error according to Desroziers *et al.* (2005) diagnostics without significant improvements. Results reveal that 2 K corresponds to an overestimation of up to $\sim 50\%$ of the Desroziers *et al.* (2005) estimate for MHS channels 4 and 5, and a smaller difference for channel 3. Using a diagonal observation-error matrix larger than diagnostics suggest is usually considered beneficial in satellite data assimilation, especially when neglecting observation-error correlations, as in our experiments (Bormann *et al.*, 2016).

No radiance bias-correction scheme is applied to radiance assimilation in this study. The operational setup at DWD likewise does not apply bias correction to SEVIRI radiances (Schomburg *et al.*, 2026). As shown in Section 4.2.5, the first-guess departures exhibit only small offsets, largely within the imposed observation error, which do not warrant bias correction for the clear-sky microwave and all-sky water-vapour infrared channels considered in the experiments of this study.

3.4 | Experimental setup

We perform five-day-long experiments starting on September 12 at 0000 UTC, thus allowing sufficient spin-up of

the assimilation cycle before the flood event. Recall that the analysis is performed hourly, using the LETKF with 40 ensemble members to estimate the background covariance, plus one deterministic run updated by applying the Kalman gain of the ensemble mean to the innovations. Boundary conditions are provided by the ECMWF global model: ECMWF-ENS at 0.2° resolution for ensemble members and ECMWF-IFS HRES at 0.1° for the deterministic run. ICON forecasts are initialized every 3 h with a lead time of 21 h, except for the 0000 UTC forecast on September 15, which runs for 24 h so as to cover the flood event fully. In total, 40 forecasts are produced, with the final one initialized on September 16 at 2100 UTC. ECMWF-IFS HRES boundary conditions are used. The analysis increments are applied to the first guess in an incremental analysis update (Bloom *et al.*, 1996) over a time span of 10 min centred on the analysis time (full hour). This procedure is applied to reduce imbalances and suppress high-frequency noise in the analysis that could degrade forecast quality. During the 1-h first-guess runs between two successive analyses, LHN toward the radar-derived surface precipitation rates is applied.

We therefore have a total of four experiments, as summarized in Table 2. The *control* experiment assimilates conventional observations from ground stations, aircraft, radiosondes, and radar volumes and applies the LHN as in the operational configuration of Arpa Emilia-Romagna and ItaliaMeteo. This serves as a benchmark to evaluate the impact of satellite assimilation in the following experiments. The SEVIRI experiment adds to the *control* protocol the two water-vapour absorption channels (nos 5, 6) from the SEVIRI satellite instrument in all-sky conditions (see Section 3.3.3). Similarly, the MHS experiment follows the same protocol as in the *control* and assimilates all conventional and radar data plus the three water-vapour absorption channels from the MHS satellite instrument in clear-sky conditions (see Section 3.3.3). Finally, in the *MHS+SEVIRI* experiment all observation types are assimilated simultaneously, to evaluate the combined impact of microwave and infrared radiances.

TABLE 2 Summary of the four experiments run in this study (control, MHS, SEVIRI, MHS+SEVIRI), showing the observations assimilated in each experiment.

Experiment	Control	MHS	SEVIRI	MHS+SEVIRI
Conventional (SYNOP, AIREP, TEMP)	yes	yes	yes	yes
Radar volumes (reflectivity and radial velocity)	yes	yes	yes	yes
Latent heat nudging	yes	yes	yes	yes
MHS channels 3, 4, 5 clear-sky	no	yes	no	yes
SEVIRI channels 5, 6 all-sky	no	no	yes	yes

3.5 | Verification metrics

The performance of the different experiments is evaluated against observations used as ground truth. Those observations employed for forecast verification are not assimilated and therefore represent an independent benchmark. Once used for verification at a given time, they may possibly be assimilated in following DA cycles. In the coming three subsections, we provide details concerning the verification of accumulated precipitation (Sections 3.5.1, 3.5.2), surface, and upper-level variables (Section 3.5.3).

3.5.1 | Fractions skill score (FSS) for precipitation

The verification of a precipitation forecast (or, more precisely, a quantitative precipitation forecast, QPF) typically requires suitable metrics to mitigate some known issues like the “double penalty” problem (Rossa *et al.*, 2008), which exacerbates in high-resolution models in particular. The fractions skill score (FSS) is a spatial verification metric that follows the neighbourhood-based framework proposed by Roberts and Lean (2008). This approach evaluates the fraction of precipitation events exceeding a prescribed threshold, within square boxes into which the model area is partitioned. By comparing the observed and forecast fractions, a dimensionless score between 0 and 1 is obtained:

$$\text{FSS} = 1 - \frac{\frac{1}{N} \sum_N (p_f - p_o)^2}{\frac{1}{N} (\sum_N p_f^2 + \sum_N p_o^2)}, \quad (2)$$

where N is the number of boxes in the domain, and p_f and p_o the fractions of forecast and observed events in each box exceeding the predefined precipitation threshold. A value of FSS equal to 1 denotes perfect agreement, with identical event frequencies in every box, whereas a value of 0 corresponds to a completely unsuccessful forecast. This formulation accounts for the fact that high-resolution models tend to be penalized in traditional grid-point verification due to their fine spatial resolution, as small spatial or temporal displacements of precipitation features are penalized more heavily at finer scales (Ebert, 2008). In the present study, the FSS is computed over the Italian domain (only over the land) using $0.2^\circ \times 0.2^\circ$ boxes, each encompassing 100 model grid points.

Observational precipitation fields are based on hourly accumulations derived from the Italian radar composite, which is adjusted using rain-gauge measurements. The procedure employed to generate these observational fields originates from the method of Koistinen and

Puhakka (1981) and has been adapted for radar composite applications following Amorati *et al.* (2012). Specifically, although the original algorithm incorporates both range-dependent and spatially varying corrections, only the latter are applied here. This choice is motivated by the fact that, within overlapping regions of the radar composite, precipitation estimates result from the merging of multiple radar observations, thereby removing explicit information about the distance from individual radar sites. In this work, the FSS is used both to evaluate the forecast of 24-h precipitation for the day of the convective event and for the verification of 3-h accumulated precipitation as a function of forecast lead time.

The uncertainty of the FSS estimates is evaluated by using 95% confidence intervals. These intervals are obtained through a resampling strategy based on the bootstrap technique (Efron & Tibshirani, 1994). Starting from the original sample of forecast and observation precipitation fractions, many alternative datasets are constructed by repeatedly drawing pairs at random with replacement, each time preserving the same sample size. This generates an ensemble of equally sized datasets and the FSS is recomputed for every resampled dataset. The spread of the resulting values is then interpreted as sampling uncertainty; finally, the confidence bounds are derived from the appropriate percentiles of this bootstrap distribution.

3.5.2 | Performance diagrams for precipitation

In addition to FSS, the verification of precipitation is also performed by using dichotomous indexes. Specifically, the analysis makes use of four categorical verification metrics: the frequency bias index (FBI), probability of detection (POD), success ratio (SR), and threat score (TS). Each of these indicators has its own advantages and limitations; therefore, they should not be interpreted in isolation but rather evaluated together. One effective approach is to take advantage of their geometric interdependence to create a performance diagram, as proposed by Roebber (2009). In such a diagram, the horizontal and vertical axes correspond to SR and POD, respectively; FBI and TS are also represented with contour lines in the diagram. Forecast quality improves as POD, SR, FBI, and TS approach one, placing an ideal forecast at the upper-right corner of the plot. Shifts away from that point reveal imbalances between POD and SR, and thus the associated variations in FBI and TS.

Verification with dichotomous indexes is performed only over the Italian land, as for FSS. However, in contrast to FSS, the verifying observations are taken from the rain-gauge network only. In addition, the evaluation

is carried out over the areas adopted by the DPC within the national weather warning framework. These zones are delineated so that each is characterized by similar hydrometeorological conditions in terms of both the nature and the severity of expected events, as well as their potential impacts on land. For the calculation of the verification metrics, the predicted rainfall field is initially interpolated onto the rain-gauge locations; subsequently, for every zone, both mean and maximum values of forecast and observed precipitation are used to compute the dichotomous indexes. The results are then averaged over two lead-time windows (0–9 h, 9–21 h) to quantify the impact of DA closer to and further from the analysis.

3.5.3 | RMSE and bias for surface and upper-level variables

Two standard verification metrics, the bias and the root-mean-square error (RMSE), are used for surface and upper-level variables. Precisely, the following quantities are considered: 2-m temperature, 2-m relative humidity, 2-m dew-point temperature, and 10-m wind at the surface; temperature, relative humidity, and wind velocity horizontal components in the upper levels. Verification for upper-level variables is performed employing radiosonde observations (TEMP) described in Section 3.3.1 and largely follows the approach of Gastaldo *et al.* (2021). For surface variables, verification is performed against ground-station data. For the sake of completeness and clarity, we summarize the key steps here. First, the forecast verification is performed in observation space, exploiting information contained in the so-called ICON *feedback files*, where observations and corresponding model equivalents are stored. Since observations are sparse over the domain, it is necessary to account for their spatial inhomogeneity. Therefore, spatial and temporal aggregation is performed: the forecast and the corresponding observations are grouped according to geographic location, vertical coordinate (only for upper-level variables), and forecast lead time.

Concerning upper-level variables, the spatial aggregation is performed in the following way. The model domain is partitioned into three-dimensional atmospheric volumes, consisting of squared horizontal cells with a side length of 2°, while the vertical coordinate is discretized using pressure-based vertical levels with uneven spacing for TEMP. This approach is chosen to achieve an approximately uniform filling of observations with height. Temporal aggregation is performed using two forecast lead-time windows covering the 0–9 h and the 9–21 h lead-time windows respectively, in order to evaluate the

impact of DA during the first and second parts of forecast. For a given verification variable, bias and RMSE are calculated for each lead-time window and for each atmospheric volume. Subsequently, bias and RMSE are averaged over all atmospheric volumes, for each vertical layer and at each forecast time interval. The averaging protocol assigns equal importance to each atmospheric volume regardless of its observational data density, provided that at least 100 observations are contained in the volume, ultimately producing a single value of bias and RMSE for each atmospheric layer and each time interval.

A very similar procedure is used for surface variables, although this time the spatial aggregation of observations is performed only horizontally. Given the higher temporal frequency of SYNOP observations compared with TEMP, the temporal aggregation is performed on shorter lead-time windows of 3 h. The calculation of bias and RMSE boils down to the two following formulae:

$$\text{bias}(k, t) = \frac{1}{N_{k,t}} \sum_{v \in S_k} \sum_{i \in v} \frac{(f_i - y_i)}{n_v}, \quad (3)$$

$$\text{RMSE}(k, t) = \frac{1}{N_{k,t}} \sum_{v \in S_k} \sum_{i \in v} \left(\sqrt{\frac{(f_i - y_i)^2}{n_v}} \right), \quad (4)$$

where k, t indicate the vertical layer and the lead-time window, respectively, v is the v th atmospheric volume, n_v is the number of observations in the v th cell, S_k is the k th atmospheric layer, and f_i, y_i are, respectively, the i th forecast and observed variable inside the cells in the observation space. For surface variables, the k index is of course irrelevant.

3.6 | Partial analysis increments

To interpret how individual observations influence the analysis produced by the LETKF, the PAI developed by Diefenbach *et al.* (2023) is used. In ensemble-based DA (as well as in DA in general), the full analysis increment results from the combined impact of many observations within a localization region, making it difficult to attribute analysis changes to specific data sources. The PAI approach addresses this by decomposing the total analysis increment into additive contributions associated with selected subsets of observations (e.g., by type, platform, channel, or spatial group).

The PAI exploits the linear structure of the LETKF update in ensemble space. After the analysis has been computed, the increments are recomputed while selectively retaining only the innovations associated with a

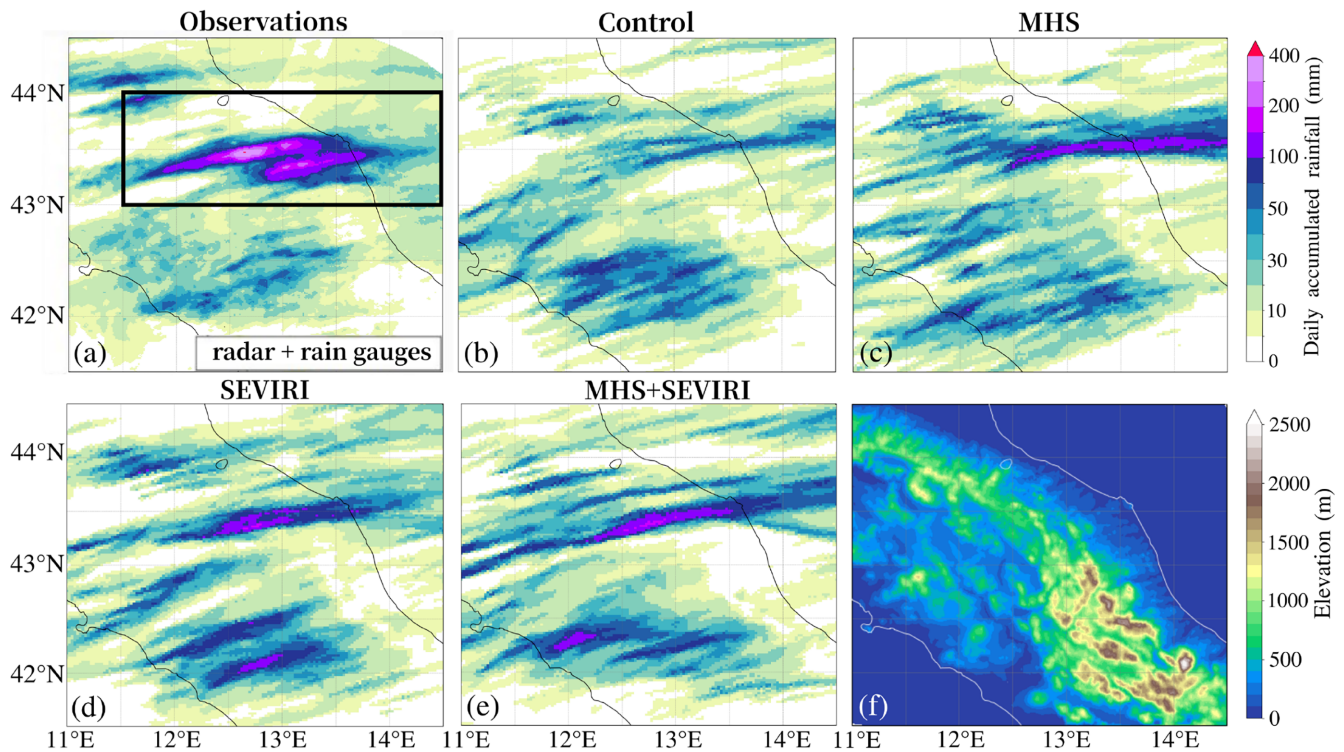


FIGURE 4 (a) 24-h accumulated rainfall on September 15 from radar-estimated precipitation corrected with rain-gauge measurements. The box shows the area considered in the computation of the FSS in Table 3. Also shown is 24-h accumulated rainfall on September 15 for (b) control, (c) MHS, (d) SEVIRI, and (e) MHS+SEVIRI experiments, respectively. Forecasts initialized from the analysis at 0000 UTC. (f) Orography map of the region. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)] [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

chosen group of observations (e.g., a given instrument or data type), with all other elements of the assimilation framework (i.e., ensemble perturbations, localization, observation error) kept unchanged. PAI diagnostics enable a quantitative and spatially explicit assessment of observation impact on analysed variables, avoiding the need for rerunning the DA system.

The main assumptions in the PAI are uncorrelated observational error (i.e., a diagonal observation-error covariance matrix $\mathbf{R}$) and the absence of background-error covariance inflation (Diefenbach *et al.*, 2023). While the first assumption holds in our experiments, since observation-error correlations are always neglected, the second one does not, because multiplicative covariance inflation using RTPS is applied. Assuming no inflation implies that the total analysis increment may differ from the sum of the partial increments of each observation. However, we claim that, even in this case, the conclusion about which observation types have the largest impact compared with the others is not much affected. In the Section 4.1.3 we will evaluate the robustness of assuming no inflation in the PAI computation.

In this study, PAI is computed over a subregion of the whole domain, located upstream of the *Marche2022* convective storm development. The main purpose is

to evaluate which observation types provides the most significant contribution in the DA cycle, focusing on the few hours before the initialization time of the forecast of September 15, the day of the *Marche2022* event.

4 | RESULTS

The section is divided into two main parts. We start by presenting the results following a top-down approach. First, we compare the different experiments evaluating the performance of a 24-h deterministic forecast for September 15 initialized at 0000 UTC, focusing on accumulated rainfall, which is the derived field of primary interest in the *Marche2022* event. The origin of the differences among the experiments is then traced back to the prognostic state variables (humidity, temperature, and wind): specifically, we investigate the differences in forecast initial conditions among the experiments focusing on specific humidity and temperature fields, also evaluating the impact of the different assimilated observation types using the PAI algorithm. Second, a more extensive forecast verification is performed over the whole five-day period of the experiments, collecting more statistics in order to get more robust results about the impact of satellite DA.

4.1 | Verification of deterministic forecast for *Marche2022* event

4.1.1 | Evaluation of daily accumulated precipitation

The exceptional rainfall amount was the most remarkable and impactful feature of the convective event, largely underestimated by numerical models. Therefore, we first evaluate the contribution of satellite DA to the ICON forecast by looking at the 24-h accumulated precipitation on September 15, the day of the storm. Figure 4 shows the comparison between the four experiments (control, MHS, SEVIRI, MHS+SEVIRI) and observations obtained from radar-derived precipitation corrected with rain-gauge measurements. The observed precipitation field is then more reliable on land than offshore, where no rain gauges are available. Figure 4 reveals that large underestimation of the event appears in the control forecast, where only a weak precipitation band is reproduced by the model, coherent with results in the previous study by Grenzi (2025). Maximum values smaller than 100 mm (Table 3) are shown in the area where the storm actually occurred, more than four times lower than observations. An overestimation is instead present to the south, upstream of the Apennines mountain range, related to precipitation in the early morning, a few hours after forecast initialization.

Large differences in the forecasts emerge when adding satellite DA to the experiments. All MHS, SEVIRI, and MHS+SEVIRI experiments are able to improve the

amount of total rainfall reproduced by the ICON model in the area of the severe storm event, identified by the box in Figure 4a. Here, we observe maximum precipitation values locally larger than ~ 150 mm and a more extended precipitation band developing downstream of the mountain range towards the coast. More precisely, the forecast from experiment MHS+SEVIRI exhibits the highest rainfall peak, followed by SEVIRI and MHS (cf. Table 3), suggesting a positive contribution of the joint assimilation of the two satellites. The rain overestimation to the south in the early morning is still present in the MHS experiment; however, it is increased further by the assimilation of SEVIRI data. A closer look reveals small differences in forecast initial conditions between MHS and SEVIRI experiments, particularly related to wind and humidity fields around 850/700 hPa in proximity to Corsica island (not shown). Here we find a local increase of specific humidity and more zonal winds in the SEVIRI experiment that favour the development of stronger convective cells upstream of the *Marche2022* mountains, which, however, do not match with observations.

For a more quantitative evaluation of the storm over the Marche region, we compute the FSS for the daily accumulated rainfall over the region inside the box in Figure 4, centred on the convective storm event. Results are shown in Table 3 for three precipitation thresholds (10, 50, and 100 mm) corresponding to light, moderate, and severe total precipitation, and demonstrate the remarkable benefit of satellite DA compared with the control run, especially for higher precipitation values. SEVIRI shows the best performance up to a 50-mm threshold, then for

TABLE 3 Fractions skill score (FSS) of the 24-h accumulated precipitation on September 15, computed over a box centred on the area of storm development (Figure 4a). All experiments considered, forecasts initialized from the analysis at 0000 UTC using $0.2^\circ \times 0.2^\circ$ boxes and three precipitation thresholds (10 mm: light rainfall, 50 mm: moderate rainfall, 100 mm: severe rainfall). The rightmost column shows maximum daily rainfall in the forecast, within the same region.

Experiment	FSS (10 mm)	FSS (50 mm)	FSS (100 mm)	Max (mm)
Control	0.81 ± 0.03	0.26 ± 0.07	0	98
MHS	0.84 ± 0.03	0.56 ± 0.09	0.40 ± 0.10	144
SEVIRI	0.88 ± 0.02	0.71 ± 0.08	0.32 ± 0.09	166
MHS+SEVIRI	0.84 ± 0.03	0.61 ± 0.09	0.48 ± 0.10	187

Note: Bold font indicates the highest value in each column.

TABLE 4 Same as Table 3 but for the full ICON-2I domain.

Experiment	FSS (10 mm)	FSS (50 mm)	FSS (100 mm)	Max (mm)
Control	0.59 ± 0.02	0.29 ± 0.05	0.13 ± 0.08	228
MHS	0.61 ± 0.02	0.47 ± 0.06	0.33 ± 0.07	378
SEVIRI	0.66 ± 0.02	0.54 ± 0.06	0.28 ± 0.06	356
MHS+SEVIRI	0.65 ± 0.02	0.46 ± 0.06	0.33 ± 0.07	405

Note: Bold font indicates the highest value in each column.

extreme precipitation MHS has a superior impact, with the MHS+SEVIRI experiment confirmed as the best one for this case study. To provide a broader assessment, in Table 4 we evaluate the performance of the different experiments over the full ICON-2I domain, considering only the points where the observations obtained from radar-estimated precipitation corrected with rain gauges are available. The results show a very similar pattern to Table 3, with a statistically significant improvement in FSS values provided by satellite DA for all precipitation thresholds compared with the control. We point out that another severe precipitation event occurred the same day over Slovenia, near the Italian border, producing ~ 300 mm of accumulated rainfall (not shown). The maximum precipitation values reported in Table 4 refer precisely to this precipitation event. The control and experiments with the addition of satellite DA partially underestimate and overestimate the maximum intensity, respectively. It is possible to conclude that, for this specific day, the assimilation of SEVIRI and MHS overall improves the precipitation forecast over the full ICON-2I domain compared with the control run; a general intensification of precipitation is also observed, leading eventually to an overestimation of accumulated rainfall in some regions. The analysis with performance diagrams in Section 4.2.2 will investigate whether this is a systematic bias towards more intense precipitation due to the introduction of satellite DA.

4.1.2 | Quantification of differences in forecast initial conditions

The forecasts in all of the four experiments under study use the same boundary conditions. Therefore, their differences

arise solely from differences in the initial conditions. To shed light on this aspect, we examine the discrepancies between the initial conditions (i.e., the analysis fields) of the control and MHS+SEVIRI forecasts initialized at 0000 UTC on September 15. Given the prevailing south-westerly flow, we focus on a region upstream of the convective storm development area, depicted by the box in Figure 5, which we conjecture might have had remarkable influence on the ability of the ICON forecast to reproduce the convective event correctly. Indeed, temperature and moisture advection by the mean flow from this region towards the Italian Peninsula during the hours following forecast initialization are expected to play a key role in determining the characteristics of the storm forecast in the early afternoon. In this region, approximately centred over the Corsica and Sardinia islands, we find the largest discrepancies from the control experiment in the analyses at 0000 UTC, especially for specific humidity and temperature fields in the mid-low troposphere (Figure 5a,b shows the difference between MHS+SEVIRI and control analyses). The differences shown in Figure 5b even reach ± 5 K. This suggests a high sensitivity of ICON to the assimilation of new satellite observations in this area, as well as the substantial informational content therein, where a large fraction of sea surface is present. Previous studies (Grenzi, 2025) have shown a large variability among LETKF ensemble members over the western part of the ICON-2I domain, particularly for the specific humidity variable. This large spread in the background ensemble increases the weight assigned to newly assimilated observations in this area, namely satellite radiances.

A more quantitative comparison among the different experiments is shown in Figure 6, which displays the aver-

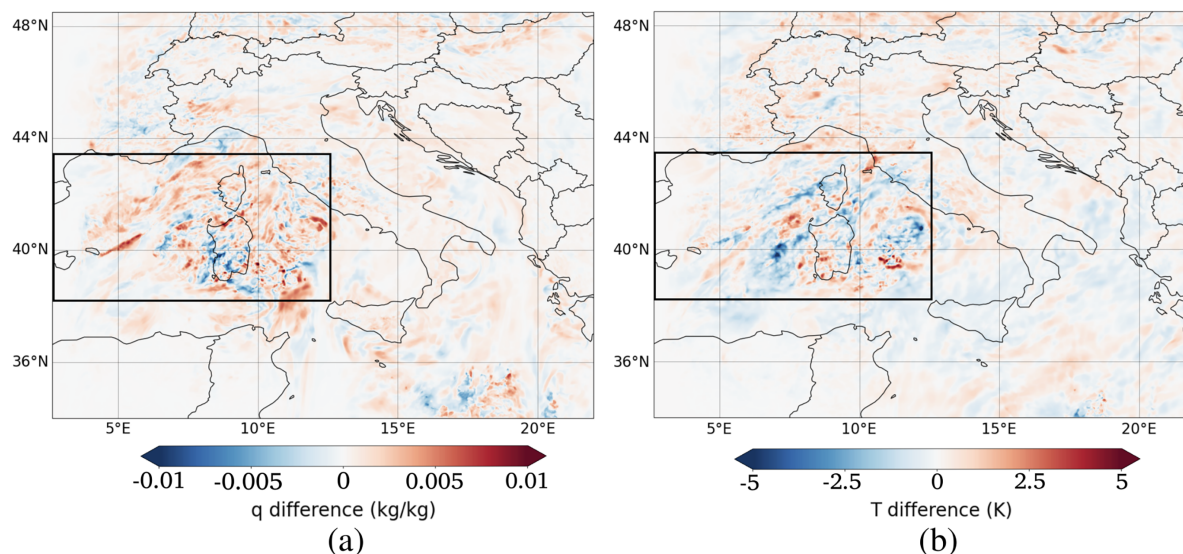


FIGURE 5 (a) Difference between MHS+SEVIRI and control analysis at 0000 UTC on September 15 for the specific humidity field at 850 hPa. (b) Same as (a) but for temperature. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

age difference of specific humidity q and temperature in the analysis at 0000 UTC on September 15, over the aforementioned region upstream of the Italian Peninsula. Given the steep variation, by a few orders of magnitude, of the specific humidity with altitude, we also show its normalized values. The normalization is done by applying the following formula:

$$q_{\text{norm}}^i = \frac{(\overline{q_{\text{exp}}^i} - \overline{q_{\text{ctrl}}^i})}{\overline{q_{\text{ctrl}}^i}}, \quad (5)$$

where i stands for the model level, the overbar is the spatial average over the selected region at the i th model level, q_{ctrl} is the specific humidity field in the control experiment, and q_{exp} is the specific humidity in the MHS, SEVIRI, or MHS+SEVIRI experiment.

Concerning specific humidity, a clear increase is observed in a large portion of the troposphere, from approximately 925–400 hPa in the MHS+SEVIRI experiment (Figure 6c). A larger moisture supply is a favourable condition for stronger precipitation and an important component for deep moist convection development. This can be seen as one key ingredient that allowed the MHS+SEVIRI forecast to perform better compared with the control in terms of total accumulated rainfall. Furthermore, a sharp decrease of specific humidity appears in upper tropospheric levels, where the absolute difference of q is small but the relative variation is significant, due to the low amount of humidity near the tropopause. Drier conditions are also found near the ground, but just of the order of -1% in terms of relative difference. The MHS experiment (Figure 6a) is able to capture the 3% increase of specific humidity in the mid-troposphere between ~ 400 and 700 hPa and a decrease at low levels, while no impact is observed in the upper troposphere. On the contrary, the SEVIRI experiment (Figure 6b) is able to resolve the sharp decrease of specific humidity in the very upper levels, while smaller variations are observed elsewhere. Interestingly, the large humidity increase in MHS+SEVIRI between ~ 700 and 925 hPa is not found in the two other experiments, apart from a small signal in SEVIRI with variations less than 1%. This feature appears only when assimilating the two satellites together, indicating that the results from the MHS+SEVIRI experiment cannot be deduced approximately from a linear combination of the SEVIRI and MHS experiments.

Similar conclusions can be drawn from the temperature field. A colder anomaly between ~ 925 and 600 hPa and a warmer anomaly above are clearly visible in the MHS+SEVIRI experiment (Figure 6f). The thick and colder layer in the mid-troposphere in MHS+SEVIRI is

a favourable ingredient for the enhancement of convective available potential energy (CAPE) values, which is a necessary, albeit not sufficient, condition for severe convection development. The profile obtained from the MHS experiment (Figure 6d) is fairly similar in the mid and low troposphere, as seen before for specific humidity, while in SEVIRI (Figure 6e) the results do not show large differences from the control run, except for the warming contribution above ~ 500 hPa.

Finally, we examine the wind field, which, despite not being constrained directly by the assimilated radiances, can be modified through the multivariate, flow-dependent background-error covariances of the LETKF. The zonal and meridional wind differences for the three experiments are shown in Figure 6g–i and Figure 6j–l, respectively. Concerning the zonal wind component, all the experiments show roughly similar behaviour in the mid–low troposphere. The analysis exhibits a significant negative zonal anomaly, peaking around ~ 850 –700 hPa and larger in MHS+SEVIRI (Figure 6i), indicating a weakening of the westerly wind intensity in the western part of the domain. A smaller, positive anomaly is instead observed closer to the surface, especially in the MHS experiment. A negative anomaly is also registered in the meridional wind component slightly above 700 hPa, again consistent among all three experiments. Larger discrepancies among the experiments can be found in the upper troposphere (near the tropopause) around 200/300 hPa: if MHS is showing a weakening of zonal winds (Figure 6g), in contrast SEVIRI (Figure 6h) and, more importantly, MHS+SEVIRI (Figure 6i) reproduce a remarkable intensification of zonal winds. A stronger upper-level jet is a typical favourable ingredient for severe convection development.

In summary, the MHS+SEVIRI experiment shows, on average, the following main features compared with the control in the area of the domain upstream of the Italian Peninsula:

- drier and warmer air in the upper troposphere near the tropopause,
- more humid and warmer air in the mid-troposphere,
- more humid and colder air in the mid–low troposphere,
- slightly drier and warmer air very close to the surface,
- weaker southwesterlies in the mid–low troposphere, and
- stronger zonal winds in the upper troposphere near the tropopause.

MHS appears to be more impactful in the mid and low troposphere, while SEVIRI is dominant in the upper levels, at least for the analysis time taken into account. In support

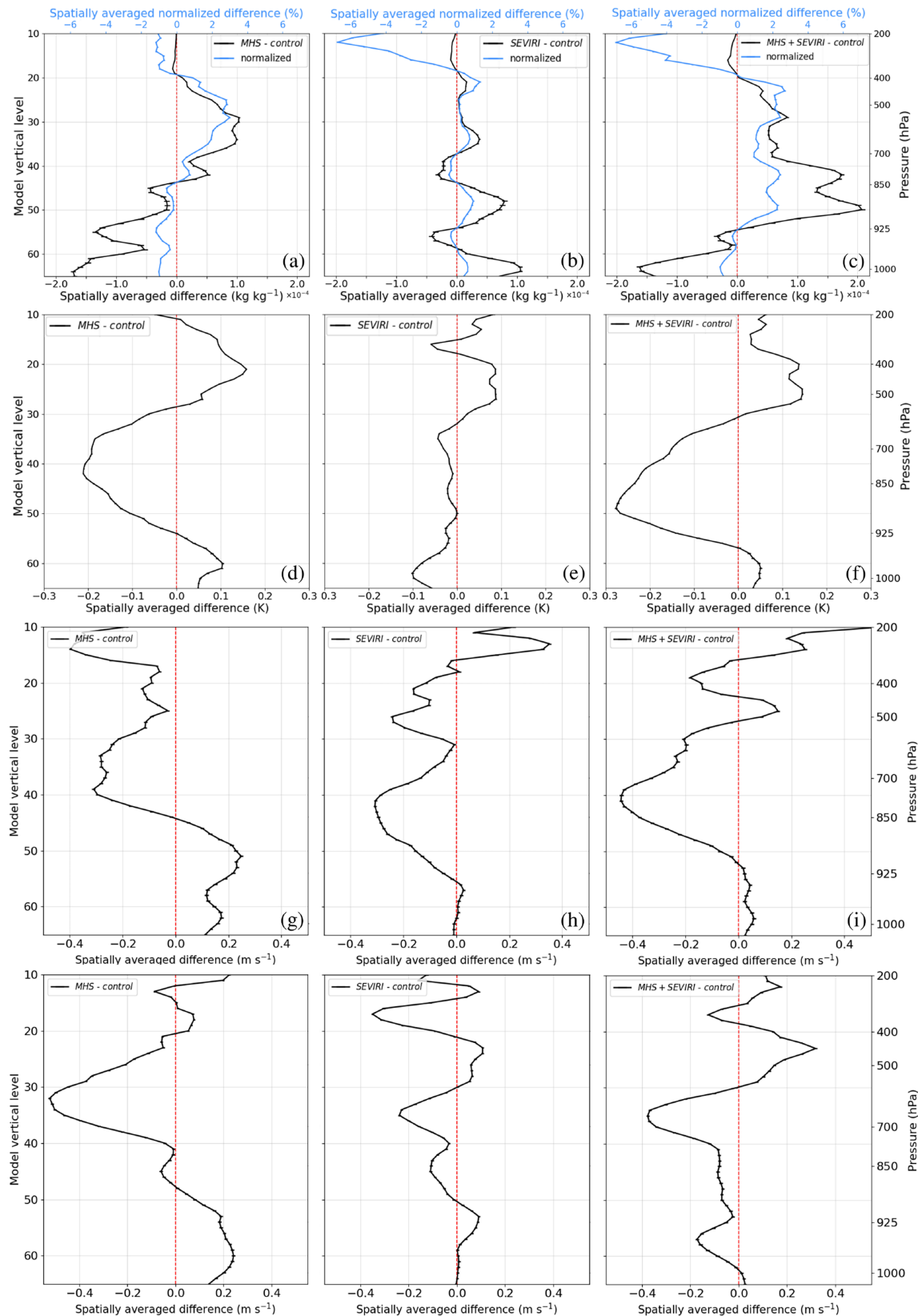


FIGURE 6 Difference of specific humidity q in the analysis at 0000 UTC on September 15, for three experiments (a) MHS, (b) SEVIRI, and (c) MHS+SEVIRI with respect to control. Values are shown at model levels. Dark curve: average q difference over a region located upstream of the development area of the convective event; light curve: same as dark curve but normalized to the average q value for each model level. (d)–(f) Same as (a)–(c) but for temperature. (g)–(i) Same as (a)–(c) but for zonal wind. (j)–(l) Same as (a)–(c) but for meridional wind. No normalized curves are shown for temperature, zonal, and meridional wind. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

of this conclusion, in the next subsection we shall investigate in further detail the contribution of each observation type to the analysis increments.

4.1.3 | Contribution of each observation type: partial analysis increments

To evaluate the relative impact of each observation type, we apply the PAI algorithm described in Section 3.6 to the MHS+SEVIRI experiment. We choose to focus only on MHS+SEVIRI, since it assimilates all the available observations and is also the one showing the highest accuracy in forecasting the *Marche2022* event. PAI is applied here to a subregion upstream of the area of development of the event, focusing on the few hours before the initialization time of the forecast presented in the previous Section 4.1.2 and in Figure 5 (i.e., 0000 UTC on September 15, 2022). The domain selected is large enough to include completely the region with the largest differences in forecast initial conditions defined in Figure 5, without increasing the computational cost too much. The computation of PAI on the whole ICON-2I domain would be unfeasible with our computational resources, especially concerning SEVIRI and radar data, which provide thousands of observations per hour. Results are shown in Figures 7 and 8 for specific humidity and temperature, respectively, at three different model levels (13, 27, 48) corresponding approximately to 300 hPa (high level), 500 hPa (mid level), and 800 hPa (low level). The PAI is computed here at 2100 UTC on September 14, 2022, coinciding with the last passage of the MHS satellite before the initialization time of the forecast at 0000 UTC. Therefore, there is a little time mismatch of 3 h with the analysis performed in the previous Section 4.1.2; we shall discuss this aspect and its consequences at the end of the section.

Figure 7 shows the specific humidity partial increments as inferred from the different observation types at three (low, mid, and high) vertical levels. The figure highlights clearly the spatial structures of each observation's contributions that exhibit a clear vertical differentiation. At high level, the total analysis increments are almost entirely controlled by SEVIRI satellite radiances (Figure 7d), with smaller influence from radar observations. This is consistent with the strong sensitivity of infrared water-vapour channels to upper tropospheric humidity and cloud top. Meteorological conditions around Sardinia and the Tyrrhenian Sea were mostly cloudy at that moment, thus SEVIRI (although assimilated in all-sky conditions), which is not able to penetrate deep into the cloudy layers, could provide information mainly from upper tropospheric levels. Furthermore, the limited impact of SEVIRI in mid and low tropospheric

levels is a direct consequence of the rather narrow vertical localization of the radiances described in Section 3.3.3, which damps distant increments. In humid or cloudy conditions, the height assigned to SEVIRI radiances is located in the upper troposphere. For example, a radiance observation localized around 300 hPa has an assigned observation weight of 5.6×10^{-4} for an analysis grid point located at 800 hPa (low level in Figure 7), computed using the Gaspari–Cohn function with a localization length scale of 0.3 in logarithmic pressure coordinates.

Radar data are responsible for large (in amplitude) increments but are very localized in space compared with SEVIRI (Figure 7b): this occurs not only due to the localized nature of precipitation itself, but also because the radar data impact only those regions where the model predicts precipitation (more precisely, where at least one member of the LETKF ensemble predicts precipitation associated with reflectivity greater than 5 dBZ). If the radar observes rain but none of the LETKF members simulates precipitation, then the radar data are not assimilated. As a consequence, the area where analysis increments due to radar assimilation are non-zero may be very localized, depending on where the ensemble members predict precipitation. The presence of large radar increments in specific humidity at the high level near the tropopause suggests the presence of deep convective cells over the sea. Conventional observations remain marginal, producing only weak signals west of the Alpine region, very likely related to aircraft measurements.

At mid level, MHS influence dominates the total increment, producing smooth, large-scale moistening structures that reflect its ability to sense deeper tropospheric layers (Figure 7h). Even if assimilated in clear-sky conditions, microwave radiances are less sensitive to cloud scattering compared with infrared. Therefore, only thick or precipitating clouds are removed by the cloud detection algorithm, while thinner and non-precipitating cloudy areas are generally assimilated in the clear-sky approach also. SEVIRI is almost negligible at the mid level, while radar increments increase their spatial extent all around Sardinia Island. It is worth noting that weather radars on Sardinia are also able to sample some tens of km offshore. No contribution is observed from conventional observations at this level (note also that no radiosondes are available at 2100 UTC). Finally, at the low level the contribution from radar observations becomes even more important, while keeping its localized structure and being confined to a limited region of the domain. MHS impact is still large and persists over a large area in the Mediterranean Sea. SEVIRI and conventional observations are negligible. To observe the growing importance of ground-station data, it is necessary to go below ~ 850 hPa (not shown).

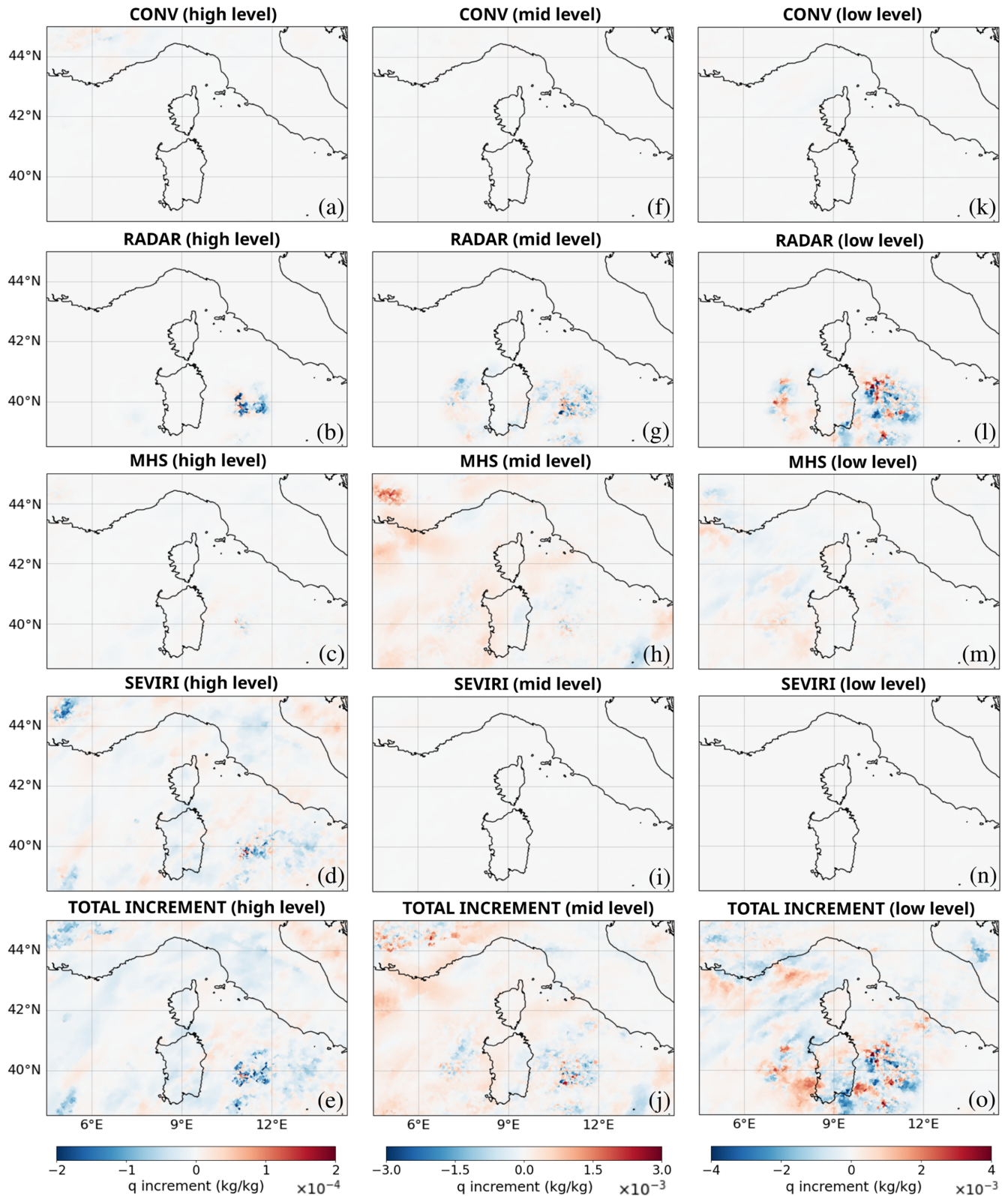


FIGURE 7 PAI results for specific humidity at three ICON model levels, roughly corresponding to 300, 500, 800 hPa (high, mid, low level, respectively). Panels in the same column correspond to the same level. Panels in the same row correspond to the same observation type: (a,f,k) conventional; (b,g,l) radar; (c,h,m) MHS; (d,i,n) SEVIRI. The bottom row shows the total analysis increment obtained in the LETKF, that is, not the sum of the partial increments of each observation type. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

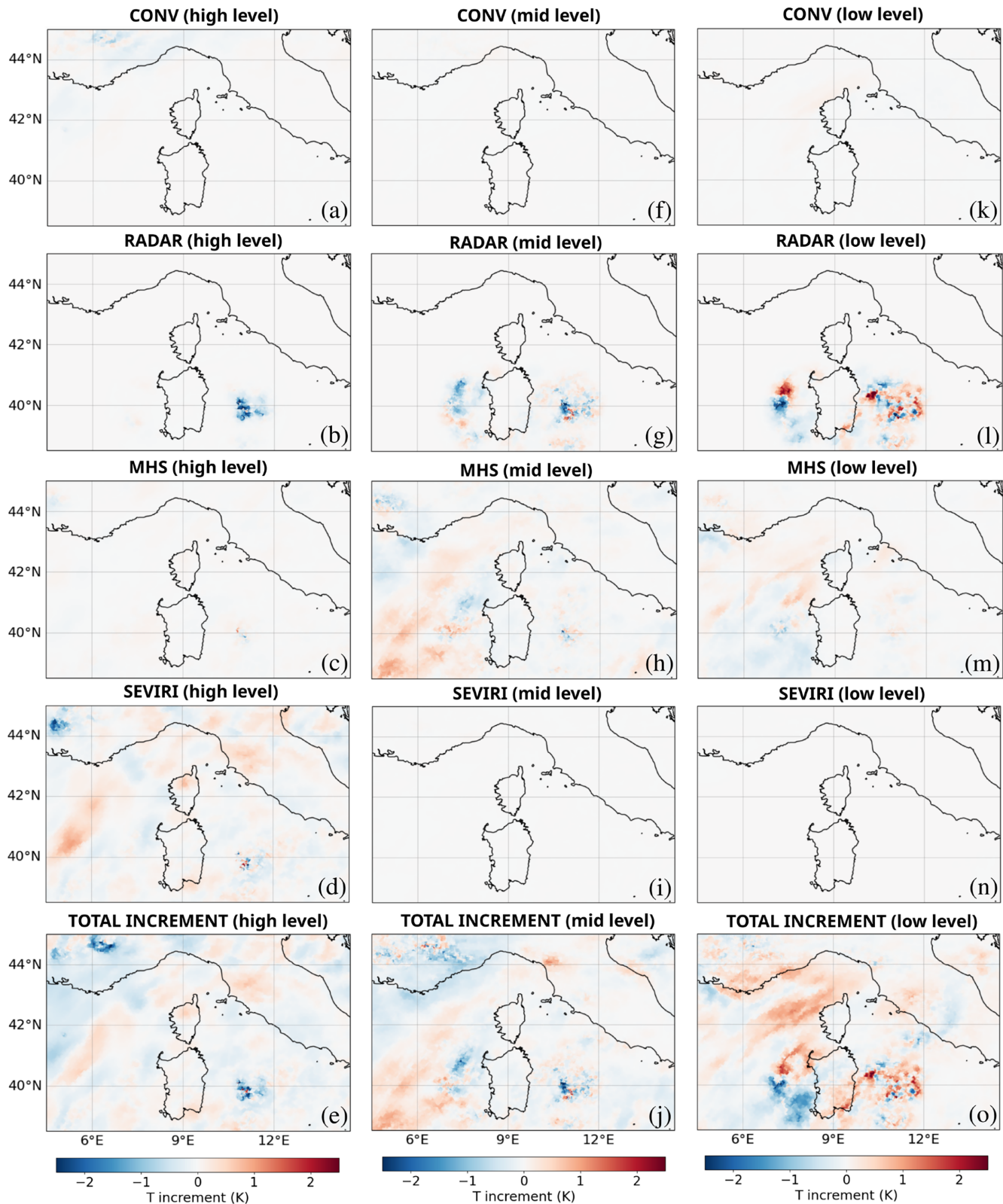


FIGURE 8 Same as Figure 7 but for the temperature field. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

Figure 8 is similar to Figure 7, but it shows the temperature. Overall results are also similar and reveal the same hierarchy of importance of different observation types in

high, mid, and low levels: SEVIRI is predominant near the tropopause, MHS in the mid-troposphere, radars and MHS at low level. Assimilation of water-vapour absorption

channels from satellites is therefore particularly impactful on both humidity and temperature fields: water-vapour channel radiances are sensitive to moisture content in the troposphere, but also depend on temperature profiles through the radiative transfer equation. The DA adjusts both temperature and humidity fields to achieve a radiatively and dynamically consistent analysis state.

Finally, we note that we can verify qualitatively whether the assumption of no inflation in PAI computation led to relevant discrepancies compared with the total increment. Without inflation, the sum of the partial increments will be equal to the total increment. Results from Figures 7 and 8 confirm that this is also almost verified, although some small differences are present. The impact of inflation is small and the order of magnitude and spatial distribution of the increments is in good agreement with the total increment given by the LETKF.

A more quantitative description of the partial increments at different atmospheric levels is provided by the histograms of PAI results shown in Figure 9. The histograms are computed using PAI results within the same spatial subregion defined in Figure 5, in order to allow a more consistent comparison with the differences in forecast initial conditions discussed in previous sections. Recall that, due to the overpass time of the MHS satellite over the domain, a 3-h difference is present between the PAI computed here (at 2100 UTC, September 14) and the forecast initial conditions analysed in Figure 5 (0000 UTC, September 15). However, we consider this difference sufficiently small that the mesoscale structures do not change significantly. Moreover, considering the sequential process of DA, analysis increments at 2100 UTC are in any case impacting on the analysis state 3 h later.

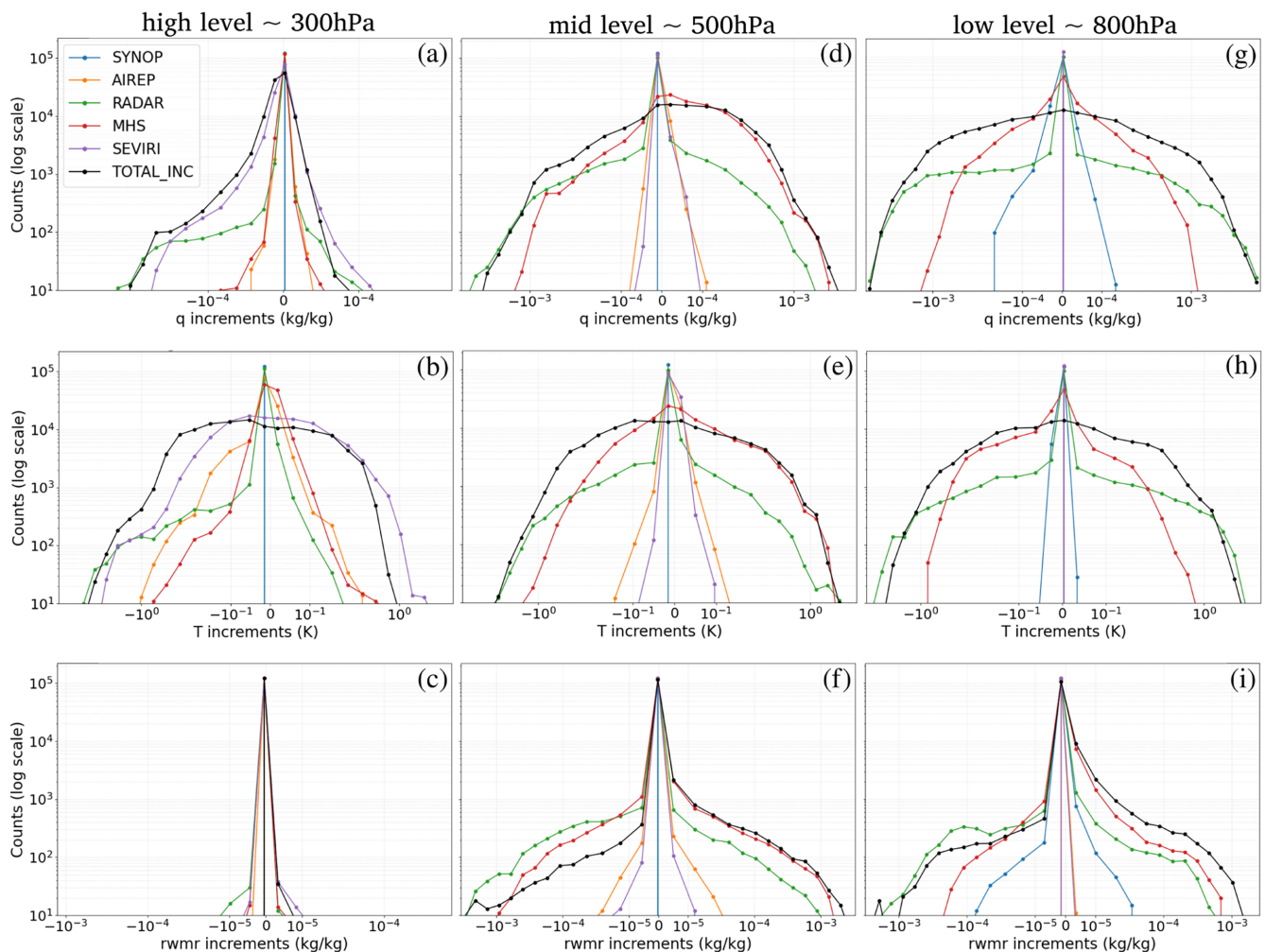


FIGURE 9 Histograms of PAI values at the same three model levels used in Figures 7 and 8. Panels in the same column correspond to the same level. Panels in the same row correspond to the same variable: (a,d,g) specific humidity; (b,e,h) temperature; (c,f,i) rainwater mixing ratio. Histograms are created using PAI results within the subregion defined in Figure 5. Different colours correspond to different observation types. Total analysis increment obtained from the LETKF is also shown. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

At ~ 300 hPa (ICON model level 13), SEVIRI dominates the total increments for specific humidity and temperature, in agreement with what was observed in Figures 7 and 8. Large, although infrequent, negative increments attributed to radar assimilation are also consistent with previous analysis. For specific humidity, the negative skewness of SEVIRI ($skew = -3.3$) and total increment ($skew = -4.3$) distributions reveals that large portions of the domain experience a decrease in moisture content (Figure 9a). The atmosphere is getting drier at this level near the tropopause, mainly due to SEVIRI assimilation, consistent with differences in forecast initial conditions shown in Figure 6b,c. Concerning temperature, a more significant contribution also coming from AIREP data is observed. The SEVIRI distribution is more symmetric ($skew = -0.8$) and the radar distribution still shows large negative increments, though very localized and less numerous (Figure 9b). The impact on rainwater mixing ratio, $rwmr$ (bottom panels), is negligible at ~ 300 hPa, consistent with the limited presence of hydrometeors at this altitude (Figure 9c).

At ~ 500 hPa (ICON model level 27), MHS is confirmed to dominate the total increment, with radar giving a large contribution, especially to rainwater mixing ratio. Positive skewness values for q (MHS: $skew = 2.3$) and T (MHS: $skew = 1.6$) indicate the contribution of MHS to increase the mid-level humidity and temperature in the model state vector of MHS+SEVIRI, coherent with the findings in Figure 6c,f. The large impact of radars on rainwater mixing ratio is possibly related to the high sensitivity of the radar to hydrometeor content. On average, the rainwater mixing ratio values are increasing in the domain of interest.

At ~ 800 hPa (ICON model level 48), large negative and positive increments are mainly associated with radar observations for all three variables, with MHS still being remarkably impactful but generally with smaller increments. SYNOP stations appear here as the third most important source, eventually becoming the most relevant one within the planetary boundary layer near the surface (not shown). Negatively skewed values for MHS at this level ($skew = -1.4$) highlight the cooling contribution of MHS observations in this atmospheric layer, again in agreement with the analysis in Figure 6d,f, which showed a clear cooling compared with the control experiment, attributable to MHS assimilation.

4.2 | Performance evaluation over five days

To increase the statistics of our results showing the impact of satellite data assimilation in ICON-2I, the forecast

verification is now extended to the whole period around the *Marche2022* event considered in the experiments (September 12–16, 2022). In this time window, we run 21-h-long forecasts every 3 h, obtaining 40 forecasts for each experiment overall. This constitutes the dataset used to compute the statistics of forecast verification. Although centred on the *Marche2022* storm, the selected five-day window also encompasses relevant convective precipitation events. In particular, the period includes a variety of convective and precipitating situations, especially during September 15–17, with sparse convection over the domain and other intense precipitation events. Severe convection occurred on September 15 at the border between Italy and Slovenia; on the morning of September 16, widespread convective activity occurred on the Tyrrhenian side of Southern Italy and isolated cells developed in the afternoon of the same day over the northeastern regions of the country; on the morning of September 17, widespread and persistent stratiform precipitation again affected the plains in the northeastern regions (not shown). We anticipate and are conscious that a five-day period may not be sufficient to assess the potential for operational implementation of satellite DA in ICON-2I; nevertheless, our analysis represents a key starting point and will pave the path for future more extensive investigation. In the following sections, precipitation, surface, and upper-level variables are considered, using the verification approaches described in Section 3.5. The statistics of observation minus background (O–B) and Observation minus Analysis (O–A) departures are also presented, to assess the possible presence of biases and check the effectiveness of the assimilation system in moving closer to the observations.

4.2.1 | Precipitation verification with FSS

The FSS is again used here, as previously done in Table 3, for the evaluation of daily cumulated precipitation. We verify the forecast of 3-h accumulated precipitation in different experiments, as a function of forecast lead time. Verifying observations are taken from radar-estimated precipitation corrected with rain-gauge data and uncertainties are computed with the bootstrap method at 95% confidence level; see details in Section 3.5.1. Results are shown in Figure 10, for three different precipitation values corresponding to the rain/no rain threshold (0.1 mm, Figure 10a), light rain (1 mm, Figure 10b), and heavy rain (10 mm, Figure 10c). Differences among the experiments up to a 1-mm threshold are generally not statistically significant, and no relevant discrepancies from the control experiment are found. Concerning the 10-mm threshold, however, a significant improvement compared with control is observed for the MHS and MHS+SEVIRI

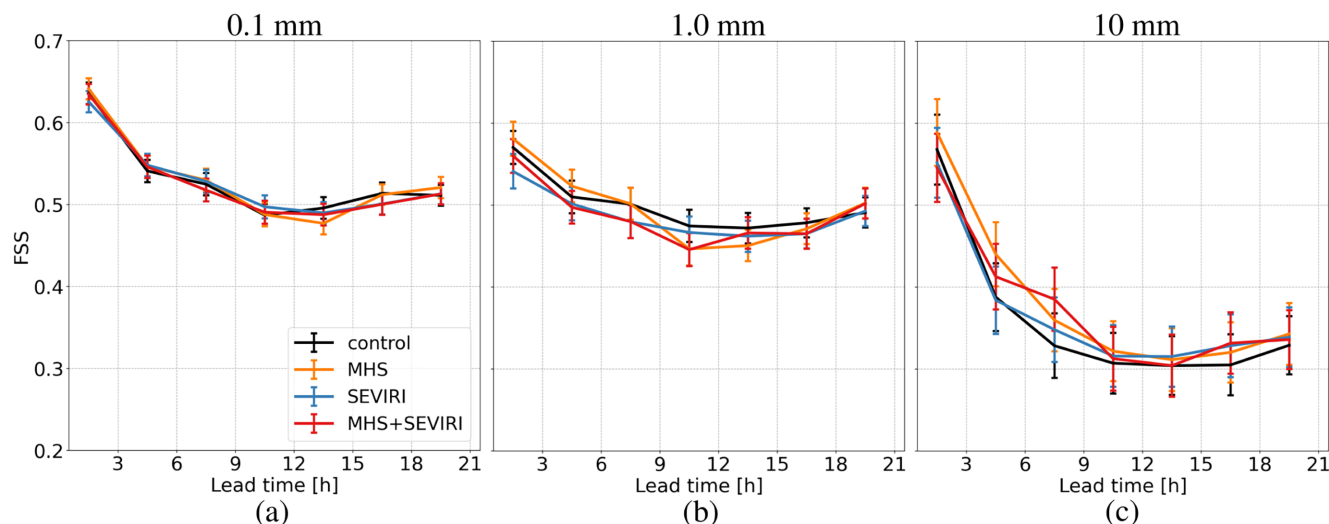


FIGURE 10 FSS verification of accumulated precipitation as described in Section 3.5.1. Results for the four different experiments are shown, varying the precipitation threshold: (a) 0.1 mm, (b) 1.0 mm, (c) 10 mm. Vertical bars indicate 95% confidence level, computed with bootstrap resampling. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

experiments, especially in the 3–6 h lead-time window. For longer forecasting horizons, the FSS values tend to converge due to the decreasing impact of the DA. The FSS analysis confirms that the assimilation of MHS data is the most beneficial to the forecast, particularly so for high precipitation thresholds.

In agreement with Schomburg *et al.* (2026), no significant difference is shown for the SEVIRI experiment. Different studies have shown the potential of improved precipitation forecasts with all-sky infrared assimilation (Honda *et al.*, 2018; Xu *et al.*, 2023; Zhang *et al.*, 2016, 2024); however, radar volume assimilation and LHN are usually not applied. In our experiments and also in the DWD setup, precipitation is already strongly constrained by the assimilation radar reflectivity and radial velocity as well as by LHN, making it difficult to get significant further improvements through the assimilation of different data types. Therefore, low impact on precipitation is probably due to our specific DA setting rather than an intrinsic limitation of all-sky infrared assimilation. Finally, the slight increase in FSS for high values of large lead time (18–21 h) is probably an artifact due to the limited dimension of the dataset. A longer experiment period would be necessary to get smoother FSS curves and smaller error bars.

4.2.2 | Precipitation verification with performance diagrams

The precipitation verification with dichotomous indices is summarized by means of performance diagrams in Figure 11. As for FSS, the three experiments with satellite DA are compared with the control experiment, estimating

the uncertainty with 95% confidence level using bootstrap resampling. Figure 11a,c shows the verification of maximum hourly precipitation computed over the areas defined by the Italian DPC, averaged on 0–9 h and 9–21 h lead-time windows, respectively. Different precipitation values are used, corresponding to light, moderate, and heavy maximum hourly rainfall. Error bars become larger with increasing precipitation values, due to the smaller size of the sample. For the smallest threshold, no significant differences are observed among the experiments, confirming the results from the FSS analysis in Section 4.2.1. By increasing the precipitation threshold, it is possible to appreciate more significant differences: more precisely, the MHS and MHS+SEVIRI experiments show higher scores compared with the control, while for SEVIRI the impact, albeit positive, is slightly smaller. As expected, the differences from the control are larger during the first 9 h of forecast and become almost negligible in the 9–21 h window, as observed for the FSS. TS, which takes into account both false alarms and missed events, is a more complete score compared with POD and SR alone, and it shows a remarkable improvement, especially for the 10-mm threshold in MHS and MHS+SEVIRI experiments (Figure 11a). During the 0–9 h lead-time window, the increase in POD is generally larger than the improvement in SR, leading to a general slight degradation of FBI compared with the control experiment. The number of events exceeding the threshold is overestimated in the forecast and the markers deviate more from the diagonal of the diagram. Therefore, the increase in TS is primarily associated with improved detection of observed precipitation events (POD), accompanied by a slight increase in frequency bias, indicating a tendency toward overforecasting moderate/high maxima

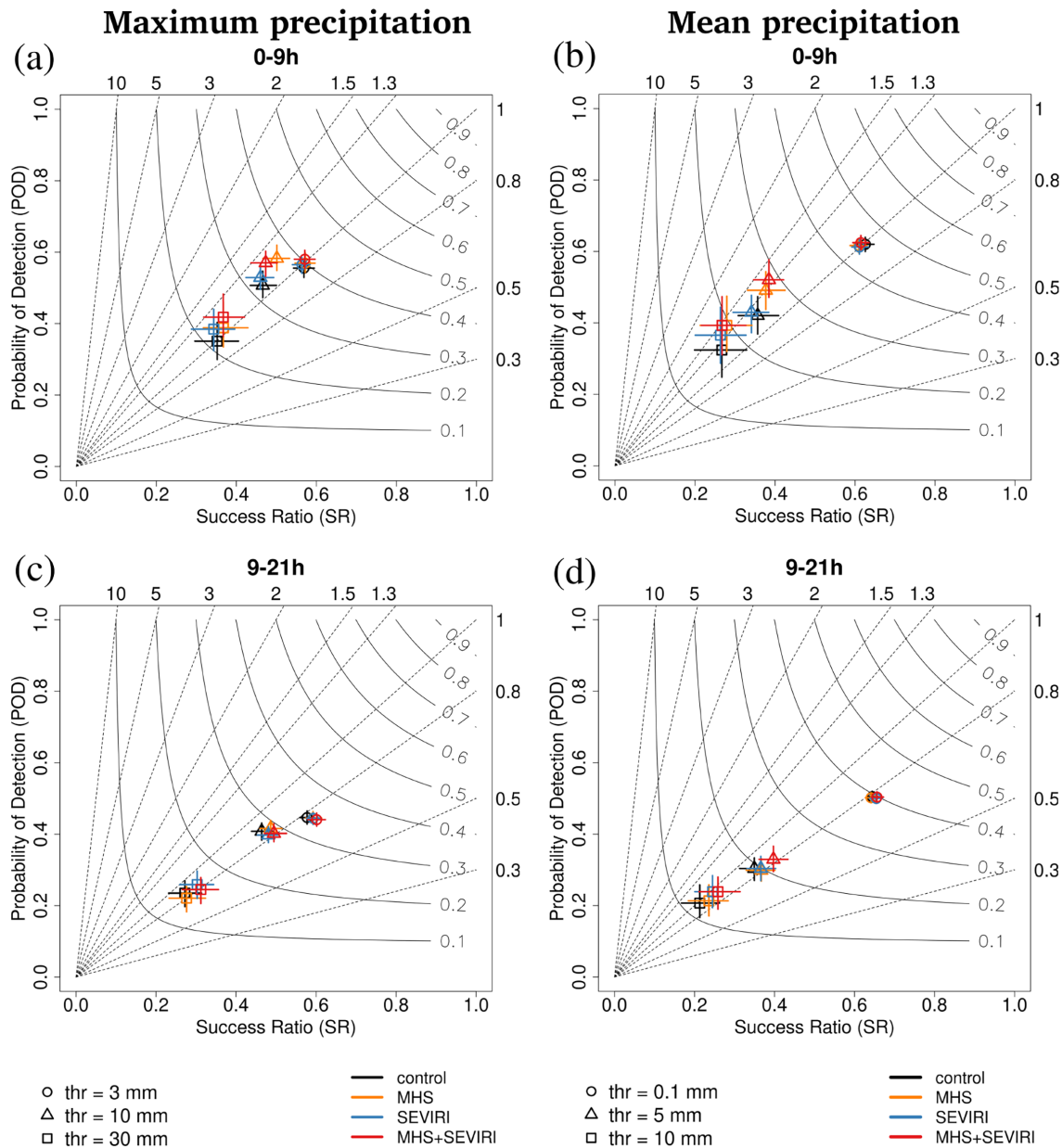


FIGURE 11 Performance diagrams for (a,c) maximum and (b,d) mean precipitation over Italian alert areas, computed as described in Section 3.5.2. Scores are aggregated on two different forecast lead-time windows. Different precipitation thresholds are shown as symbols. Horizontal and vertical error bars refer to 95% confidence levels estimated by bootstrap resampling. Dashed lines indicate FBI values, while solid lines indicate TS. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

of precipitation while maintaining overall skill gain. This is in agreement with the results of Section 4.1.1 for the single forecast of the *Marche2022* event.

Concerning the evaluation of mean hourly precipitation, similar results are obtained (Figure 11b,d) using different precipitation thresholds, again corresponding to low (0.1 mm), medium (1 mm), and high (10 mm) mean precipitation over the DPC alert areas. Larger improvements are observed for higher thresholds, especially for the MHS+SEVIRI experiment. The joint assimilation of the two satellites is beneficial in this case, being able to

increase the TS significantly not only in the 0–9 h window, but also for longer time horizons. The improvement given by combined use of MHS and SEVIRI observations suggests that complementary information coming from microwave and infrared radiances has a positive impact on the mean precipitation forecast quality.

The results obtained with FSS and performance diagram verification are in agreement with the conclusions in Section 4.1.1 and Table 3 concerning the deterministic forecast for the *Marche2022* event. The addition of satellite DA improves the precipitation forecast compared with

the control, especially for high rainfall thresholds. The combination of MHS and SEVIRI provides the best results overall.

4.2.3 | Surface variables

In addition to precipitation, we perform the verification of different surface variables. RMSE and bias are computed as described in Section 3.5.3 for four main variables: 2-m temperature, 2-m relative humidity, 2-m dew point, and 10-m wind. Results are shown in Figure 12. Ground-station data are used as verifying observations. Concerning RMSE, the assimilation of satellite observations is generally positive compared with the control for all the variables considered, although the impact on the 10-m wind appears very small or almost negligible. The improvement is larger for the SEVIRI experiment and even greater during the second part of the forecast for temperature, relative humidity, and dew point. A similar behaviour is also found in MHS+SEVIRI, while for MHS the impact is positive but smaller. The reasons behind this larger improvement during the second half of the forecast may be various. First, a larger statistic would be useful to mitigate possible fluctuations due to the small dimension of the dataset. In addition, infrared and microwave radiances primarily constrain the free troposphere, with analysis increments redistributed through model dynamics during the model run. This may explain the delayed improvement at the surface, especially for SEVIRI, which

is mostly sensitive to upper levels in the troposphere and is localized so that distant increments in the low troposphere are strongly damped at the analysis time, as shown in Section 4.1.3. The positive impact of SEVIRI assimilation on surface variables such as temperature and relative humidity confirms the results by Schomburg *et al.* (2026) regarding the all-sky assimilation of water-vapour SEVIRI channels in the convection-permitting ICON model.

As for the bias (bottom row panels in Figure 12), the improvement is larger for relative humidity and dew point, especially for the MHS+SEVIRI experiment, while no remarkable differences are observed for 2-m temperature and 10-m wind. The assimilation of satellite radiances shows a general increase in humidity and dew-point levels, helping to mitigate the dry bias present in the control experiment, especially in the second half of the forecast. The increase in relative humidity and dew-point values without a corresponding increase in temperature suggests that the levels of specific and absolute humidity are also increasing in the model. The improvement in precipitation forecast provided by satellite DA described in Sections 4.2.1 and 4.2.2 can result in a positive impact on humidity bias. At the same time, as other studies have demonstrated (Dierer *et al.*, 2009), modifications in the initial specific humidity field at convective scales can influence precipitation forecasts strongly, pointing to a two-way interaction between these two quantities. Furthermore, the intensification of rainfall extremes has also been related to increases in absolute humidity values

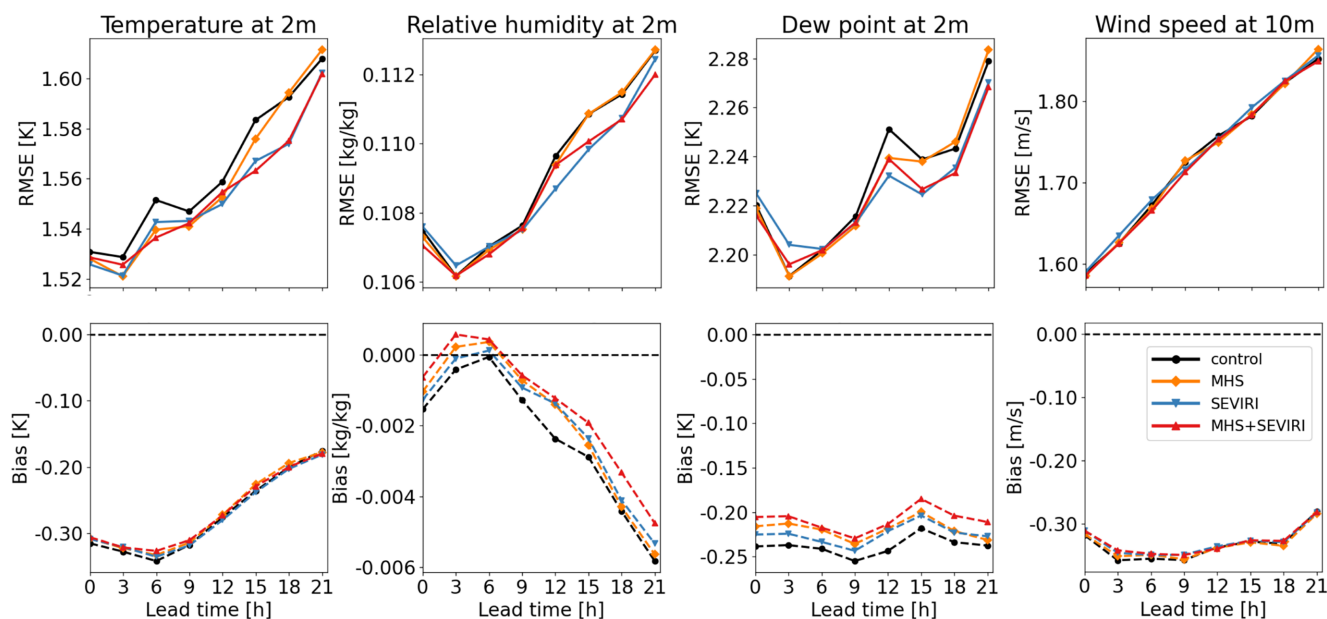


FIGURE 12 RMSE (top row, solid lines) and bias (bottom row, dashed lines) for 2-m temperature, 2-m relative humidity, 2-m dew-point temperature, and 10-m wind speed. Different colours indicate different experiments. Ground-station data are used as verifying observations. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

in convection-permitting climate models (Lenderink *et al.*, 2025).

4.2.4 | Upper-level variables

The verification of upper-level variables follows the approach explained in Section 3.5.3. This is important to determine the impact of radiance assimilation far from the surface, across the whole tropospheric depth. The results are shown in Figure 13 for three variables (temperature, relative humidity, and wind) and for two different forecast lead-time windows: 0–9 h and 9–21 h. Radiosonde data are used as verifying observations for temperature and relative humidity, while aircraft data are used for the wind field. For a better comparison, the RMSE values corresponding to MHS, SEVIRI, and MHS+SEVIRI experiments are expressed in terms of relative variation with respect to the RMSE of the control experiment.

The assimilation of humidity-sensitive satellite radiances is particularly beneficial for the tropospheric humidity forecast. All experiments show an improvement compared with the control in the first 9 h (Figure 13b), exceeding 4% in the mid-troposphere. The improvement in humidity also persists longer (Figure 13e), especially for the MHS+SEVIRI experiment, which is again confirmed as the best overall according to this verification strategy.

SEVIRI provides better results compared with MHS in the first part of the forecast, and a slight degradation of roughly 1% is observed in upper levels during the 9–21 h time window. Relative humidity values above 400 hPa are not shown, due to the very low humidity content in the upper troposphere. The temperature field is also improved, especially in the low troposphere, while a neutral impact is observed in the upper levels (Figure 13a). The improvement decreases for longer lead-time values (Figure 13d), with a slight degradation in the MHS experiment. However, the combination of the two satellites is still beneficial in the mid-troposphere.

The evaluation of U (zonal) and V (meridional) wind components is shown in Figure 13c,d,g,h. In the short-range (0–9 h), the assimilation of SEVIRI radiances produces a consistent reduction of RMSE for the zonal component throughout the tropospheric depth (Figure 13c). Concerning MHS assimilation, slightly positive or neutral impact is observed. Overall, the MHS+SEVIRI experiment provides the largest benefit for the U component, particularly remarkable in the mid-troposphere (~ 600 hPa), with a RMSE reduction of almost 5%. The RMSE improvement is also present in the 9–21 h window, although a degradation is observed around 775 hPa (Figure 13g). The RMSE of the meridional wind component has similar behaviour for the different experiments. In the 0–9 h window, improvements in the

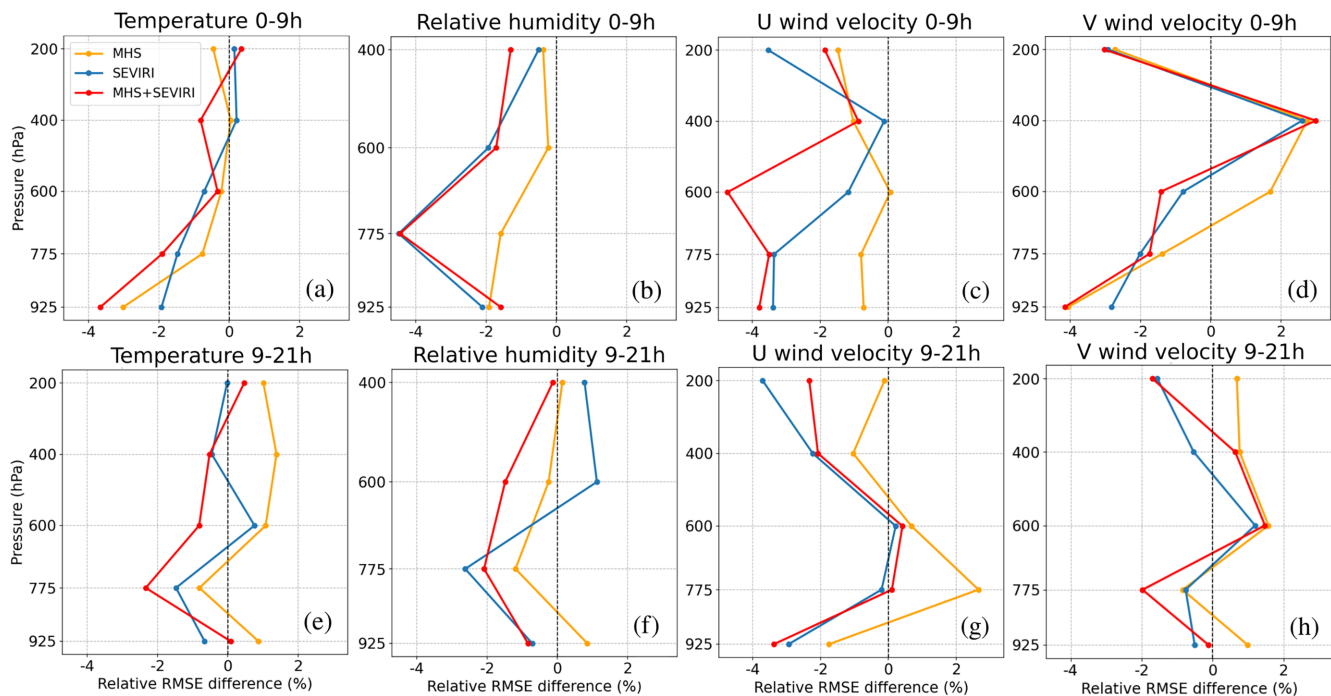


FIGURE 13 Difference in percentage between the control experiment and MHS, SEVIRI, and MHS+SEVIRI. Negative values indicate improvement compared with the control. Radiosondes are used as verifying observations. Panels (a–d) refer to 0–9 h forecast lead windows; panels (e–h) refer to 9–21 h forecast lead windows. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/terms-and-conditions)]

low and upper troposphere are found, reaching 4% for MHS+SEVIRI (Figure 13d), but a degradation consistent among all the experiments is observed around 400 hPa. The reason for this pattern requires further investigation. For longer lead times (Figure 13h), the results are mixed and the impact is overall neutral, with relative variations always smaller than $\pm 2\%$. To sum up, verification of upper-level variables highlights that SEVIRI provides on average a larger positive impact on the forecast compared with MHS, probably also thanks to the much higher frequency of data compared with MHS. In any case, MHS+SEVIRI is confirmed to be the best experiment overall according to this verification, pointing again to the constructive synergy between these two different types of satellite radiance. The largest improvement is generally observed in the mid-troposphere, which is the region where satellite channel weighting functions approximately peak. The improvement given by humidity-sensitive radiance assimilation to free-troposphere winds can be related to the “wind tracing” effect already found in previous studies (Allen *et al.*, 2015; Geer *et al.*, 2018). The humidity field far from the surface is mainly driven by winds, acting as an

active tracer: improving the humidity field representation in the analysis may thus be beneficial for inferring the wind through model tracing of water vapour. In addition, a better representation of organized convection offered by the assimilation of humidity-sensitive radiances can result in a more accurate representation of the wind field.

Concerning the bias (not shown), results are mixed and do not show a significant impact of satellite DA compared with the control for any of the variables considered in this study. More statistics are needed in this case for more robust quantification.

4.2.5 | Statistics of brightness-temperature innovations and analysis residuals

A standard way to assess how effectively the assimilation system fits the observations is to inspect the statistics of the observation-minus-first-guess (O–B, the innovation) and observation-minus-analysis (O–A, the analysis residual) brightness-temperature departures. Figure 14 shows their distributions for the MHS+SEVIRI experiment,

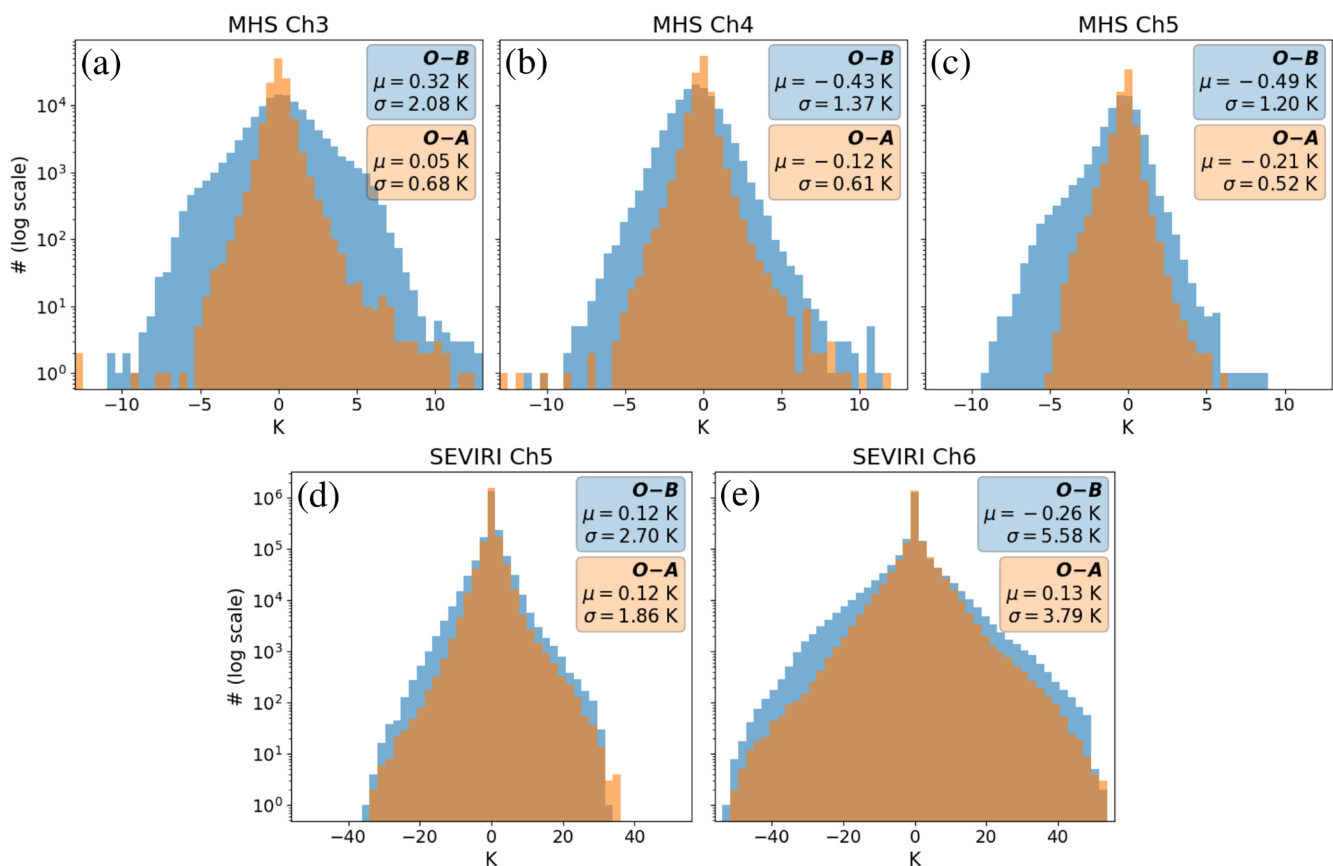


FIGURE 14 Distribution of observation-minus-first-guess (O–B) and observation-minus-analysis (O–A) for the experiment MHS+SEVIRI. (a–c) Three assimilated channels of MHS and (d–e) two assimilated channels of SEVIRI are shown. μ and σ indicate the mean and standard deviation, respectively. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/qj.70296)]

accumulated over all assimilation cycles of the five-day period, separately for the three MHS clear-sky channels (Figure 14a,b,c) and the two SEVIRI all-sky channels (Figure 14d,e). The far larger sample size of SEVIRI (note the different vertical scales) reflects the continuous, all-sky geostationary sampling, as opposed to the twice-daily, clear-sky-only overpasses of the polar-orbiting MHS. For every channel, the analysis distribution (O–A) is markedly narrower and more peaked than the background one (O–B), confirming that the LETKF draws the analysis closer to the assimilated radiances. The reduction in the standard deviation of the departures is largest for the MHS clear-sky channels (about 60% reduction) and more moderate for the SEVIRI all-sky channels (about 30%).

The departure distributions are approximately symmetric and close to Gaussian around their mode, consistent with the error assumptions underlying the LETKF; the SEVIRI all-sky channels display somewhat heavier tails, as expected for cloud-affected radiances. In terms of systematic errors, the mean O–B departures are small for all channels, with the largest magnitude (–0.49 K) found in MHS channel 5, which is more sensitive to surface emission (Figure 14c). These biases correspond to a fraction of both the innovation spread and the assigned observation error: at most about one quarter of the 2-K error prescribed for MHS and only a few per cent of the SEVIRI all-sky error. Because the innovations do not show a severe or systematic offset, and given that these channels are already monitored and assimilated routinely in the global ICON system after DWD preprocessing, no radiance bias-correction scheme was applied in the present experiments. We regard this choice as justified for the clear-sky microwave and mid/upper-tropospheric infrared water-vapour channels considered in the experiments of this study. However, longer experiments are required in order to evaluate the need for bias correction with a larger sample and over different seasons.

5 | CONCLUSIONS AND PERSPECTIVES

This study investigates the impact of assimilating humidity-sensitive satellite radiances in a convection-permitting LAM, with particular focus on microwave channels, which are typically under-used in such models. The severe convective storm *Marche2022* of September 15, 2022 is considered as a case study: a quasi-stationary convective system developed in a complex orography region, which produced over 400 mm of accumulated rainfall and caused 13 fatalities in

Central Italy. We employed the operational ICON-21 model at 2.1-km horizontal resolution, coupled with the LETKF within the KENDA ensemble DA system. Four experiments have been compared. These are a control (benchmark) run that assimilates conventional observations and three-dimensional radar volumes and is also equipped with latent heat nudging, and three experiments involving satellite data that, on top of the measurements (and LHN) used in the control run, assimilate MHS microwave clear-sky radiances alone (MHS), SEVIRI infrared all-sky radiances alone (SEVIRI), and both (MHS+SEVIRI). The control experiment, corresponding to the current operational configuration of Arpa Emilia-Romagna and ItaliaMeteo, severely underestimated the *Marche2022* event. In contrast, the assimilation of satellite radiances improves the representation of this extreme event substantially. All satellite DA experiments increased peak precipitation values and produced a more realistic spatial distribution of the total accumulated rainfall, with the MHS+SEVIRI experiment achieving the best performance overall, with the highest FSS values at the 100-mm threshold and the largest maximum daily accumulation.

Analysis of forecast initial conditions reveals that satellite DA, particularly the joint MHS+SEVIRI configuration, introduces consistent modifications to the upstream atmospheric state over the Tyrrhenian Sea and the islands of Corsica and Sardinia, an area poorly sampled by conventional and radar observations. The combined assimilation of MHS and SEVIRI produced an anomaly characterized by increased specific humidity and a colder mid-to-low troposphere, along with a drier signal near the tropopause. These modifications to the pre-convective moisture field, which is a key factor controlling the initiation and persistence of deep convection, yield favourable conditions for the development of moist convection and are consistent with the improved precipitation forecasts. Notably, the profiles obtained in the MHS+SEVIRI experiment cannot be linearly inferred from (the sum of) the individual MHS and SEVIRI results, highlighting a nonlinear, constructive synergy between microwave and infrared water-vapour observations.

The partial analysis increments algorithm confirmed a clear vertical stratification in the relative contribution of different observation types: SEVIRI dominates the analysis increments near the tropopause (~300 hPa) and MHS is the most impactful in the mid-troposphere (~500 hPa), while radar plays the leading role at lower levels (~700 hPa). This vertical complementarity between microwave and infrared radiances, due to their different cloud penetration capability and weighting function profiles, motivates their joint assimilation further. This vertical partitioning is, however, also partly shaped by

our experimental configuration, using a narrow vertical localization applied to the radiances. This results in the damping of increments far from the upper-tropospheric height assigned to SEVIRI channels, particularly in humid and cloudy conditions, while MHS observations, especially in channel number 5, are typically assigned closer to the surface. Without such localization, all-sky infrared radiances could still exert a non-negligible influence on lower levels, including the boundary layer, through the background-error covariances that couple upper-level fields to the mid and lower troposphere via radiative and convective processes.

A more extended verification over a five-day period around the event, characterized by sparse convective activity and localized intense rainfall events, provided more robust evidence of the benefit of satellite DA. A longer verification period of a few weeks is beyond the intended scope of the present study, but will be required before an operational implementation, in order to evaluate the performance across different seasons and different synoptic configurations and draw more general conclusions. For precipitation, FSS and performance-diagram metrics consistently showed that MHS assimilation leads to larger improvements for high rainfall thresholds (10 mm). Verification of surface and upper-level variables against ground stations and radiosonde data, respectively, confirmed the positive impact for temperature, humidity, and zonal wind component, with the most notable gain in the mid-troposphere. The improvement in free-troposphere wind fields is consistent with a “wind tracing” mechanism, by which the ensemble-based DA system infers dynamical information from water-vapour observations that act factually as atmospheric tracers. The MHS + SEVIRI experiment emerged as the best-performing configuration overall across the different variables and forecast ranges.

Despite their low temporal resolution, our results demonstrate the added value of assimilating microwave water-vapour radiances in a convection-permitting LAM, albeit still limited to a severe convection case study. In combination with infrared radiances, which offer a complementary spectral view of the atmosphere, the benefit for the DA in LAM is even larger. These findings offer a solid basis in support of, and as guidance for, future introduction of satellite radiances in the Arpa Emilia-Romagna and ItaliaMeteo ICON-2I system DA operational pipeline. In this perspective, tests over longer verification periods are currently ongoing, with the goal of evaluating the performance over different seasons and meteorological conditions. The data from other satellite instruments sampling at similar frequencies like the Advanced Technology Microwave Sounder (ATMS), and the future availability of the MicroWave Sounder (MWS) on board the *MetOp*

Second Generation satellites (Munro *et al.*, 2026), will provide much larger availability of microwave sensors that can partially overcome the current low temporal resolution of such instruments over LAM domains.

On the methodological side, further developments are planned for the PAI diagnostic framework. In its current formulation, PAI neglects the contribution of posterior covariance inflation, as in Diefenbach *et al.* (2023), which may introduce departures from the total LETKF increment. Future work will aim at revisiting and extending the PAI formulation to account properly for the effects of covariance inflation and localization, with the goal of providing a more complete and rigorous attribution of analysis increments across observation types.

The implementation of all-sky assimilation of water-vapour microwave channels, already performed operationally in several global NWP models, is also considered a major future development. The RTTOV-SCATT package, necessary for hydrometeor scattering computations in the microwave, is still not implemented in the KENDA system, which is currently using RTTOV v13.2 as satellite forward operator. With the switch to RTTOV v14 (NWPSAF, 2025) in KENDA, planned for the near future, the microwave scattering will be run through the main RTTOV interface and the separate RTTOV-SCATT model will no longer exist. The assimilation of cloud-affected radiances allows access to complementary information on cloud and moisture fields in regions that are otherwise unsampled by clear-sky observations. The associated increased data volume is expected to comprise approximately 20%–40% more actively assimilated radiances compared with the clear-sky case (Candy & Migliorini, 2021; Lee *et al.*, 2020; Shahabadi & Buehner, 2024). In these potential upcoming scenarios, a careful estimation of the observation error becomes even more crucial (Janjić *et al.*, 2018). This may be done by following the symmetric observation-error model by Geer and Bauer (2011) to compute the observation-error standard deviation as a function of the cloud amount used as predictor. All-sky assimilation will also require assessing the need for a bias-correction scheme in the case of a systematic offset in the innovations. In view of an operational implementation, introducing an online bias-correction scheme would make the system less sensitive to issues such as instrument drift.

Finally, the present results may also offer some perspectives in the broader and rapidly evolving context of machine-learning weather prediction (MLWP). The suitability of using ensemble-based DA systems coupled with MLWP models remains underexplored (Tian *et al.*, 2024), and the feasibility of assimilating satellite radiances in

such frameworks is still an open question, partly due to the coarse vertical resolution at which current MLWP models typically operate. In this context, the assimilation of microwave clear-sky radiances explored here may provide a tractable benchmark for future investigations on how ensemble-based DA systems can be coupled effectively with MLWP models for operational convective-scale forecasting.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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