Progress, challenges and future steps in data assimilation for convection-permitting numerical weather prediction: report on the virtual meeting held on 10 and 12 November 2021

Received: 24 February 2022 | Revised: 25 July 2022 | Accepted: 11 August 2022

DOI: 10.1002/asl.1130

RESEARCH ARTICLE

Atmospheric Science Letters RMetS

Progress, challenges, and future steps in data assimilation for convection-permitting numerical weather prediction: Report on the virtual meeting held on 10 and 12 November 2021

Guannan Hu[1] | **Sarah L. Dance**[1,2,3] | **Ross N. Bannister**[1,3] | **Hristo G. Chipilski**[4] | **Oliver Guillet**[5] | **Bruce Macpherson**[6] | **Martin Weissmann**[7] | **Nusrat Yussouf**[8,9,10]

[1]Department of Meteorology, School of Mathematical, Physical and Computational Sciences, University of Reading, Reading, UK

[2]Department of Mathematics and Statistics, School of Mathematical, Physical and Computational Sciences, University of Reading, Reading, UK

[3]National Centre for Earth Observation, University of Reading, Reading, UK

[4]Advanced Study Program, National Center for Atmospheric Research, Boulder, Colorado, USA

[5]CNRM, Université de Toulouse, Toulouse, France

[6]Weather Science Division, Met Office, Exeter, UK

[7]Department of Meteorology and Geophysics, Faculty of Earth Sciences, Geography and Astronomy, University of Vienna, Vienna, Austria

[8]Cooperative Institute for Severe & High-Impact Weather Research and Operations (CIWRO), University of Oklahoma, Norman, Oklahoma, USA

[9]Forecast Research and Development Division, NOAA/National Severe Storms Laboratory, Norman, Oklahoma, USA

[10]School of Meteorology, University of Oklahoma, Norman, Oklahoma, USA

Abstract

In November 2021, the Royal Meteorological Society Data Assimilation (DA) Special Interest Group and the University of Reading hosted a virtual meeting on the topic of DA for convection-permitting numerical weather prediction. The goal of the meeting was to discuss recent developments and review the challenges including methodological developments and progress in making the best use of observations. The meeting took place over two half days on the 10 and 12 November, and consisted of six talks and a panel discussion. The scientific presentations highlighted some recent work from Europe and the USA on convection-permitting DA including novel developments in the assimilation of observations such as cloud-affected satellite radiances in visible channels, ground-based profiling networks, aircraft data, and radar reflectivity data, as well as methodological advancements in background and observation error covariance modelling and progress in operational systems. The panel discussion focused on key future challenges including the handling of multiscales (synoptic-, meso-, and convective-scales), ensemble design, the specification of background and observation error covariances, and better use of observations. These will be critical issues to address in order to improve short-range forecasts and nowcasts of hazardous weather.

KEYWORDS

convection-permitting data assimilation, covariance modelling, multiscale data assimilation, novel observations, operational data assimilation systems

The National Center for Atmospheric Research is sponsored by the National Science Foundation.

Correspondence
Guannan Hu, Department of Meteorology, School of Mathematical, Physical and Computational Sciences, University of Reading, Reading, UK.
Email: guannan.hu@reading.ac.uk

Funding information
Engineering and Physical Sciences Research Council, Grant/Award Number: EP/P002331/1

1 | INTRODUCTION

Convection-permitting (or convective-scale or storm-scale) data assimilation (DA) refers to DA in regional numerical weather prediction (NWP) systems with horizontal grid-lengths of around 1–4 km, where convection is modelled explicitly rather than parametrized. Such systems have been used in research and operational NWP for more than fifteen years (e.g., Ballard et al., 2016; Dance, 2004; Gustafsson et al., 2018; Park & Županski, 2003; Sun, 2005). These systems can provide improved short-term (0–36 h) nowcasts and forecasts (Milan et al., 2020), particularly for hazardous weather such as convective storms (Dance et al., 2019) and fog (Clark et al., 2008).

Convection-permitting DA differs in four main aspects from global DA. First, there is a need for observation information on appropriate scales (e.g., roughly 1 km horizontal spacing, 250 m vertical spacing, and every 15 min in time in the boundary layer; WMO OSCAR, 2022). There are a variety of observations available that may provide some of the required information (e.g., geostationary satellite, radar, and ground-based remote-sensing observations). However, assimilating these observations can be challenging due to the need to develop complex observation operators (e.g., Hawkness-Smith & Simonin, 2021) and to properly represent the observation uncertainties (Janjić et al., 2018; Simonin et al., 2019). Furthermore, there are few suitable observation impact measures to help guide future observing network design for these systems (Fowler et al., 2020). Second, the convection-permitting DA problem spans multiple scales (synoptic-, meso-, and convective-scales). It is an open question to what extent we should attempt to analyze all of these scales in regional prediction systems (Baxter et al., 2011; Caron et al., 2019; Gustafsson et al., 2018; Wang et al., 2021). Third, the nonlinearity of convective processes leads to an increased need for nonlinear and flow-dependent DA techniques (e.g., Bishop, 2016; Hodyss, 2011; van Leeuwen, 2009). The tools developed for global DA (such as background error covariance modelling using linear balance constraints) are no longer appropriate (Bannister, 2021). Fourth, systematic errors in the model representation of hydrometeors (and their radiative properties) present significant challenges (e.g., Grabowski et al., 2019).

In November 2021, the Royal Meteorological Society (RMetS) DA Special Interest Group (SIG) hosted a virtual meeting with the goal of discussing recent developments and the continuing challenges of improving convection-permitting DA. This meeting was held on 10 and 12 November, 2021. Over 70 people registered for the meeting from weather services, research institutes, and universities in seventeen countries. The meeting consisted of six presentations and a panel discussion on topics proposed by the participants and organizers. The presentations were

- The assimilation of cloud-affected radiances in convective-scale NWP (Martin Weissmann, Universität Wien)
- National Oceanic and Atmospheric Administration (NOAA's) Experimental Warn-on-Forecast System: Progresses and Challenges of Ensemble Data Assimilation for Storm-scale NWP (Nusrat Yussouf, University of Oklahoma/NOAA NSSL)
- The value of assimilating different ground-based profiling networks for convective-scale NWP (Hristo G. Chipilski, NCAR)
- Operational convective-scale data assimilation at the Met Office–some selected highlights (Bruce Macpherson, Met Office)
- Perspectives on convective-scale data assimilation (Ross N. Bannister, University of Reading)
- Recent work on correlation modelling at Météo France and topics of interests for the next two years (Oliver Guillet, Météo France)
- Three questions were discussed in the panel discussion:
- In regional DA systems, should we correct all scales, from synoptic to convective, or focus on convective scales? If we focus on convective scales, how should a system be designed to use the best synoptic-scales, while keeping convective-scales spun-up?
- What are the challenges in specifying observation and background error covariances in convection-permitting DA? How can we ensure observation impact on appropriate scales?

- Which scientific questions should we focus on for convection-permitting DA methods in the next 5 years (and why)?

In the rest of this report, we summarize the recent progress presented during the meeting (section 2), ongoing challenges (section 3), and recommendations for future research (section 4).

2 | PROGRESS

This section presents operational systems used by some meteorological centers (section 2.1), studies on the assimilation of novel remote-sensing and aircraft observations (section 2.2), and research on the modelling of background and observation error covariances (section 2.3). Instead of providing a comprehensive review, we have synthesized the material presented at the meeting. The reader is referred to Gustafsson et al. (2018) for a broader perspective on operational convection-permitting DA.

2.1 | Operational and quasi-operational systems and methods

2.1.1 | The Met Office UKV hourly 4D-Var system

Convection-permitting DA has been operational in the UK since 2005 (Ballard et al., 2016). In July 2017, hourly-cycling four-dimensional variational data assimilation (4D-Var) was implemented operationally in the Met Office's convection-permitting (approximately 1.5 km) forecast model known as the UKV (Milan et al., 2020). The previous operational system used Latent Heat Nudging (LHN) for radar-derived surface rain rate and 3D-Var-FGAT (First Guess at Appropriate Time) plus Incremental Analysis Updating (IAU) for all other observations (e.g., Waller, Simonin, et al., 2016). The motivation for using hourly 4D-Var was to improve post-processing products in the 0–6 h forecast period and hourly forecasts up to 12 h. The hourly 4D-Var has been found to bring positive impacts to forecasts of storms and precipitation and it is an affordable single operational system that covers both nowcasting and "day one" timescales (Milan et al., 2020).

Due to the small domain size, it is questionable how well analyses can fit large scale information coming from the observations (e.g., Baxter et al., 2011). To address this issue, the Met Office will incorporate large-scale blending into the convection-permitting DA system for operational forecasting in early 2022. The global analysis will first be downscaled and then

TABLE 1 The configuration of NOAA's WoFS

Model version:	WRF-ARW v3.8+
Grid points:	300 × 300 × 50
Grid spacing:	3 km
Ensemble members:	36-member multiphysics ensemble
Long- and short-wave radiation:	Dudhia/rapid radiative transfer model (RRTM) or rapid radiative transfer model for GCMs (RRTMG)
Microphysics:	NSSL 2-moment
Planetary boundary layer:	Yonsei University (YSU), Mellor–Yamada–Janjić (MYJ), or Mellor-Yamada-Nakanishi-Niino (MYNN)
Data assimilation technique:	Ensemble Kalman Filter
Initial and boundary conditions:	HRRRE convection-permitting ensemble
Observations assimilated:	Weather Surveillance Radar-1988 Doppler (WSR-88D) reflectivity and radial velocity; geostationary operational environmental satellites (GOES) cloud water path and clear sky radiances; conventional National Centers for Environmental Prediction (NCEP) prepbufr observations: METeorological Aerodrome Report (METAR), automated surface observing systems (ASOS), radiosonde, aircraft, marine, mesonets

blended with the background from a Limited Area Model (LAM). The algorithm for the large-scale blending is to calculate a blended background increment, $\delta\mathbf{x}^h$, such that

$$\delta\mathbf{x}^h = \mathbf{S}\left(\mathbf{G}\mathbf{x}^h - \mathbf{x}^b\right),$$

where $\mathbf{x}^h$ is the model state downscaled from the global analysis, $\mathbf{x}^b$ is the LAM background and the two linear operators, $\mathbf{S}$ and $\mathbf{G}$ denote a low-pass filter and a reconfiguration function respectively. The low-pass filter removes small scales and the reconfiguration function interpolates $\mathbf{x}^h$ to the same grid as the LAM background, accounting for the surface terrain. Then the observation innovations are calculated as

$$\mathbf{d} = \mathbf{y} - \left(H\left(\mathbf{x}^b\right) + \mathbf{H}\left(\delta\mathbf{x}^h + \delta\mathbf{x}\right)\right),$$

where $\delta\mathbf{x}$ denotes LAM increments and $\mathbf{y}$ denotes observations. The symbols H and $\mathbf{H}$ are the nonlinear and linear observation operators respectively. Trial results have shown that large-scale blending improves the fit between the merged background and observations.

2.1.2 | The NOAA experimental warn-on-forecast system

Currently, in the USA, warnings for severe storms, tornadoes, and intense rainfall and flash floods are usually based on radar- and spotter-based detections. Guidance from numerical models has not been geared toward these warnings. Therefore, NOAA is developing an ensemble analysis and forecast system that can provide probabilistic forecasts of individual thunderstorms and their hazards from the time they are generated until 6 h later (Stensrud et al., 2009; Stensrud et al., 2013). Table 1 shows the configuration of NOAA's experimental Warn-on-Forecast System (WoFS). WoFS produces forecast graphics every 5 min, measuring the probability and the severity of events. Experimental results indicate that WoFS can predict thunderstorm events with associated hazards reasonably well at 0–6 h lead time and from regional to local spatial scales (Clark et al., 2021; Yussouf et al., 2020; Yussouf & Knopfmeier, 2019).

2.1.3 | The Météo-France AROME 3DEnVar, 4DEnVar, and EDA systems

The object-oriented prediction system (OOPS) project started in 2009 at European Centre for Medium-Range Weather Forecasts (ECMWF), in collaboration with Météo-France and the ACCORD consortium. OOPS is a framework that eases research, development, and maintenance of new DA algorithms for several forecast models. Under the OOPS framework, Météo-France has implemented experimental versions of a variety of DA algorithms in their convection-permitting numerical prediction model, AROME, and also in the global model, ARPEGE. The algorithms include 3D-Var (Brousseau et al., 2011), 3DEnVar (Montmerle et al., 2018), 4DEnVar (e.g., Bannister, 2017; Desroziers et al., 2016) and (Ensemble of Data Assimilations [EDA]; Brousseau et al., 2012). The EDA is an ensemble of independent 3D-Var data assimilations that are performed by randomly perturbing observations, forecast model, and lateral boundary conditions. The AROME 3DEnVar and 4DEnVar use flow-dependent background error covariance matrices that are computed using the ensemble members from AROME EDA. The AROME 3DEnVar has been shown to improve over 3D-Var, which uses a static background error covariance matrix, in forecasting many meteorological variables such as geopotential height, temperature, wind and humidity (Michel & Brousseau, 2021). The 3DEnVar will undergo intensive testing for its final operational implementation in 2023. A case study over France on May 26, 2018 showed that 4DEnVar produced a closer 24-hour rainfall accumulation in comparison with radar observations than 3D-Var and 3DEnVar. Thus, the 4DEnVar will be further tested in 2023 for possible operational use in 2024. Another area of research is model error representation, which is currently based on Stochastically Perturbed Parametrization Tendencies (Palmer et al., 2009). Météo-France is undertaking work on using model parameter perturbations to represent model uncertainties for AROME-EPS (and later for EDA). This allows model uncertainties to also be represented in areas where physical tendencies are small.

2.1.4 | The DWD COSMO-KENDA and ICON-D2 systems

In February 2021, the Deutscher Wetterdienst (DWD) convection-permitting ensemble prediction system COSMO-D2 (-EPS) was replaced with ICON-D2(-EPS), an ICOsahedral Nonhydrostatic (ICON) model with a horizontal resolution of about 2.2 km (Reinert et al., 2020; Zängl et al., 2015). The operational DA system, known as KENDA, provides hourly analyses, using an Local Ensemble Transform Kalman Filter scheme (Schraff et al., 2016). In operational predictions, it assimilates radiosonde ascent and descent profiles, AMDAR and Mode-S aircraft data, wind profiler data, observations from surface stations, and Doppler radar winds and reflectivity from the German radar network. In addition, a latent heat nudging scheme (Stephan et al., 2008) assimilates radar-derived precipitation rates from the European radars within the model domain between analysis steps, during the first 30 min of the forecast. A separate system updates sea surface temperatures once per day and snow depth every 6 h.

2.2 | Novel observations

Current observing networks do not meet user requirements for convection-permitting DA (WMO OSCAR, 2022). This section describes some efforts to reduce data-gaps by assimilating novel observations.

2.2.1 | Cloud-affected satellite radiances

Many centers are moving toward an "all-sky" approach for satellite DA in operational forecasting, in which the satellite radiances that are affected by cloud are directly assimilated. This could improve forecasts of weather phenomena that are poorly observed by conventional instruments, such as low stratus clouds and convective precipitation (e.g., Geer et al., 2018).

Idealised experiments using the COSMO-KENDA system and simulated observations showed that assimilating cloud-affected satellite observations can bring improvements that are of similar magnitude to the benefits of radar assimilation (Bachmann et al., 2019; Bachmann et al., 2020; Schröttle et al., 2020). These benefits usually lasted longer than the lifetime of a convective system. These experiments also showed that assimilating both infrared and visible radiances was more effective than assimilating only infrared radiances.

In addition to these idealized experiments, real-observation experiments using the ICON-D2 system have been carried out (Geiss, 2021). The observations assimilated consisted of all operational observations, plus the visible channel of Spinning Enhanced Visible and Infrared Imager (SEVIRI). These experiments showed that assimilating SEVIRI visible channel satellite observations improved the forecasts of satellite specific quantities such as solar reflectance as well as meteorological quantities such as precipitation (up to 12 h). Furthermore, the assimilation improved the prediction of global horizontal irradiance at the Earth's surface which is expected to benefit solar energy forecasting.

2.2.2 | Ground-based remote-sensing observations

Many operational centers have been improving their treatment of radar observations (e.g., Simonin et al., 2019; Zeng et al., 2021). At the Met Office, LHN of surface rain rate has been applied for 25 years (Jones & Macpherson, 1997). Following development of improved observation operators and better treatment of observation errors, direct 4D-Var assimilation of radar reflectivity became part of the Met Office operational system in May 2022. The new trial results showed that directly assimilating radar reflectivity improves the analysis and forecast of organized bands of convection (Hawkness-Smith & Simonin, 2021).

In an experimental study in the USA, Chipilski et al. (2022) explored the impacts of assimilating ground-based remote-sensing observations on the forecasts of bore-generating nocturnal convection using the GSI-EnKF-WRF system (Johnson et al., 2015). The observations assimilated were from Radar Wind Profilers, Doppler Wind Lidar, Atmospheric Emitted Radiance Interferometers, and radiosondes. They found that assimilating all observations considered brought the largest benefit to precipitation forecasts compared to assimilating observations from a single instrument. Assimilating observations from single instruments was shown to have neutral impacts due to (1) forecast sensitivity to the initial moisture and wind fields, (2) deficiencies in the EnKF algorithm for nonlinear processes and (3) insufficient temporal frequency of radiosonde data. Overall, the promising findings from these experiments are in agreement with earlier work (e.g., Chipilski et al., 2020; Degelia et al., 2020) and pave the way for the integration of these instruments in operational convective-scale NWP systems.

2.2.3 | Mode-S EHS aircraft data

Mode-S EHS (enhanced surveillance) aircraft data allow the derivation of wind and temperature observations from air traffic management reports (e.g., de Haan, 2011). At the Met Office, Mode-S EHS wind observations have been assimilated operationally in the UKV convection-permitting system since 2018. Li (2021) showed that assimilating Mode-S winds has a positive benefit on the forecast skill in wind profiles in the first 6 h of the forecast, and for hourly precipitation accumulations up to 9 h into the forecast. The assimilation of Mode-S EHS temperature data is more challenging as the temperature observations have been shown to be of lower quality, particularly in the boundary layer (Mirza et al., 2016; Mirza et al., 2019; Mirza et al., 2021). However, these data can be used after some processing (de Haan, 2013; de Haan & Stoffelen, 2012). The Met Office has brought these temperature observations into operational use in May 2022.

2.3 | Covariance modelling

2.3.1 | Balance relationships in background error covariance modelling

In global DA, extensive use is made of balance relationships in modelling multivariate relationships in background error statistics. Geostrophic and hydrostatic balances are though weaker and less relevant for convective events (e.g., Vetra-Carvalho et al., 2012). A simplified model of convective-scale flow developed from the Euler equations (the “ABC model”; Petrie et al., 2017) and its DA system (Bannister, 2020) have been used to investigate the role of these geophysical balances in DA. Bannister (2021) showed that switching on the geophysical balances minimizes errors in the large-scale components of the analyzed flow fields. This allows wind and pressure observations of the large-scale flow to complement each other. On the other hand, switching off these balances is beneficial for the small-scale (smaller than a few 10s km). This implies that the assimilation problem should be split into two parts–one analyzing the larger scales, where geophysical balances provide useful information, and another analyzing the smaller scales, where geophysical balances are not relevant and can in fact be harmful.

2.3.2 | Modelling spatial correlations in observation errors

Many observation types have spatially correlated observation representation errors (e.g., Cordoba et al., 2017; Janjić et al., 2018; Michel, 2018; Waller et al., 2019; Waller, Ballard, et al., 2016; Waller, Simonin, et al., 2016; Zeng et al., 2021). It has been shown that accounting for spatial observation error correlations allows more observation information to be extracted in idealized systems (Fowler et al., 2018; Rainwater et al., 2015; Stewart et al., 2008; Stewart et al., 2013) and leads to improved forecast skill in operational systems (Simonin et al., 2019). A spatially correlated observation error covariance matrix model has been proposed by Guillet et al. (2019), based on a finite-element discretization of a diffusion operator. The performance of the method depends on the distribution of the observations, as this determines the mesh for the finite element technique. New observation thinning strategies and their impact on the observation distribution are currently being investigated, with possible application to radar reflectivity.

3 | CHALLENGES

Forecasting of low stratus clouds, fog, convective precipitation, and storms is a major challenge for convection-permitting NWP (e.g., Dance et al., 2019; Hu & Franzke, 2020). The prediction of these fast processes requires rapid DA cycling and careful treatment of many aspects of the system. In this section, we present some of the challenges discussed at the meeting.

3.1 | The handling of multiple spatial scales

Convection-permitting DA may require knowledge from both synoptic and meso scales. However, it is very difficult to correct all scales with a LAM (e.g., Baxter et al., 2011; Johnson et al., 2015). Some discussion at the meeting addressed whether we should better focus our efforts on improving just the small scales (incorporating larger scales by blending with a large-scale analysis) or whether truly multiscale assimilation techniques should be pursued. Can we produce ensembles that can represent small-scale background error statistics well? On the other hand, accurate large scale information can be important even for forecasts of very short periods (Durran & Gingrich, 2014). Furthermore, tropical regions may require different approaches from midlatitude regions.

3.2 | Model errors

In ICON-D2 simulations, model deficiencies in representing cloud statistics are observed in the following aspects: (1) too few mid-level and semi-transparent clouds; (2) too many thick ice clouds; and (3) too many clouds with low brightness temperatures. These issues have also been found in many other weather prediction models (Geiss et al., 2021). Thus, improving the representation of clouds in weather prediction models is of utmost importance. It is also important for DA algorithms to be able to take account of known model deficiencies, by accounting for model errors, through weak constraint variational DA (Trémolet, 2007), ensembles (Raynaud et al., 2012), model bias correction (Bell et al., 2004) or other approaches (e.g., Brajard et al., 2021). Development of NWP models and DA systems is a continuously ongoing process. Closer interactions between modelers and DA scientists may lead to better systems.

3.3 | Background uncertainty

Small-scale atmospheric processes, such as convection and cloud microphysical processes, are usually strongly nonlinear, so that models describing these processes can produce non-Gaussian forecast errors (e.g., following gamma or inverse-gamma distributions; Posselt & Bishop, 2018). In addition, the nonlinearity of the model enhances the need for flow-dependent background error covariances. Therefore, forecast ensembles are likely to benefit the estimation of background error statistics. The ensembles replace proxies such as forecast differences (Berre et al., 2006; Parrish & Derber, 1992). However, unlike in synoptic-scale DA, the ensemble mean should not be used as the best estimate in this non-Gaussian case (Lorenc & Payne, 2007). For instance, positive variables like rainfall amount may deviate considerably from their mean. Moreover, for highly complex distributions, one would ideally need to obtain a representative sample and the notion of a single best estimate may not be useful.

3.4 | Observation uncertainty

The assimilation of geostationary satellite and radar observations has brought great benefits to convection-permitting NWP (Gustafsson et al., 2018). However, the assimilation of these observations can be a challenge due to the non-Gaussian characteristics of observation errors and strong spatial observation error correlations.

The non-Gaussianity of observation errors needs to be carefully introduced into convection-permitting DA systems, because it will result in differently shaped error distributions (e.g., Bannister et al., 2020; Bocquet et al., 2010).

Many recent works have addressed the issue of including the spatial observation error correlations in convective-scale DA systems. In addition to the work by Guillet et al. (2019) on modelling wind error correlations (see section 2.3.2), methods such as eigenvalue decomposition (e.g., Fowler, 2019; Michel, 2018; Stewart et al., 2013), spatial difference observations (Bédard & Buehner, 2020), and spectral transformation (e.g., Chabot et al., 2020; Ying, 2020) have also been studied. Moreover, pragmatic parallelization strategies (Simonin et al., 2019) and numerical approximation methods (Hu & Dance, 2021) have been explored in order to reduce computational costs (particularly parallel communication costs). While the approach of Simonin et al. (2019) is already used for operational assimilation of Doppler radar winds at the Met Office, the challenge going forwards is to extend these methods to other operational centers and observation types.

3.5 | Satellite observation operators

While geostationary satellites provide spatially dense and frequent-in-time observations, many of these data are not used in DA. Many observations are discarded due to cloud-affected radiances, a lack of understanding of land-surface emissivity, a lack of knowledge on how to treat observations in visible bands and systematic model errors in representing the observed quantities. The problem of assimilating cloud-affected radiances has already been addressed in section 2.2.1. Land-surface emissivity atlases for use with fast radiative transfer schemes have recently been improved (Borbas & Feltz, 2019), but further research is needed to allow for a greater proportion of observations over land to be used in operations. An efficient and accurate forward operator for visible geostationary satellite observations has been developed over the last ten years (VISOP; Kostka et al., 2014; Scheck et al., 2016, Scheck et al., 2018; Geiss et al., 2021). It is based on a method for fast 1D radiative transfer (Scheck et al., 2016) and now implemented in RTTOV (radiative transfer for TOVS), which makes it available for operational use. Several weather services are planning to use it for monitoring in the near future. However, there is still ongoing development to account for 3D-effects in this 1D operator (Scheck et al., 2018).

4 | OUTLOOK AND RECOMMENDATIONS

A number of future steps for convection-permitting DA research were discussed at the meeting. This section provides some outlook and recommendations for the future, focusing on the use of novel observations and better generation of ensembles.

4.1 | Improving the use of currently available observations

Despite the exciting progress described in section 2.2, work is still needed to improve the use of currently available observations via improvements in satellite observation operators (see section 3.5), and increasing understanding of polarimetric radar observations such as nonprecipitation echoes (e.g., Augros et al., 2018;Rennie et al., 2011), radar refractivity (Dance et al., 2019) and differential phase (Augros et al., 2018). Waller et al. (2021) showed that representation error biases and correlations may be critical for convection-permitting NWP. However, computationally feasible methods for treating large datasets with long spatial error correlation lengths still need to be developed for operational purposes (see sections 2.3.2 and 3.4).

4.2 | Assimilating new and emerging observation-types

There are many gaps in the observing network that affect our ability to forecast on convection-permitting scales (WMO OSCAR, 2022). There are few suitable observation impact measures to help guide strategic future observing network design for these systems (Fowler et al., 2020) and more work needs to be done to provide these tools and the evidence for new international observing networks. However, it is known that storm prediction requires accurate model representation of rapid changes in the near-storm environment. Ground-based remote-sensing instruments (see section 2.2.2), and unmanned aircraft systems could provide well-resolved information about these environments. The use of these observations could improve the prediction of convection initiation as well as the evolution of storms. New observation operators may need to be developed for effective assimilation of ground-based remote-sensing observations (for instance, the use of raw observations instead of retrievals).

Crowdsourcing may provide new, inexpensive sources of observations (Hintz, Vedel, & Kaas, 2019). For example, private citizen's automatic weather stations (Chapman et al., 2017), surface pressure observations from mobile phones (e.g., Hintz, O'Boyle, et al., 2019) and temperature observations from cars or other vehicles (Bell et al., 2022; Siems-Anderson et al., 2020), are potentially useful sources of observations for convection-permitting DA. However, there are complex issues regarding data ownership and privacy, quality control (particularly for moving observing platforms such as mobile phones and cars), and dealing with large data volumes to be resolved before these data will see widespread use in NWP.

4.3 | Ensemble design

The use of ensembles is important for the provision of non-Gaussian, flow-dependent estimates of background uncertainty (see section 3.3), and for the provision of seamless probability forecasts (such as WoFS in section 2.1.2). Hence, there is a need for ensembles that can better describe the error statistics of small-scale atmospheric processes. Stochastic approaches and multiphysics could be considered as part of the future ensemble generation system.

5 | SUMMARY

This article reports on the RMetS DA SIG meeting on convection-permitting DA held in November 2021. Progress in operational DA systems at several centers, the assimilation of novel observations, and the estimation and treatment of background and observation error covariances were addressed in this report. A number of future steps for convection-permitting DA research were discussed at the meeting with a particular focus on improving the observing network in the boundary layer, better observation operators for existing observations, better treatment of observation uncertainty and better ensemble design. It is essential that these challenges are addressed to protect lives and livelihoods from hazardous weather events.

AUTHOR CONTRIBUTIONS

Guannan Hu: Conceptualization; investigation; methodology; writing – original draft; writing – review and editing. **Sarah L. Dance:** Conceptualization; funding acquisition; investigation; methodology; project administration; supervision; writing – original draft; writing – review and editing. **Ross N. Bannister:** Conceptualization; investigation; methodology; resources; writing – review and editing. **Hristo G. Chipilski:** Conceptualization; investigation; methodology; resources; writing – review and editing. **Oliver Guillet:** Conceptualization; investigation; methodology; resources; writing – review and editing. **Bruce Macpherson:** Conceptualization; investigation; methodology; resources; writing – review and editing. **Martin Weissmann:** Conceptualization; investigation; methodology; resources; writing – review and editing. **Nusrat Yussouf:** Conceptualization; investigation; methodology; resources; writing – review and editing.

ACKNOWLEDGEMENT

The meeting received support from the EPSRC DARE project (EP/P002331/1). We thank L. Berre from Météo-France for the useful input. We thank two anonymous reviewers for their valuable comments. We also thank J. A. Waller, Secretary of the RMetS DA SIG, and J. Gardner for their administrative support.

CONFLICT OF INTEREST

We declare we have no competing interests.

ORCID

Guannan Hu https://orcid.org/0000-0003-4305-3658
Sarah L. Dance https://orcid.org/0000-0003-1690-3338

REFERENCES

Augros, C., Caumont, O., Ducrocq, V. & Gaussiat, N. (2018) Assimilation of radar dual-polarization observations in the AROME model. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1352–1368.

Bachmann, K., Keil, C., Craig, G.C., Weissmann, M. & Welzbacher, C.A. (2020) Predictability of deep convection in idealized and operational forecasts: effects of radar data assimilation, orography, and synoptic weather regime. *Monthly Weather Review*, 148(1), 63–81. https://doi.org/10.1175/MWR-D-19-0045.1 https://journals.ametsoc.org/view/journals/mwre/148/1/mwr-d-19-0045.1.xml

Bachmann, K., Keil, C. & Weissmann, M. (2019) Impact of radar data assimilation and orography on predictability of deep convection. *Quarterly Journal of the Royal Meteorological Society*, 145(718), 117–130. https://doi.org/10.1002/qj.3412

Ballard, S.P., Li, Z., Simonin, D. & Caron, J.-F. (2016) Performance of 4D-Var NWP-based nowcasting of precipitation at the Met Office for summer 2012. *Quarterly Journal of the Royal Meteorological Society*, 142(694), 472–487. https://doi.org/10.1002/qj.2665

Bannister, R.N. (2017) A review of operational methods of variational and ensemble-variational data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 143, 607–633.

Bannister, R.N. (2020) The ABC-DA system (v1.4): a variational data assimilation system for convective-scale assimilation research with a study of the impact of a balance constraint. *Geoscientific Model Development*, 13(8), 3789–3816. https://doi.org/10.5194/gmd-13-3789-2020 https://gmd.copernicus.org/articles/13/3789/2020/

Bannister, R.N. (2021) Balance conditions in variational data assimilation for a high-resolution forecast model. *Quarterly Journal of the Royal Meteorological Society*, 147(738), 2917–2934. https://doi.org/10.1002/qj.4106

Bannister, R.N., Chipilski, H.G. & Martinez-Alvarado, O. (2020) Techniques and challenges in the assimilation of atmospheric water observations for numerical weather prediction towards convective scales. *Quarterly Journal of the Royal Meteorological Society*, 146(726), 1–48. https://doi.org/10.1002/qj.3652

Baxter, G., Dance, S., Lawless, A. & Nichols, N. (2011) Four-dimensional variational data assimilation for high resolution nested models. *Computers & Fluids*, 46(1), 137–141.

Bédard, J. & Buehner, M. (2020) A practical assimilation approach to extract smaller-scale information from observations with spatially correlated errors: an idealized study. *Quarterly Journal of the Royal Meteorological Society*, 146(726), 468–482. https://doi.org/10.1002/qj.3687

Bell, M.J., Martin, M. & Nichols, N. (2004) Assimilation of data into an ocean model with systematic errors near the equator. *Quarterly Journal of the Royal Meteorological Society: A Journal of the Atmospheric Sciences, Applied Meteorology and Physical Oceanography*, 130(598), 873–893.

Bell, Z., Dance, S.L. & Waller, J.A. (2022) Exploring the characteristics of a vehicle-based temperature dataset for kilometre-scale data assimilation. *Meteorological Applications*, 29(3), e2058. https://doi.org/10.1002/met.2058

Berre, L., Ştefaănescu, S.E. & Pereira, M.B. (2006) The representation of the analysis effect in three error simulation techniques. *Tellus A: Dynamic Meteorology and Oceanography*, 58(2), 196–209. https://doi.org/10.1111/j.1600-0870.2006.00165.x

Bishop, C.H. (2016) The GIGG-EnKF: ensemble Kalman filtering for highly skewed non-negative uncertainty distributions. *Quarterly Journal of the Royal Meteorological Society*, 142(696), 1395–1412. https://doi.org/10.1002/qj.2742

Bocquet, M., Pires, C.A. & Wu, L. (2010) Beyond Gaussian Statistical Modeling in Geophysical Data Assimilation. *Monthly Weather Review*, 138(8), 2997–3023. https://doi.org/10.1175/2010MWR3164.1 https://journals.ametsoc.org/view/journals/mwre/138/8/2010mwr3164.1.xml

E. Borbas and M. Feltz. Updating the CAMEL surface emissivity atlas for RTTOV. Report of Visiting Scientist mission NWP_AS18_01, EUMETSAT Numerical Weather Prediction Satellite Applications Facility, 2019.

Brajard, J., Carrassi, A., Bocquet, M. & Bertino, L. (2021) Combining data assimilation and machine learning to infer unresolved scale parametrization. *Philosophical Transactions of the Royal Society A*, 379(2194), 20200086.

Brousseau, P., Berre, L., Bouttier, F. & Desroziers, G. (2011) Background-error covariances for a convective-scale data-assimilation system: AROME–France 3D-Var. *Quarterly Journal of the Royal Meteorological Society*, 137(655), 409–422. https://doi.org/10.1002/qj.750

Brousseau, P., Berre, L., Bouttier, F. & Desroziers, G. (2012) Flow-dependent background-error covariances for a convective-scale data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 138(663), 310–322. https://doi.org/10.1002/qj.920

Caron, J.-F., Michel, Y., Montmerle, T. & Arbogast, É. (2019) Improving background error covariances in a 3D ensemble–variational data assimilation system for regional NWP. *Monthly Weather Review*, 147(1), 135–151.

Chabot, V., Nodet, M. & Vidard, A. (2020) Multiscale representation of observation error statistics in data assimilation. *Sensors*, 20(5), 1–20. https://doi.org/10.3390/s20051460 https://hal.inria.fr/hal-02421699

Chapman, L., Bell, C. & Bell, S. (2017) Can the crowdsourcing data paradigm take atmospheric science to a new level? a case study of the urban heat island of london quantified using netatmo weather stations. *International Journal of Climatology*, 37(9), 3597–3605. https://doi.org/10.1002/joc.4940

Chipilski, H.G., Wang, X. & Parsons, D.B. (2020) Impact of assimilating PECAN profilers on the prediction of bore-driven nocturnal convection: a multiscale forecast evaluation for the 6 july 2015 case study. *Monthly Weather Review*, 148(3), 1147–1175. https://doi.org/10.1175/MWR-D-19-0171.1 https://journals.ametsoc.org/view/journals/mwre/148/3/mwr-d-19-0171.1.xml

Chipilski, H.G., Wang, X., Parsons, D.B., Johnson, A. & Degelia, S. K. (2022) The value of assimilating different ground-based profiling networks on the forecasts of bore-generating nocturnal convection. *Monthly Weather Review*, 150(6), 1273–1292. https://doi.org/10.1175/MWR-D-21-0193.1 https://journals.ametsoc.org/view/journals/mwre/150/6/MWR-D-21-0193.1.xml

Clark, A.J., Jirak, I.L., Gallo, B.T., Roberts, B., Dean, A.R., Knopfmeier, K.H. et al. (2021) A real-time, virtual spring forecasting experiment to advance severe weather prediction. *Bulletin of the American Meteorological Society*, 102(4), E814–E816. https://doi.org/10.1175/BAMS-D-20-0268.1 https://journals.ametsoc.org/view/journals/bams/102/4/BAMS-D-20-0268.1.xml

Clark, P.A., Harcourt, S.A., Macpherson, B., Mathison, C.T., Cusack, S. & Naylor, M. (2008) Prediction of visibility and aerosol within the operational Met Office Unified Model. I: Model formulation and variational assimilation. *Quarterly Journal of the Royal Meteorological Society*, 134(636), 1801–1816. https://doi.org/10.1002/qj.318

Cordoba, M., Dance, S.L., Kelly, G.A., Nichols, N.K. & Waller, J.A. (2017) Diagnosing atmospheric motion vector observation errors for an operational high-resolution data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 143(702), 333–341. https://doi.org/10.1002/qj.2925

Dance, S.L. (2004) Issues in high resolution limited area data assimilation for quantitative precipitation forecasting. *Physica D: Nonlinear Phenomena*, 196, 1–27.

Dance, S.L., Ballard, S.P., Bannister, R.N., Clark, P., Cloke, H.L., Darlington, T. et al. (2019) Improvements in Forecasting Intense Rainfall: Results from the FRANC (Forecasting Rainfall Exploiting New Data Assimilation Techniques and Novel Observations of Convection) Project. *Atmosphere*, 10(3), 125. https://doi.org/10.3390/atmos10030125 https://www.mdpi.com/2073-4433/10/3/125

de Haan, S. (2011) High-resolution wind and temperature observations from aircraft tracked by Mode-S air traffic control radar. *Journal of Geophysical Research*, 116(D10), D10111. https://doi.org/10.1029/2010jd015264

de Haan, S. (2013) An improved correction method for high quality wind and temperature observations derived from Mode-S EHS. Technical report TR-338. In: *Technical Report TR-338, Royal Netherlands Meteorological Institute*. Netherlands: De Bilt. http://a.knmi2.nl/knmi-library/knmipubTR/TR338.pdf

de Haan, S. & Stoffelen, A. (2012) Assimilation of high-resolution Mode-S EHS wind and temperature observations in a regional NWP model for nowcasting applications. *Weather and Forecasting*, 27(4), 918–937. https://doi.org/10.1175/WAF-D-11-00088.1

Degelia, S.K., Wang, X., Stensrud, D.J. & Turner, D.D. (2020) Systematic Evaluation of the Impact of Assimilating a Network of

Ground-Based Remote Sensing Profilers for Forecasts of Nocturnal Convection Initiation during PECAN. *Monthly Weather Review*, 148(12), 4703–4728. https://doi.org/10.1175/MWR-D-20-0118.1 https://journals.ametsoc.org/view/journals/mwre/148/12/MWR-D-20-0118.1.xml

Desroziers, G., Arbogast, E. & Berre, L. (2016) Improving spatial localization in 4DEnVar. *Quarterly Journal of the Royal Meteorological Society*, 142(701), 3171–3185. https://doi.org/10.1002/qj.2898

Durran, D.R. & Gingrich, M. (2014) Atmospheric Predictability: Why Butterflies Are Not of Practical Importance. *Journal of the Atmospheric Sciences*, 71(7), 2476–2488. https://doi.org/10.1175/JAS-D-14-0007.1 https://journals.ametsoc.org/view/journals/atsc/71/7/jas-d-14-0007.1.xml

Fowler, A. (2019) Data compression in the presence of observational error correlations. *Tellus A: Dynamic Meteorology and Oceanography*, 71(1), 1634937.

Fowler, A., Simonin, D. & Waller, J. (2020) Measuring theoretical and actual observation influence in the Met Office UKV: application to Doppler radial winds. *Geophysical Research Letters*, 47(24), e2020GL091110.

Fowler, A.M., Dance, S.L. & Waller, J.A. (2018) On the interaction of observation and prior error correlations in data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 144(710), 48–62. https://doi.org/10.1002/qj.3183

Geer, A.J., Lonitz, K., Weston, P., Kazumori, M., Okamoto, K., Zhu, Y. et al. (2018) All-sky satellite data assimilation at operational weather forecasting centres. *Quarterly Journal of the Royal Meteorological Society*, 144(713), 1191–1217. https://doi.org/10.1002/qj.3202

S. Geiss. New approaches for using satellite observations in numerical weather prediction. PhD thesis 2021. URL http://nbn-resolving.de/urn:nbn:de:bvb:19-291186.

Geiss, S., Scheck, L., de Lozar, A. & Weissmann, M. (2021) Understanding the model representation of clouds based on visible and infrared satellite observations. *Atmospheric Chemistry and Physics*, 21(16), 12273–12290. https://doi.org/10.5194/acp-21-12273-2021 https://acp.copernicus.org/articles/21/12273/2021/

Grabowski, W.W., Morrison, H., Shima, S.-I., Abade, G.C., Dziekan, P. & Pawlowska, H. (2019) Modeling of Cloud Microphysics: Can We Do Better? *Bulletin of the American Meteorological Society*, 100(4), 655–672. https://doi.org/10.1175/BAMS-D-18-0005.1

Guillet, O., Weaver, A.T., Vasseur, X., Michel, Y., Gratton, S. & Gürol, S. (2019) Modelling spatially correlated observation errors in variational data assimilation using a diffusion operator on an unstructured mesh. *Quarterly Journal of the Royal Meteorological Society*, 145(722), 1947–1967. https://doi.org/10.1002/qj.3537

Gustafsson, N., Janjić, T., Schraff, C., Leuenberger, D., Weissmann, M., Reich, H. et al. (2018) Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres. *Quarterly Journal of the Royal Meteorological Society*, 144(713), 1218–1256. https://doi.org/10.1002/qj.3179

Hawkness-Smith, L. & Simonin, D. (2021) Radar reflectivity assimilation using hourly cycling 4D-Var in the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 147(736), 1516–1538.

Hintz, K.S., O'Boyle, K., Dance, S.L., Al-Ali, S., Ansper, I., Blaauboer, D. et al. (2019) Collecting and utilising crowdsourced data for numerical weather prediction: Propositions from the meeting held in copenhagen, 4–5 december 2018. *Atmospheric Science Letters*, 20(7), e921. https://doi.org/10.1002/asl.921

Hintz, K.S., Vedel, H. & Kaas, E. (2019) Collecting and processing of barometric data from smartphones for potential use in numerical weather prediction data assimilation. *Meteorological Applications*, 26(4), 733–746. https://doi.org/10.1002/met.1805

Hodyss, D. (2011) Ensemble state estimation for nonlinear systems using polynomial expansions in the innovation. *Monthly Weather Review*, 139(11), 3571–3588. https://doi.org/10.1175/2011MWR3558.1

Hu, G. & Dance, S.L. (2021) Efficient computation of matrix-vector products with full observation weighting matrices in data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 147, 4101–4121. https://doi.org/10.1002/qj.4170

Hu, G. & Franzke, C.L.E. (2020) Evaluation of daily precipitation extremes in reanalysis and gridded observation-based data sets over Germany. *Geophysical Research Letters*, 47(18), e2020GL089624. https://doi.org/10.1029/2020GL089624

Janjić, T., Bormann, N., Bocquet, M., Carton, J.A., Cohn, S.E., Dance, S.L. et al. (2018) On the representation error in data assimilation. *Quarterly Journal of the Royal Meteorological Society*, 144(713), 1257–1278. https://doi.org/10.1002/qj.3130

Johnson, A., Wang, X., Carley, J.R., Wicker, L.J. & Karstens, C. (2015) A comparison of multiscale GSI-based EnKF and 3DVar data assimilation using radar and conventional observations for midlatitude convective-scale precipitation forecasts. *Monthly Weather Review*, 143(8), 3087–3108. https://doi.org/10.1175/MWR-D-14-00345.1

Jones, C. & Macpherson, B. (1997) A latent heat nudging scheme for the assimilation of precipitation data into an operational mesoscale model. *Meteorological Applications*, 4(3), 269–277.

Kostka, P.M., Weissmann, M., Buras, R., Mayer, B. & Stiller, O. (2014) Observation operator for visible and near-infrared satellite reflectances. *Journal of Atmospheric and Oceanic Technology*, 31(6), 1216–1233.

Li, Z. (2021) Impact of assimilating Mode-S EHS winds in the Met Office's high-resolution NWP model. *Meteorological Applications*, 28(3), e1989.

Lorenc, A.C. & Payne, T. (2007) 4D-Var and the butterfly effect: Statistical four-dimensional data assimilation for a wide range of scales. *Quarterly Journal of the Royal Meteorological Society*, 133(624), 607–614. https://doi.org/10.1002/qj.36

Michel, Y. (2018) Revisiting Fisher's approach to the handling of horizontal spatial correlations of observation errors in a variational framework. *Quarterly Journal of the Royal Meteorological Society*, 144(716), 2011–2025. https://doi.org/10.1002/qj.3249

Michel, Y. & Brousseau, P. (2021) A square-root, dual-resolution 3DEnVar for the AROME Model: formulation and evaluation on a summertime convective period. *Monthly Weather Review*, 149(9), 3135–3153. https://doi.org/10.1175/MWR-D-21-0026.1

Milan, M., Macpherson, B., Tubbs, R., Dow, G., Inverarity, G., Mittermaier, M. et al. (2020) Hourly 4D-Var in the Met Office UKV operational forecast model. *Quarterly Journal of the Royal Meteorological Society*, 146(728), 1281–1301.

Mirza, A.K., Ballard, S.P., Dance, S.L., Maisey, P., Rooney, G.G. & Stone, E.K. (2016) Comparison of aircraft-derived observations with in situ research aircraft measurements. *Quarterly Journal of the Royal Meteorological Society*, 142(701), 2949–2967. https://doi.org/10.1002/qj.2864

Mirza, A.K., Ballard, S.P., Dance, S.L., Rooney, G.G. & Stone, E.K. (2019) Towards operational use of aircraft-derived observations: a case study at London Heathrow airport. *Meteorological Applications*, 26, 542–555. https://doi.org/10.1002/met.1782

Mirza, A.K., Dance, S.L., Rooney, G.G., Simonin, D., Stone, E.K. & Waller, J.A. (2021) Comparing diagnosed observation uncertainties with independent estimates: A case study using aircraft-based observations and a convection-permitting data assimilation system. *Atmospheric Science Letters*, 22(5), el01029. https://doi.org/10.1002/asl.1029

Montmerle, T., Michel, Y., Arbogast, E., Ménétrier, B. & Brousseau, P. (2018) A 3D ensemble variational data assimilation scheme for the limited-area AROME model: Formulation and preliminary results. *Quarterly Journal of the Royal Meteorological Society*, 144(716), 2196–2215. https://doi.org/10.1002/qj.3334

Palmer, T., Buizza, R., Doblas-Reyes, F., Jung, T., Leutbecher, M., Shutts, G. et al. (2009) Stochastic parametrization and model uncertainty, 42(598), 10. https://doi.org/10.21957/ps8gbwbdv https://www.ecmwf.int/node/11577

Park, S.K. & Županski, D. (2003) Four-dimensional variational data assimilation for mesoscale and storm-scale applications. *Meteorology and Atmospheric Physics*, 82(1), 173–208.

Parrish, D.F. & Derber, J.C. (1992) The national meteorological center's spectral statistical-interpolation analysis system. *Monthly Weather Review*, 120(8), 1763. https://doi.org/10.1175/1520-0493(1992)120<17472

Petrie, R.E., Bannister, R.N. & Cullen, M.J.P. (2017) The ABC model: a non-hydrostatic toy model for use in convective-scale data assimilation investigations. *Geoscientific Model Development*, 10(12), 4419–4441. https://doi.org/10.5194/gmd-10-4419-2017

Posselt, D.J. & Bishop, C.H. (2018) Nonlinear data assimilation for clouds and precipitation using a gamma inverse-gamma ensemble filter. *Quarterly Journal of the Royal Meteorological Society*, 144(716), 2331–2349. https://doi.org/10.1002/qj.3374

Rainwater, S., Bishop, C.H. & Campbell, W.F. (2015) The benefits of correlated observation errors for small scales. *Quarterly Journal of the Royal Meteorological Society*, 141(693), 3439–3445. https://doi.org/10.1002/qj.2582

Raynaud, L., Berre, L. & Desroziers, G. (2012) Accounting for model error in the Météo-France ensemble data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 138(662), 249–262.

Reinert, D., Prill, F., Frank, H., Denhard, M., Baldauf, M., Schraff, C. et al. (2020) DWD Database Reference for the Global and Regional ICON and ICON-EPS Forecasting System. *Technical report Version 2.1.8, Deutscher Wetterdienst*. https://www.dwd.de/DWD/forschung/nwv/fepub/icon_database_main.pdf

Rennie, S.J., Dance, S.L., Illingworth, A.J., Ballard, S. & Simonin, D. (2011) 3D-Var assimilation of insect-derived Doppler radar radial winds in convective cases using a high-resolution model. *Monthly Weather Review*, 139(4), 1148–1163.

Scheck, L., Frerebeau, P., Buras-Schnell, R. & Mayer, B. (2016) A fast radiative transfer method for the simulation of visible satellite imagery. *Journal of Quantitative Spectroscopy and Radiative Transfer*, 175, 54–67.

Scheck, L., Weissmann, M. & Mayer, B. (2018) Efficient methods to account for cloud-top inclination and cloud overlap in synthetic visible satellite images. *Journal of Atmospheric and Oceanic Technology*, 35(3), 665–685.

Schraff, C., Reich, H., Rhodin, A., Schomburg, A., Stephan, K., Periáñez, A. et al. (2016) Kilometre-scale ensemble data assimilation for the COSMO model (KENDA). *Quarterly Journal of the Royal Meteorological Society*, 142(696), 1453–1472. https://doi.org/10.1002/qj.2748

Schröttle, J., Weissmann, M., Scheck, L. & Hutt, A. (2020) Assimilating visible and infrared radiances in idealized simulations of deep convection. *Monthly Weather Review*, 148, 1–51.

Siems-Anderson, A., Lee, J.A., Brown, B., Wiener, G. & Linden, S. (2020) Impacts of assimilating observations from connected vehicles into a numerical weather prediction model. *Transportation Research Interdisciplinary Perspectives*, 8, 100253.

Simonin, D., Waller, J.A., Ballard, S.P., Dance, S.L. & Nichols, N.K. (2019) A pragmatic strategy for implementing spatially correlated observation errors in an operational system: An application to Doppler radial winds. *Quarterly Journal of the Royal Meteorological Society*, 145(723), 2772–2790.

Stensrud, D.J., Wicker, L.J., Xue, M., Dawson, D.T., II, Yussouf, N., Wheatley, D.M. et al. (2013) Progress and challenges with Warn-on-Forecast. *Atmospheric Research*, 123, 2–16.

Stensrud, D.J., Xue, M., Wicker, L.J., Kelleher, K.E., Foster, M.P., Schaefer, J.T. et al. (2009) Convective-Scale Warn-on-Forecast System: A Vision for 2020. *Bulletin of the American Meteorological Society*, 90(10), 1487–1500. https://doi.org/10.1175/2009BAMS2795.1

Stephan, K., Klink, S. & Schraff, C. (2008) Assimilation of radar-derived rain rates into the convective-scale model COSMO-DE at DWD. *Quarterly Journal of the Royal Meteorological Society*, 134(634), 1315–1326. https://doi.org/10.1002/qj.269

Stewart, L.M., Dance, S. & Nichols, N. (2008) Correlated observation errors in data assimilation. *International Journal for Numerical Methods in Fluids*, 56(8), 1521–1527.

Stewart, L.M., Dance, S.L. & Nichols, N.K. (2013) Data assimilation with correlated observation errors: experiments with a 1-D shallow water model. *Tellus A: Dynamic Meteorology and Oceanography*, 65(1), 19546.

Sun, J. (2005) Convective-scale assimilation of radar data: progress and challenges. *Quarterly Journal of the Royal Meteorological Society*, 131(613), 3439–3463. https://doi.org/10.1256/qj.05.149

Trémolet, Y. (2007) Model-error estimation in 4D-Var. *Quarterly Journal of the Royal Meteorological Society: A Journal of the Atmospheric Sciences, Applied Meteorology and Physical Oceanography*, 133(626), 1267–1280.

van Leeuwen, P.J. (2009) Particle Filtering in Geophysical Systems. *Monthly Weather Review*, 137(12), 4089–4114. https://doi.org/10.1175/2009MWR2835.1

Vetra-Carvalho, S., Dixon, M., Migliorini, S., Nichols, N.K. & Ballard, S.P. (2012) Breakdown of hydrostatic balance at convective scales in the forecast errors in the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 138(668), 1709–1720.

Waller, J.A., Ballard, S.P., Dance, S.L., Kelly, G., Nichols, N.K. & Simonin, D. (2016) Diagnosing horizontal and inter-channel observation error correlations for SEVIRI observations using observation-minus-background and observation-minus-analysis statistics. *Remote Sensing*, 8(7), 581. https://doi.org/10.3390/rs8070581

Waller, J.A., Bauernschubert, E., Dance, S.L., Nichols, N.K., Potthast, R. & Simonin, D. (2019) Observation error statistics for doppler radar radial wind superobservations assimilated into the DWD COSMO-KENDA system. *Monthly Weather Review*, 147(9), 3351–3364. https://doi.org/10.1175/MWR-D-19-0104.1

Waller, J.A., Dance, S.L. & Lean, H.W. (2021) Evaluating errors due to unresolved scales in convection-permitting numerical weather prediction. *Quarterly Journal of the Royal Meteorological Society*, 147(738), 2657–2669. https://doi.org/10.1002/qj.4043

Waller, J.A., Simonin, D., Dance, S.L., Nichols, N.K. & Ballard, S.P. (2016) Diagnosing observation error correlations for Doppler radar radial winds in the Met Office UKV model using observation-minus-background and observation-minus-analysis statistics. *Monthly Weather Review*, 144(10), 3533–3551. https://doi.org/10.1175/MWR-D-15-0340.1

Wang, X., Chipilski, H.G., Bishop, C.H., Satterfield, E., Baker, N. & Whitaker, J.S. (2021) A multiscale local gain form ensemble transform Kalman filter (MLGETKF). *Monthly Weather Review*, 149(3), 605–622.

World Meteorological Organization (WMO), Observing Systems Capability Analysis and Review (OSCAR). https://space.oscar.wmo.int/: 2022.

Ying, Y. (2020) Assimilating observations with spatially correlated errors using a serial ensemble filter with a multiscale approach. *Monthly Weather Review*, 148(8), 3397–3412. https://doi.org/10.1175/MWR-D-19-0387.1

Yussouf, N. & Knopfmeier, K.H. (2019) Application of the Warn-on-Forecast system for flash-flood-producing heavy convective rainfall events. *Quarterly Journal of the Royal Meteorological Society*, 145(723), 2385–2403. https://doi.org/10.1002/qj.3568

Yussouf, N., Wilson, K.A., Martinaitis, S.M., Vergara, H., Heinselman, P.L. & Gourley, J.J. (2020) The coupling of NSSL warn-on-forecast and flash systems for probabilistic flash flood prediction. *Journal of Hydrometeorology*, 21(1), 123–141. https://doi.org/10.1175/JHM-D-19-0131.1

Zängl, G., Reinert, D., Rípodas, P. & Baldauf, M. (2015) The ICON (ICOsahedral Non-hydrostatic) modelling framework of DWD and MPI-M: Description of the non-hydrostatic dynamical core. *Quarterly Journal of the Royal Meteorological Society*, 141(687), 563–579. https://doi.org/10.1002/qj.2378

Zeng, Y., Janjic, T., Feng, Y., Blahak, U., de Lozar, A., Bauernschubert, E. et al. (2021) Interpreting estimated observation error statistics of weather radar measurements using the ICON-LAM-KENDA system. *Atmospheric Measurement Techniques Discussions*, 1–28, 2021. https://doi.org/10.5194/amt-2021-95

How to cite this article: Hu, G., Dance, S. L., Bannister, R. N., Chipilski, H. G., Guillet, O., Macpherson, B., Weissmann, M., & Yussouf, N. (2022). Progress, challenges, and future steps in data assimilation for convection-permitting numerical weather prediction: Report on the virtual meeting held on 10 and 12 November 2021. *Atmospheric Science Letters*, e1130. https://doi.org/10.1002/asl.1130