

Diagnosing observation error correlations for Doppler radar radial winds in the Met Office UKV model using observation-minus-background and observation-minus-analysis statistics

Article

Accepted Version

Waller, J. A., Simonin, D., Dance, S. L., Nichols, N. K. and 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). pp. 3533-3551. ISSN 0027-0644 doi: <https://doi.org/10.1175/MWR-D-15-0340.1> Available at <https://centaur.reading.ac.uk/65806/>

It is advisable to refer to the publisher's version if you intend to cite from the work. See [Guidance on citing](#).

To link to this article DOI: <http://dx.doi.org/10.1175/MWR-D-15-0340.1>

Publisher: American Meteorological Society

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in

the [End User Agreement](#).

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

1 **Diagnosing observation error correlations for Doppler radar radial winds in**
2 **the Met Office UKV model using observation-minus-background and**
3 **observation-minus-analysis statistics**

4 J. A. Waller *

5 *School of Mathematical and Physical Sciences, University of Reading, Reading, Berkshire,*
6 *RG6 6BB, United Kingdom*

5 D. Simonin

5 *MetOffice@Reading, Meteorology Building, University of Reading, Reading, Berkshire,*
6 *RG6 6BB, United Kingdom*

5 S. L. Dance, N. K. Nichols

5 *School of Mathematical and Physical Sciences, University of Reading, Reading, Berkshire,*
6 *RG6 6BB, United Kingdom*

5 S. P. Ballard

5 *MetOffice@Reading, Meteorology Building, University of Reading, Reading, Berkshire,*
6 *RG6 6BB, United Kingdom*

5 *Corresponding author address: Department of Meteorology, University of Reading, Earley Gate,
6 PO Box 243, Reading, RG6 6BB, United Kingdom

5 E-mail: j.a.waller@reading.ac.uk

ABSTRACT

5 With the development of convection-permitting numerical weather predic-
6 tion the efficient use of high-resolution observations in data assimilation is
7 becoming increasingly important. The operational assimilation of these obser-
8 vations, such as Doppler radar radial winds (DRWs), is now common, though
9 to avoid violating the assumption of uncorrelated observation errors the ob-
10 servation density is severely reduced. To improve the quantity of observations
11 used and the impact that they have on the forecast requires the introduction of
12 the full, potentially correlated, error statistics. In this work, observation error
13 statistics are calculated for the DRWs that are assimilated into the Met Office
14 high-resolution UK model using a diagnostic that makes use of statistical aver-
15 ages of observation-minus-background and observation-minus-analysis resid-
16 uals. This is the first in-depth study using the diagnostic to estimate both hor-
17 izontal and along-beam observation error statistics. The new results obtained
18 show that the DRW error standard deviations are similar to those used oper-
19 ationally and increase as the observation height increases. Surprisingly the
20 estimated observation error correlation length-scales are longer than the op-
21 erational thinning distance. They are dependent both on the height of the ob-
22 servation and on the distance of the observation away from the radar. Further
23 tests show that the long correlations cannot be attributed to the background
24 error covariance matrix used in the assimilation, although they are, in part, a
25 result of using superobservations and a simplified observation operator. The
26 inclusion of correlated error statistics in the assimilation allows less thinning
27 of the data and hence better use of the high-resolution observations.

5 **1. Introduction**

6 With the recent development of convection permitting numerical weather prediction (NWP),
7 such as the Met Office UK variable resolution (UKV) model (Lean et al. 2008; Tang et al. 2013),
8 the assimilation of observations that have high frequency both in space and time has become in-
9 creasingly important (Park and Zupanski 2003; Dance 2004; Sun et al. 2014; Ballard et al. 2016;
10 Clark et al. 2015). The potential for assimilating one such set of observations, the Doppler radar
11 radial winds (DRWs) (Lindskog et al. 2004; Sun 2005), has been explored by a number of opera-
12 tional centers e.g., Lindskog et al. (2001); Salonen et al. (2007); Rihan et al. (2008); Salonen et al.
13 (2009). The assimilation of the DRWs has been shown to provide a significant positive impact
14 on the forecast (Xiao et al. 2005; Lindskog et al. 2004; Montmerle and Faccani 2009; Simonin
15 et al. 2014; Xue et al. 2013, 2014) and as a result they are now included in operational assimilation
16 (Xiao et al. 2008; Simonin et al. 2014).

17 Currently at the Met Office the error statistics associated with DRWs are assumed uncorrelated
18 (Simonin et al. 2014). To reduce the large quantity of data and ensure the assumption of uncorre-
19 lated errors is reasonable the DRW observations are ‘superobbed’ and thinned before assimilation
20 (Simonin et al. 2014). These processes result in a large number of observations being discarded.
21 To improve convection-permitting NWP it is necessary to make better use of high frequency DRW
22 observations. This requires less thinning of the observational data and, hence, the inclusion of
23 correlated observation error statistics in the assimilation system is required (Liu and Rabier 2003).
24 Currently the full observation error statistics associated with the DRWs are unknown. Therefore,
25 the aim of this manuscript is both to estimate and to provide an understanding of the correlated
26 observation errors associated with DRW.

27 In general, the errors associated with the observations can be attributed to four main sources:

- 28 • Instrument error.
- 29 • Error introduced in the observation operator.
- 30 • Errors of representativity - errors that arise where the observations can resolve spatial scales
31 that the model cannot.
- 32 • Pre-processing errors - errors introduced by pre-processing.

33 For DRWs the instrument errors are independent and uncorrelated. Observation error correlations,
34 which may be state dependent and dependent on the model resolution, are likely to arise from the
35 other sources of error (Janjic and Cohn 2006; Waller 2013; Waller et al. 2014a,b) (see Section 5
36 for a more detailed description). The inclusion of correlated observation errors in the assimilation
37 has been shown to lead to a more accurate analysis, the inclusion of more observation information
38 content and improvements in the forecast skill score (Stewart et al. 2013; Stewart 2010; Healy and
39 White 2005; Stewart et al. 2008; Weston et al. 2014). Significant benefit may even be provided by
40 using only a crude approximation to the observation error covariance matrix (Stewart et al. 2013;
41 Healy and White 2005).

42 A number of methods exist for estimating the observation error covariances e.g. Hollingsworth
43 and Lönnberg (1986); Dee and Da Silva (1999). Xu et al. (2007) presented an innovation method
44 based on that of Hollingsworth and Lönnberg (1986) for estimating DRW error and background
45 wind error covariances. Simonin et al. (2012) previously calculated observation error statistics
46 for DRWs using the method of Xu et al. (2007). The work of Simonin et al. (2012) suggests
47 that the observation error standard deviation increases with the height of the observation and that
48 the observations errors have a correlation length scale of 1-3km. However, the Hollingsworth and
49 Lönnberg (1986) method was initially designed to provide estimates of the background error statis-
50 tics under the assumption of uncorrelated observation errors. The method can be used to estimate

51 both correlated background and correlated observation errors; however, determining how to split
52 the estimated quantity into observation and background errors is non-trivial (Bormann and Bauer
53 2010). Indeed the result is subjective. To overcome this difficulty most recent attempts to diagnose
54 the observation error correlations have made use of the diagnostic proposed in Desroziers et al.
55 (2005). Initially designed as a consistency check, the diagnostic provides an estimate of the obser-
56 vation error covariance matrix using the statistical average of observation-minus-background and
57 observation-minus-analysis residuals. However, in theory it relies on the use of exact background
58 and observation error statistics in the assimilation. Despite this limitation, the diagnostic has been
59 used to estimate inter-channel observation error statistics (Stewart et al. 2009, 2014; Bormann and
60 Bauer 2010; Bormann et al. 2010; Weston et al. 2014) even when the error statistics used in the
61 assimilation are not exact. The method of Desroziers et al. (2005) has also been used by Wattrelot
62 et al. (2012) to calculate observation error statistics for the Doppler radial winds assimilated into
63 the Météo-France system. Their results, published as a conference paper, show a similar error
64 standard deviation to those found in Simonin et al. (2012), but suggest that the observation errors
65 have a larger correlation length scale of approximately 10km. (we cannot determine the length
66 scale precisely due the data thinning they have applied).

67 Here we present the first in-depth study using the diagnostic of Desroziers et al. (2005) to calcu-
68 late observation error statistics for the DRWs assimilated into the Met Office high resolution UK
69 (UKV) model. Due to the limitations of the diagnostic we consider the sensitivity of the estimated
70 observation error statistics to the choice of assimilated background error statistics. To aid our
71 understanding of the source of observation error we also consider the sensitivity of the estimated
72 observation error statistics to the use of superobservations and the use of a more sophisticated
73 observation operator. We find that, for summer season observations, the DRW error standard devi-
74 ations are similar to those used operationally, though surprisingly, the observation error correlation

length scales are longer than the operational thinning distance. Due to the uncertainty in the results arising from the diagnostic the estimated correlation lengthscales should be interpreted as indicative, rather than necessarily quantitatively perfect. However, results from the diagnostics can still provide useful information as further tests show that the long correlations cannot be attributed to the background error covariance matrix used in the assimilation, although they may, in part, be a result of using superobservations and a simplified observation operator.

This paper is organised as follows. In Section 2 we give a description of the diagnostic of Desroziers et al. (2005). We describe the DRW observations and their model representations in Section 3 and in Section 4 we describe the experimental design. In Section 5 we consider the estimated observation error statistics from four different cases. Finally we conclude in Section 6.

2. The diagnostic of Desroziers et al. (2005)

Data assimilation techniques combine observations $\mathbf{y} \in \mathbb{R}^{N^p}$ with a model prediction of the state, the background $\mathbf{x}^b \in \mathbb{R}^{N^m}$, often determined by a previous forecast. Here N^p and N^m denote the dimensions of the observation and model state vectors respectively. In the assimilation the observations and background are weighted by their respective errors, using the background and observation error covariance matrices $\mathbf{B} \in \mathbb{R}^{N^m \times N^m}$ and $\mathbf{R} \in \mathbb{R}^{N^p \times N^p}$, to provide a best estimate of the state, $\mathbf{x}^a \in \mathbb{R}^{N^m}$, known as the analysis. To calculate the analysis the background must be projected into the observation space using the possibly non-linear observation operator, $\mathcal{H} : \mathbb{R}^{N^p} \rightarrow \mathbb{R}^{N^m}$. After an assimilation step the analysis is evolved forward in time to provide a background for the next assimilation.

Desroziers et al. (2005) assume that the analysis is determined using,

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{K}(\mathbf{y} - \mathcal{H}(\mathbf{x}^b)), \quad (1)$$

96 where $\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$ is the gain matrix and \mathbf{H} is the linearised observation operator,
 97 linearised about the current state.

98 The diagnostic described in Desroziers et al. (2005) estimates the observation error covariance
 99 matrix by using the observation-minus-background and observation-minus-analysis residuals. The
 100 background residual, also known as the innovation,

$$\mathbf{d}_b^o = \mathbf{y} - \mathcal{H}(\mathbf{x}^b), \quad (2)$$

101 is the difference between the observation \mathbf{y} and the mapping of the forecast vector, \mathbf{x}^b , into obser-
 102 vation space by the observation operator \mathcal{H} . The analysis residual,

$$\mathbf{d}_a^o = \mathbf{y} - \mathcal{H}(\mathbf{x}^a), \quad (3)$$

$$\approx \mathbf{y} - \mathcal{H}(\mathbf{x}^b) - \mathbf{H}\mathbf{K}\mathbf{d}_b^o. \quad (4)$$

103 is similar to the background residuals, but with the forecast vector replaced by the analysis vector
 104 \mathbf{x}^a . By taking the statistical expectation of the product of the analysis and background residuals
 105 results in

$$E[\mathbf{d}_a^o \mathbf{d}_b^{oT}] \approx \mathbf{R}, \quad (5)$$

106 assuming that the forecast and observation errors are uncorrelated. Equation (5) is exact if the
 107 observation and background error statistics used in assimilation are exact. The theoretical work of
 108 Waller et al. (2016) provides insight on how results from the diagnostic can be interpreted when
 109 the incorrect background and observation error statistics are used in the assimilation. Due to the
 110 statistical nature of the diagnostic the resulting matrix will not be symmetric. Therefore, if the
 111 matrix is to be used it must be symmetrised.

112 **3. Doppler Radar radial wind observations and their model representation**

113 *a. The Met Office UKV model and 3D variational assimilation scheme*

114 The operational UKV model is a variable resolution convection permitting model that covers the
115 UK (Lean et al. 2008; Tang et al. 2013). The model has 70 vertical levels. The horizontal grid has
116 a 1.5km fixed resolution on the interior surrounded by a variable resolution grid which increases
117 smoothly in size to 4km. The variable resolution grid allows the downscaled boundary conditions,
118 taken from the global model, to spin up before reaching the fixed interior grid. The initial condi-
119 tions are provided from a 3D variational assimilation scheme that uses an incremental approach
120 (Courtier et al. 1994) and is a limited-area version of the Met Office variational data assimilation
121 scheme (Lorenc et al. 2000; Rawlins et al. 2007). The assimilation uses an adaptive mesh, that
122 allows the accurate representation of boundary layer structures (Piccolo and Cullen 2011, 2012) .
123 The background error covariance statistics used in this study are described in Section 4.

124 *b. Doppler radar radial wind data*

125 Doppler radar is an active remote sensing instrument that provides observations of radial wind
126 by measuring the phase shift between a transmitted electromagnetic wave pulse and its backscatter
127 echo. The radial velocity of a scattering target is then estimated from the ‘Doppler shift’ (Doviak
128 and Zrnich 1993). While it is possible to derive clear air radar returns e.g. Rennie et al. (2010,
129 2011), in this work we consider only observations where the scattering targets are assumed to be
130 raindrops. The DRW data used at the Met Office are acquired using 18 C-Band weather radars.
131 Each radar completes a series of scans out to a range of 100km every 5 minutes at different el-
132 evation angles (typically 1° , 2° , 4° , 6° and 9°) with a $1^\circ \times 600\text{m}$ resolution volume. Before
133 being assimilated the data is processed and a quality control procedure is applied. This ensures

134 that no observations that disagree with neighbouring observations or have a large departure from
 135 the background are assimilated. The observations errors are assumed Gaussian and uncorrelated
 136 in space or time with standard deviations that range from $1.8ms^{-1}$ for observations close to the
 137 radar to $2.8ms^{-1}$ for observations furthest away from the radar. Further details of the operational
 138 assimilation of DRWs at the Met Office can be found in Simonin et al. (2014).

139 1) THE CURRENT OPERATIONAL OBSERVATION OPERATOR

140 To compare the background with the observations it is necessary to map the model state into
 141 observation space. The current operational observation operator, following Lindskog et al. (2000),
 142 first interpolates the NWP model horizontal and vertical wind components u , v and w to the ob-
 143 servation location. The horizontal wind is then projected in the direction of the radar beam and
 144 projected onto the slant of the radar beam using,

$$v_r = (u \sin \phi + v \cos \phi) \cos(\theta) + w \sin(\theta), \quad (6)$$

145 where ϕ is the radar azimuth angle clockwise from due north and θ is the beam center elevation
 146 angle. The elevation angle $\theta = \varepsilon + \alpha$ includes a correction term, α , that must be added to the
 147 measurement elevation angle ε . The correction term

$$\alpha = \tan^{-1}\left(\frac{r \cos(\varepsilon)}{r \sin(\varepsilon) + a_e + h_r}\right), \quad (7)$$

148 where h_r is the height of the radar above sea level, r is the range of the observation and a_e is
 149 the effective earth radius (1.3 times the actual earth radius) required to take account of the earth's
 150 curvature and the radar beam refraction (Doviak and Zrnic 1993). The correction term is not
 151 exact. The value of a_e is only valid in the international standard atmosphere. This simple oper-
 152 ational observation operator does not account for the beam broadening or reflectivity weighting.
 153 Additionally, only the horizontal wind components are updated in the minimisation, the vertical

154 component of wind is ignored, which for small elevation angles should be acceptable. In addition
 155 no information about hydrometeor fall speed is available to the assimilation system.

156 This operational observation operator is used in the majority of results discussed in this article.

157 2) AN IMPROVED OBSERVATION OPERATOR

158 An improved observation operator has been trialled in the operational system; it accounts for
 159 some broadening of the beam (vertical only), as well as a reflectivity weighting. Both of these
 160 processes are often ignored in operational DRW assimilation (Ge et al. 2010). This improved
 161 observation operator is similar to the operator described by Xu and Wei (2013), although it differs
 162 in some important details. The beam broadening model, W_{bb} , takes the form,

$$W_{bb}(\theta_z) = \exp(-2\ln(2) \frac{\theta_z^2}{\theta_{3dB}^2}), \quad (8)$$

163 with $\theta_z = \theta - \theta_b$ where θ is the beam centre elevation as in equation (6), θ_b is the elevation within
 164 the beam and θ_{3dB} is the half power bandwidth (angular range of the antenna pattern in which at
 165 least half of the maximum power is still emitted (Toomay and Hannen 2004)). For the reflectivity
 166 weighting, a climatological profile with height h is used,

$$W_{ref}(h) = Zh + c, \quad (9)$$

167 where,

$$Z = \begin{cases} -6dB : h < Brightband_L \\ -2dB : h > Brightband_U \end{cases}, \quad (10)$$

168 c is a constant scaling factor, $Brightband_L$ is the lower limit of the Bright band and $Brightband_U$ is
 169 the upper limit of the Bright band. The height of the Bright band (a layer of melting ice resulting
 170 in intense reflectivity return (Kitchen 1997)) is derived from the forecast model temperature field,
 171 and has a thickness set to 250m. The reflectivity profile increases by 10dB from the bottom to

172 the centre of the bright band and then decreases linearly. The beam broadening and reflectivity
 173 weighting are combined to give a single weight, $W = W_{ref}W_{bb}$ and this weighting is included in
 174 the new observation operator,

$$v_r = \sum_{ML_{\theta_{beam}}} W(u \sin \phi + v \cos \phi) \cos(\theta). \quad (11)$$

175 The summation in 11 is made over the model levels ($ML_{\theta_{beam}}$) present within the beam thick-
 176 ness. In this formulation, $\sum W$ is equal to one over the $ML_{\theta_{beam}}$. The implementation of this new
 177 observation operator has been shown to reduce the error in the background residuals. This new
 178 observation operator may be further improved (Fabry 2010), though the operational use of a more
 179 complex observation operator may not be feasible. While these simplifications and omissions in
 180 the observation operator exist, they will introduce additional error when the model background
 181 is projected into observation space. These errors may well be correlated and should ideally be
 182 accounted for in the observation error covariance matrix.

183 3) SUPEROBSERVATION CREATION

184 To reduce the density of the observations, multiple observations are made into a single superob-
 185 servation. Only observations that have passed the quality control procedure described in Simonin
 186 et al. (2014) are combined to make the superobservations. There are a number of methods for
 187 calculating the superobservations. The Doppler radar superobservations used at the Met Office
 188 are calculated using innovations following the method of Salonen et al. (2008). The radar scan is
 189 divided into 3° by $3km$ cells and one observation is created per cell using the following procedure:

- 190 1. Project background winds into observation space using equation (6);
- 191 2. Calculate the background residual at each observation location;
- 192 3. Average all background residuals that fall within a superobservation cell;

193 4. Add the average residual to the simulated background radial wind at the center of the super-
194 observation cell to give a value for the superobservation.

195 The calculated superobservations are subject to a second quality control procedure (Simonin et al.
196 2014). They are then further thinned to 6km, where is assumed that the observations will have
197 uncorrelated error, using Poisson disk sampling (Bondarenko et al. 2007).

198 4) SUPEROBSERVATION ERROR

199 The calculated superobservations have an associated superobservation error, ϵ^{so} . The literature
200 shows that the superobbing procedure reduces the uncorrelated portion of the error; however, the
201 correlated error is not reduced (Berger and Forsythe 2004). Berger and Forsythe (2004) showed
202 that the covariance of the superobservation error will be equivalent to the averaged observation
203 error covariance matrix for the raw observations (i.e. creating the superobservations using the
204 background does not introduce any background error into ϵ^{so}) if:

- 205 1. The observation and background errors are independent;
- 206 2. The background state errors are fully correlated within the superobservation cell;
- 207 3. The background state errors in a superobservation cell all have the same magnitude and
- 208 4. The background residuals are equally weighted within a superobservation cell.

209 However, for DRWs it is not clear that all the assumptions will hold. In particular assumptions 1
210 and 2 are valid at close range to the radar where the superobservation cells are small. However, at
211 far range the superobservation cells are large and the assumptions are likely to be invalid. There-
212 fore, it is possible that at large ranges there is a small influence of the background errors on the
213 error associated with the superobservation.

214 5) ERROR SOURCES FOR DOPPLER RADAR RADIAL WINDS

215 In the introduction the four main sources of observation error are introduced. The observation
216 error will not only be a function of the observation type, but also of the observation pre-processing,
217 observation operator and model resolution. Here we list some of the observation error sources
218 specific to DRWs:

- 219 • Errors introduced by clutter removal.
- 220 • Error introduced when creating the superobservations.
- 221 • Misrepresentation of radar beam bending.
- 222 • Misrepresentation of beam broadening.
- 223 • Approximation of volume measurement as point measurement.
- 224 • Discrete approximation of continuous mapping from model to observation space .
- 225 • Errors of representativity.
- 226 • Instrument error.

227 There may be additional unknown sources of error.

228 It has been shown that some of these errors, such as the instrument error or those caused by
229 the misrepresentation of radar beam bending, are small Xu and Wei (2013). However there are
230 other errors, such as the error introduced when creating the superobservations, misrepresentation
231 of beam broadening and the approximation of volume measurement as a point measurement that
232 we hypothesise will have a more significant contribution to the observation error statistics. Indeed,
233 Fabry and Kilambi (2011), suggest that if the antenna beamwidth and reflectivity weighting are

234 ignored in the observation operator then the observation errors will have long correlation length
235 scales greater than 10 km.

236 **4. Experimental Design**

237 To calculate estimates of the observation error covariances we require background and analysis
238 residuals. We use archived observations and background data produced by the operational Met
239 Office system from June, July and August 2013. To generate the analyses we run four different
240 assimilation configurations, detailed below. Using these backgrounds, analyses and observations
241 we are able to determine the background, \mathbf{d}_b^o , and analysis, \mathbf{d}_a^o , residuals. Observations in this
242 study come from 9 of the 18 radars in the network. Although observation errors are likely to be
243 state dependent (Waller et al. 2014b), we have used 3 months worth of data to ensure that we
244 have enough data for the statistical sampling error to be small. We have restricted ourselves to the
245 summer season as we expect mainly convective rainfall (Hand et al. 2004; Hawcroft et al. 2012),
246 which is likely to result in state dependent observation errors which are all similar.

247 Case 1 uses residuals produced by running the UKV under the January 2014 operational con-
248 figuration. This uses superobservations (calculated as described in Section 3) thinned to 6km and
249 the observation operator given in equation (6). The background error covariance ('New') has been
250 derived using the Covariances and VAR Transforms (CVT) software which is the new Met Office
251 covariance calibration and diagnostic tool that analyses training data representing forecast errors
252 (either using the so-called NMC lagged forecast technique or ensemble perturbations). Here a
253 NMC method has been applied to (T+6 hour)-(T+3 hour) forecast differences to diagnose a vari-
254 ance and correlation length scale for each vertical mode.

255 Case 2 considers the effect of using the old (used prior to January 2013) operational UKV
256 background error covariance matrix ('Old'). These statistics were generated from (T+24 hour)-

257 (T+12 hour) forecast differences and, contrary to the CVT approach, the correlation functions
258 used specific fixed length scales (Ballard et al. 2016). This background error covariance matrix
259 has larger variances than the matrix used in Case 1 and the correlations length scales are slightly
260 longer. A comparison between Cases 1 and 2 shows the impact of the assimilated background
261 error covariance matrix on the estimated observation error statistics.

262 Case 3 uses the same background error covariance as Case 1, but used raw observations (thinned
263 to 6km) rather than using the superobservations. A comparison between Cases 1 and 3 shows the
264 impact of the superobservations on the estimated observation error statistics.

265 Case 4 uses the same design as Case 3, the assimilation of raw observations, but the operational
266 observation operator is replaced with the observation operator described in equation (11). A com-
267 parison between Cases 3 and 4 shows the impact of the observation operator on the estimated
268 observation error statistics.

269 We summarise the different cases in Table 1. For each case the available data for each radar
270 scan is stored in 3D arrays of size $N^s \times N^r \times N^a$ where N^s is the number of scans containing data,
271 $N^r = 16$ is the number of ranges and $N^a = 120$ is the number of azimuths. Figure 1 shows a
272 radar scan with the typical superobservation cells. The data is also separated by elevation, with
273 data available at elevation angles 1° , 2° , 4° and 6° . (We do not estimate the observation error
274 statistics for the 9° beam due the lack of available data). The position of these observations at
275 these elevations are shown in Figure 2, we note that the colour scheme for each given elevation
276 is used throughout the figures in this manuscript. It is important to note that these observations
277 are only available in areas where there is precipitation and it is possible that only part of the
278 scan contains observations. Furthermore, the use of the superobservations, thinning and quality
279 control results in a limited amount of data in each scan. The amount of data available differs for
280 each elevation, with data for the lower elevations available out to far range (a result of the quality

281 control procedures), and for higher elevations available only for near range. This lack of data
282 means that standard deviations and correlations are not available for every range at each elevation.
283 Results are only plotted for standard deviations if 1500 or more samples were available and for
284 correlations if the number of samples was greater than 500. The minimum number of samples
285 is chosen to ensure that sampling error does not contaminate our estimates of the error statistics.
286 Observations may be correlated along the beam, horizontally or vertically. Here we consider both
287 horizontal correlations and those along the beam.

288 Horizontal correlations consider how observations at a given height are correlated. The blue
289 cells in Figure 1 show a set of observations that would be compared for a given height. For each
290 radar scan, data is sorted into 200m height bins. Here the height takes into account the height of
291 the radar above sea level. All observations that fall into a particular height bin are considered. The
292 data is binned by separation distance for each pair of observations and from this the correlations
293 are calculated.

294 When calculating along-beam correlations we consider how observations in the same beam are
295 correlated to each other, where correlations are expressed for the separation distance along the
296 beam. The red cells in Figure 1 show one set of observations that would be considered in this
297 case. Here the samples used for calculating equation (5) are taken to be the individual scans along
298 the azimuth. Samples are taken on all dates, from all radars and from each azimuth. When calcu-
299 lating results along the beam we do not expect to obtain symmetric correlation functions. When
300 considering the along-beam correlations at any given range the positive separation distance will
301 result in a different correlation to the negative separation distance. For example, say we are con-
302 sidering the correlations for the observation located at 30km range, the correlation with the 18km
303 observation (-12km separation) will have a smaller measurement volume whereas the observation
304 at 42km (+12km separation) will have a larger measurement volume. This is an important factor

305 to consider when analysing the along-beam correlation results. When plotting the along beam
306 correlation functions, it can appear as though the plot is incomplete for data at low elevations, far
307 range and high height (e.g. Figures 10 and 11). This is a result of the range limit of the radar. For
308 example, as depicted in Figure 2, at elevation 1° and height of 2.5km, the range of the observation
309 is 94km. There are no observations available beyond a range of 100km from the radar, so therefore
310 we are unable to calculate the correlation beyond a separation distance of +6km (i.e. 6km further
311 from the radar).

312 For both horizontal and along-beam correlations it is possible to calculate an average correlation
313 function using all available data that is homogeneous for all elevations, heights and ranges. These
314 average correlation functions provide an overall impression of how the calculated covariance dif-
315 fers between cases. The average along-beam correlation functions are also comparable to those
316 calculated in Wattrelot et al. (2012). The disadvantage of this method is that different elevations
317 represent different heights in the atmosphere, and also have interaction with different model levels.
318 Therefore it is difficult to distinguish how the error correlations arise, whether they are a result of
319 errors in the observation operator, or arise from the misrepresentation of scales. In an attempt to
320 understand exactly what is contributing to the error we also calculate the correlations for different
321 elevations separately as this allows us to better understand the origin and behaviour of the errors.

322 **5. Results**

323 *a. Case 1 - Results from the operational system*

324 We begin by calculating the observation error covariances for Case 1. Here data was acquired
325 using the January 2014 operational system. This uses superobservations (calculated as described in

326 Section 3) thinned to 6km, the observation operator given in equation (6) and the ‘new’ background
327 error covariance statistics.

328 1) HORIZONTAL CORRELATIONS

329 We first calculate the average horizontal correlation function using all data from all elevations.
330 We show the standard deviation for this case in Table 2 and the correlation in Figure 3. (Note that
331 the table and figure contain results for all cases; in this section we discuss the results for Case 1
332 only). The standard deviation falls within the range of operational DRW standard deviations. We
333 see that the estimated correlation length scale (defined to be the distance at which correlation
334 becomes insignificant (< 0.2) (Liu and Rabier 2002)) is approximately 24km. This is much larger
335 than the distance of 1 - 3km calculated in Simonin et al. (2012) using the method of Xu et al. (2007)
336 and the operational thinning distance of 6km. This indicates that the assumption of uncorrelated
337 errors is incorrect.

338 We now consider the horizontal correlations for different heights and each elevation separately.
339 In Figure 4 we plot the standard deviation with height for each elevation. We see that the standard
340 deviations increase with height with the exception of the lowest levels, and are similar for each
341 elevation. For each elevation the volume of atmosphere sampled by the observation increases with
342 height. (Note that at any given height the volume sampled by the 6° beam will be smaller than the
343 1° beam). Observations that sample larger volumes are expected to have a larger instrument error
344 as the Doppler shift is calculated from multiple scattering targets in the measurement volume. In
345 addition these observations will be subject to more error from the observation operator as only
346 information from the model level nearest to the centre of the sample volume is utilised, even when
347 the sample volume spans several model layers. The increased errors at the lowest height may be
348 a result of larger representativity errors as the observations at the lower heights sample smaller

349 volumes than the model resolution. Our results support previous work in Simonin et al. (2014)
350 and we find that the standard deviations are similar to those used operationally.

351 Next we consider how the horizontal correlation length scale changes for a given elevation at
352 different heights. We plot the calculated correlation functions for a range of heights in Figure 5.
353 We see that the correlation length scale increases with height and ranges between 17km and 32km.
354 For all heights the correlation length scale is longer than the operational thinning distance. An
355 increase in height corresponds to an increase in both the distance of observation away from the
356 radar and the volume of the measurement box and therefore the change in correlation length scale
357 could be attributed to either of these variables.

358 In an attempt to determine the cause of the change in length scale we consider the horizontal
359 correlations at the 2.5km height for the different elevations. At any given height the measurement
360 volume of the observation is larger for lower elevations. Figure 6 shows that the correlation length
361 scales are larger for the lower elevations. This suggests that it is the change in measurement
362 volume that affects the correlation length scale. As in this case the observation operator does not
363 account for the observation volume, it is likely that the correlated error is, in part, caused by the
364 error in the observation operator.

365 It is also possible to compare observations at the same range, observations will have the same
366 measurement volume but will be at different heights in the atmosphere. In this case we find that
367 for each elevation the correlation length scale is similar, e.g. at a range of 40km each elevation has
368 a correlation length scale of ≈ 23 km (not shown). This suggests that the measurement volume of
369 the observation has the largest impact on the horizontal correlation length scale, with correlation
370 length scale increasing with measurement volume.

371 2) ALONG-BEAM CORRELATIONS

372 Next we calculate the along-beam observation errors using the data from Case 1. We begin by
373 calculating the average observation error covariance and comparing these results with those from
374 Météo-France (Wattrelot et al. 2012). We do not expect estimated statistics to be equal to those
375 found by Météo-France as there are differences in the operational set up (e.g. observation and
376 background error covariance statistics, observation processing, observation operators and thinning
377 distances) and the region and time scale covered by the data.

378 Our estimated standard deviation (Table 2) is larger than the standard deviation found by Météo-
379 France which is $1.51ms^{-1}$. This is likely to be the result of the different operational set up and
380 observation processing. We plot our estimated correlation function along with the correlation
381 found by Météo-France in Figure 7. We see that the correlation length scales are approximately
382 $5km$ longer than those found by Météo-France. Given the different operational setup used by
383 Météo-France the similarities between the results are reassuring and suggest that we are obtaining
384 a reasonable estimate of the observation error correlations.

385 Next we calculate the error statistics along the beam for each elevation. In Figure 8 (square
386 symbols) we plot the change in standard deviation with height for beam elevations 1° , 2° , 4° and
387 6° . (For the horizontal correlations the height of the radar above sea level was accounted for; here
388 height is calculated assuming that the radar is at sea level). For all elevations the observation error
389 standard deviation generally increases with height, with the exception of the lowest levels. This is
390 similar to the behaviour of the standard deviations for the horizontal case. Unlike the horizontal
391 case the standard deviations for each elevation are not so similar. For any given height the standard
392 deviations are larger for the lower elevations. At any given height the lower elevations will be

393 sampling larger volumes of the atmosphere. Observations sampling large volumes are subject to
394 both larger instrument error and more error in the observation operator.

395 We now consider how the correlation length scale changes for a given elevation at different
396 heights. The estimated observation error correlations for a range of heights are plotted in Figure 9.
397 The along-beam correlation length scales are shorter than the horizontal correlations, though the
398 correlation length scale still increases with height for any given elevation. This highlights the
399 relationship between the increase in correlation length scale with the increasing height, range and
400 volume measurement of the observation.

401 In Figure 10 we consider how the correlation function differs with measurement volume. We
402 plot the along-beam correlation function for each elevations at a height of 2.5km. Here the height
403 for each observation is the same, but the measurements are taken at different ranges with the
404 lowest elevation at the furthest range. Figure 10 shows that the correlation length scale increases
405 with range. Again this likely to be a result of the larger measurement volumes at far range.

406 In Figure 11 we plot the correlation function for each elevation at a range of 40km. Here the
407 volume of measurement for each observation is the same, but measurements from lower elevations
408 are at lower heights. We see that the correlation length scale differs with elevation and decreases
409 with height. We hypothesise that the change in correlation is a result of the different levels of the
410 atmosphere sampled by different beam elevations. For the low elevation angles the beam gradient
411 is shallow, hence different gates measure similar heights in the atmosphere; this results in larger
412 error correlations. Larger elevation angles have larger beam gradients, different gates sample a
413 wider range of heights in the atmosphere; this results in small observation error correlations.

414 3) SUMMARY

415 For this case we have calculated observation error statistics using background residuals from
416 June, July and August 2013, the analysis residuals are produced by running the UKV model using
417 the January 2014 operational configuration. We find that:

- 418 • DRW standard deviations increase with height (with the exception of the lowest heights).
419 This is likely due to the increasing measurement volume with height. The larger errors at the
420 lowest height are likely to be a result of representativity errors.
- 421 • The correlation length scale is larger than the thinning distance of 6km chosen to ensure that
422 the assumption of uncorrelated errors is valid.
- 423 • For both horizontal and along-beam correlations and for all elevations the observation error
424 correlation length scale increases with height. We hypothesise that this is in part due to the
425 larger errors in the observation operator and correlated superobservation errors at large range.
426 This will be the subject of further investigation (see sections c and d).

427 *b. Case 2 - The effect of changing the assimilated background error statistics*

428 The diagnostic of Desroziers et al. (2005) uses the assumption that the observation and back-
429 ground error covariance matrices used in the assimilation are exact. In the operational assimila-
430 tion, Case 1, the observation errors are assumed uncorrelated and the background error variance
431 and correlation length scale are believed to be too large. (The Met Office have an ongoing project
432 to develop an improved background error covariance matrix; this is expected to reduce error vari-
433 ances and correlation length scales compared to those used in Case 1 of this study). Results given
434 in Waller et al. (2016) relating to the diagnostic suggest that under these circumstances the diag-
435 nostic will underestimate the observation error correlation length scale. Therefore it is possible

436 that the true observation error statistics have longer correlation lengths than those calculated for
437 Case 1.

438 To provide information on how results in Case 1 may compare to the true observation error
439 statistics, we consider the sensitivity of the estimated observation error statistics to using different
440 background statistics. Here we use previous operational background error statistics that have
441 larger variances and larger length scales than the background error statistics used in the previous
442 experiments.

443 1) HORIZONTAL CORRELATIONS

444 The average standard deviation given in Table 2 shows that the use of background error statistics
445 with larger variance and longer length scales results in a lower estimate of the observation error
446 standard deviation. The correlation function, plotted in Figure 3, shows clearly that using a dif-
447 ferent background error covariance matrix has reduced the estimated observation error correlation
448 length scale. These results agree with the theoretical results in Waller et al. (2016) (larger overes-
449 timates of variance and correlation length scale in the assimilated background statistics results in
450 more severe underestimates of observation error variance and correlation length scale) and suggest
451 that the theoretical results developed under simplifying assumptions are still applicable in an op-
452 erational setting. The theoretical work and results from Cases 1 and 2 suggest that if the variances
453 and length scales in the assumed covariance matrix \mathbf{B} were further reduced compared to Case 1,
454 the estimated observation error correlation length scales would be larger.

455 Figure 4 shows that the change in standard deviation with height for each elevation is similar to
456 Case 1. However, the standard deviations for Case 2 are smaller than those from Case 1, a result
457 of the larger background error variances used in the assimilation.

458 As with the average correlations, results relating to the correlations for each individual elevation
459 and height have smaller correlation length scales than Case 1 (not shown). However, we still find
460 that the qualitative behaviour of the correlation length scales remains the same; that is, for any
461 elevation the correlation length scale increases with height and for any given height the length
462 scale decreases as elevation increases.

463 2) ALONG-BEAM CORRELATIONS

464 For the average along-beam correlation we find the standard deviation (Table 2) is reduced com-
465 pared to Case 1. The correlations plotted in Figure 7 also have a shorter length scale (approx-
466 imately 10km) and are more comparable to those found by Météo-France.

467 When considering the standard deviations for each elevation we again see that they are reduced
468 (see diamonds Figure 8). Though the change in standard deviation with height is qualitatively
469 similar to Case1. We find that the shape of the correlation function is similar, but the length scales
470 are shorter than those calculated in Case 1 (not shown). The variation in the correlation length
471 scale with elevation, height and range is, however, unaltered.

472 3) SUMMARY

473 For this case we have calculated observation error statistics using different background error
474 statistics which have larger variances and correlation length scales. We find that:

- 475 • Estimated observation error standard deviations (length scales) are smaller (shorter) when
476 using the alternative background error statistics with larger standard deviations and longer
477 correlation length scales. This result follows the theoretical work of Waller et al. (2016).
- 478 • Changes in observation error standard deviation and correlation length scale with height re-
479 main qualitatively similar to Case 1.

480 • Given that the background error standard deviations and correlation length scales in Case 1
481 are believed to be too large and long, it is likely that the true observation error statistics have
482 larger standard deviations and longer length scales than those calculated in Case 1.

483 *c. Case 3 - The effect of the superobservations*

484 The creation of the superobservations, discussed in section 3, results in an observation error
485 that is only independent of the background error if the errors in the background states used in the
486 calculation of each superobservation are of the same magnitude and are fully correlated (Berger
487 and Forsythe 2004). This assumption is true at close range to the radar, but it is possible that
488 it is violated at far range resulting in increased observation error correlation length scales. To
489 determine if the superobservations have this effect we consider the results from Case 3, where the
490 assimilation uses thinned raw data. We return to using the ‘New’ background error statistics.

491 1) HORIZONTAL CORRELATIONS

492 Table 2 shows that the average standard deviation for this case is very similar to that of Case 1.
493 However, the correlation length scale is slightly reduced compared to Case 1 (Figure 3). This
494 suggests that the use of superobservations may introduce some observation error correlation, but
495 does not appear to be the main source of correlations.

496 Figure 4 shows that the standard deviations for individual elevations are similar to those found
497 in Case 1. In general we find that the use of the thinned data results in slightly shorter observation
498 error correlation length scales for observations that are at lower elevations and far range. For ex-
499 ample, Figure 12 shows, for the 2^o elevation, that the use of the superobservtions has little impact
500 on the correlation length scale at short range. However, at far range the correlation length scale
501 for Case 1 is approximately 5km longer than that for Case 3. This result supports our hypothe-

502 sis that the use of superobservations increases the observation error correlation length scale at far
503 range. This is a result of the invalid assumption that the errors in the background states used in the
504 superobservation creation are of the same magnitude and fully correlated.

505 2) ALONG-BEAM CORRELATIONS

506 From Table 2 we see that the average along-beam observation error standard deviation is similar
507 to that found using the data from Case 1. Figure 7 shows that the correlation length scale is also
508 slightly reduced.

509 Figure 8 shows that the standard deviations for separate elevations are similar to Case 1. Figures
510 10 and 11 show that using the raw observations results in a similar shaped correlation function
511 to Case 1 but with a slightly reduced length scale. The exception is the highest elevation (closest
512 range) where the length scales are slightly larger. These results suggest that using the superobser-
513 vation has the opposite effect, namely the introduction of correlation at far range, but a reduction
514 of correlation in the higher elevations.

515 3) SUMMARY

516 We have calculated observation error statistics using thinned raw observations. We find that:

- 517 • Using thinned raw data has little impact on the estimated observation error standard devia-
518 tions; these are similar to Case 1.
- 519 • In general, horizontal correlation length scales at far range are reduced. This implies that
520 using superobservations introduces correlated error at far range, possibly as a result of an
521 invalid assumption in the superobservation creation.
- 522 • In general along-beam correlation length scales are reduced for the lower elevations, however
523 they slightly increased for the 6° beam.

524 *d. Case 4 - The effect of an improved observation operator*

525 The previous cases have all used the simplified observation operator described in equation (6).
526 The omission of the more complex terms introduces both additional error variance and correlation
527 (Fabry 2010). It may not be possible to use a full observation operator in operational assimilation,
528 though the use of the sophisticated observation operator in equation (11) may be considered. In
529 this case we use this new observation operator to see if including beam broadening and reflectiv-
530 ity weighting in the observation operator has any effect on the observation error statistics. Here
531 we use the thinned raw observations rather than the superobservations (the creation of the super-
532 observation involves the observation operator, and ideally we wish to isolate the impact of the
533 observation operator in the assimilation), hence the results here must be compared to Case 3.

534 1) HORIZONTAL CORRELATIONS

535 For the average horizontal error statistics both the standard deviation and correlation length scale
536 have decreased compared to Case 3 (see Table 2 and Figure 3).

537 For the separate elevations, as with all previous cases, we find that the standard deviations in-
538 crease with height (Figure 4), though here the actual values for the lower elevations are reduced
539 compared to the standard deviations found in Case 3. The reduction is not seen in the higher
540 elevations as observations are at near range where the effects of beam bending and broadening,
541 accounted for in the new observation operator, are not so significant. In general we find that the
542 correlations for every elevation are decreased when using the improved observation operator. In
543 Figure 13 we show that using an improved observation operator reduces the correlation length
544 scale slightly at near range and, at far range, by approximately 40%.

545 When considering horizontal correlations we compare observations at the same range away
546 from the radar that have the same measurement volume, and hence the new observation operator

547 should have the same improvement for each observation we compare. The reduction in error
548 standard deviation and correlation shows that the inclusion of the beam broadening and reflectivity
549 weighting has improved the observation operator. It also suggests that the use of an even more
550 sophisticated observation operator may further reduce the observation error correlation.

551 2) ALONG-BEAM CORRELATIONS

552 In this case Table 2 and Figure 8 show that the error standard deviation is reduced compared
553 to Case 3 suggesting that the more sophisticated observation operator is indeed an improved map
554 from background to observation space. Both Figure 7 and the correlations for separate elevations
555 suggest that introducing the new observation operator slightly increases the correlation length
556 scale. We hypothesise that this is a result of the inclusion of the beam broadening. When using
557 the old observation operator observations at different ranges at any elevation were unlikely to
558 consider data from the same model levels. With the introduction of the beam broadening different
559 observations will now use information from the same model levels and this is likely to be the cause
560 of the increased correlation length scales.

561 3) SUMMARY

562 For this case we have calculated observation error statistics using thinned raw observations and
563 an improved observation operator. We find that:

- 564 • Using the new observation operator reduces the error standard deviations for the lower ele-
565 vations. Less impact is seen in the higher elevations where the effects of beam bending and
566 broadening (accounted for in the new observation operator) are not so significant.

- 567 • For the horizontal correlations using the new observation operator reduces the estimated ob-
568 servation correlation length scale. This suggests that error in the observation operator may be
569 in part responsible for the large correlation length scales.
- 570 • Using the new observation operator increases the along-beam correlation. This is likely to be
571 the result of close observation residuals sharing increased amounts of background data.

572 **6. Conclusions**

573 With the development of convection-permitting NWP the assimilation of high resolution obser-
574 vations is becoming increasingly important. Currently large quantities of high resolution data are
575 discarded to ensure the assumption of uncorrelated observation errors is reasonable. The assimi-
576 lation of high resolution observations will require less thinning of the observational data and, hence,
577 the inclusion of correlated observation error statistics in the assimilation system. Observation er-
578 rors can be attributed to a number of different sources, some of which may be state dependent
579 and dependent on the model resolution. Calculation of observation error statistics is difficult as
580 they cannot be measured directly. Recently the diagnostic of Desroziers et al. (2005) has been
581 used to estimate inter-channel observation error correlations for a number of different observation
582 types. When inexact background and observation errors are used in the assimilation cost function,
583 theory (Waller et al. 2016) shows that the results arising from the diagnostic are uncertain and
584 should be interpreted as indicative, rather than necessarily quantitatively perfect. However, results
585 from the diagnostics can still provide useful information on the sources of error correlation and
586 how it may be reduced. Furthermore, idealised studies using correlated observation error matrices
587 indicate that much of the benefit in assimilation accuracy can be obtained from using approximate
588 correlation structures (Stewart et al. 2013; Healy and White 2005). The aim of this manuscript is
589 to use the diagnostic to estimate spatially correlated errors for Doppler radar radial wind (DRW)

590 observations that are assimilated into the Met Office UKV model. Errors for DRWs may be corre-
591 lated horizontally, vertically or along the path of the radar beam. In this work we consider both the
592 horizontal and along-beam error statistics. We also considered if results from the Hollingsworth
593 and Lönnerberg (1986) diagnostic could provide further information. We note that, for the data used
594 in this study, there was no clear way to partition the results from the Hollingsworth and Lönnerberg
595 (1986) diagnostic into the observation and background error portions. Any observation error cor-
596 relations estimated from this data using the Hollingsworth and Lönnerberg (1986) method would
597 have been highly dependent on the subjective choice of correlation function fitted.

598 Initially error statistics were calculated for observations assimilated into the UKV model oper-
599 ational in January 2014. This provided information on the general structure of the observation
600 errors and how they vary throughout the atmosphere. Error statistics were also calculated using
601 data from an assimilation run using alternative background error statistics. This provided infor-
602 mation on how sensitivity of the results to the specification of the background error statistics. The
603 diagnostic was then applied to data from a further two assimilation runs. These evaluated the im-
604 pact that the use of superobservations and errors in the observation operator have on the estimated
605 observation error statistics.

606 Results from all four cases showed similar behaviour for the estimated statistics. We are able to
607 conclude, that most DRW error standard deviations, horizontal and along-beam correlation length
608 scales increase with height, as a function of the increase in measurement volume. Thus at least
609 part of the correlated errors are likely to be related to the uncertainty in the observation opera-
610 tor. The exceptions are the standard deviations at the lowest heights. Observations at the lowest
611 heights have the smallest measurement volumes, smaller than the model grid spacing, and hence
612 representativity errors may well account for the larger standard deviations at lower heights. The
613 results presented here are for summer season observations; however results considered for winter

614 season observations show that the qualitative behaviour of the estimated DRW error statistics is
615 similar to the summer case.

616 Results showed that the estimated standard deviations are similar to those used operationally.
617 However for the majority of cases, with exception of the 6° beam, the correlation length scales
618 are much larger than those found in Simonin et al. (2012) and the operational thinning distance of
619 6km. Despite the differences in operational system, our estimated average along-beam correlations
620 are similar to those calculated by Météo-France (Wattrelot et al. 2012). Furthermore, observation
621 error statistics estimated when using an alternative background error covariance matrix in the
622 assimilation and the results from Waller et al. (2016) imply that the observation error correlation
623 length scale is underestimated. This suggests that the errors are correlated to a degree that it should
624 be accounted for in the assimilation.

625 In an attempt to understand the source of the error correlations, the effect of using superobser-
626 vations and an improved observation operator are considered. The use of the superobservations
627 does not affect the error standard deviations. However, results suggest that the use of superobser-
628 vations introduces correlated error at far range, possibly as a result of an invalid assumption in the
629 superobservation creation. The use of an improved observation operator reduces the error standard
630 deviations, particularly at low elevations and at far range where observations have large measure-
631 ment volumes. This is expected since the new observation operator takes into account the beam
632 broadening and bending, both of which affect the beam most at far range. The improvement in
633 the low elevations is related to the inclusion in the observation operator of information from more
634 model levels. These are denser in the lower atmosphere where the low elevations provide observa-
635 tions. The use of the new observation operator results in an increase of the along-beam correlation
636 length scale. We hypothesise that this is a result of nearby observation residuals now sharing infor-
637 mation from the same model levels. However, the horizontal correlations were slightly reduced.

638 This suggests not only that some of the horizontal correlations previously seen were a result of
639 omissions in the observation operator, but also that the horizontal correlation length scale may be
640 further reduced with the use of an even more complex observation operator.

641 These results provide a better understanding of DRW observation error statistics and the sources
642 that contribute to them. We have shown that these observation errors exhibit large spatial cor-
643 relations that are much larger than the operational thinning distance. This implies that, if high
644 resolution DRW observations are to be assimilated correctly, the inclusion of correlated observa-
645 tion error statistics in the assimilation system is required.

646 *Acknowledgments.* This work is funded in part by the NERC Flooding from Intense Rainfall pro-
647 gramme and the NERC National Centre for Earth Observation. We also thank the two anonymous
648 reviewers whose comments were greatly appreciated.

649 **References**

650 Ballard, S. P., Z. Li, D. Simonin, and J.-F. Caron, 2016: Performance of 4D-Var NWP-based
651 nowcasting of precipitation at the Met Office for summer 2012. *Quarterly Journal of the Royal*
652 *Meteorological Society*, doi:10.1002/qj.2665, URL <http://dx.doi.org/10.1002/qj.2665>.

653 Berger, H., and M. Forsythe, 2004: Satellite wind superobbing. Tech. rep., Met Office, UK. Fore-
654 casting Research Technical Report 451.

655 Bondarenko, V., T. Ochotta, and D. Saupe, 2007: The interaction between model resolution, ob-
656 servation resolution and observations density in data assimilation: A two-dimensional study.
657 *Preprints, 11th Symp. on Integrated Observing and Assimilation Systems for the Atmosphere,*
658 *Oceans, and Land Surface, San Antonio, TX, Amer. Meteor. Soc., P5.19.*, available online at
659 <http://ams.confex.com/ams/pdfpapers/117655.pdf>.

660 Bormann, N., and P. Bauer, 2010: Estimates of spatial and interchannel observation-error charac-
661 teristics for current sounder radiances for numerical weather prediction. I: Methods and appli-
662 cation to ATOVS data. *Quarterly Journal of the Royal Meteorological Society*, **136**, 1036–1050.

663 Bormann, N., A. Collard, and P. Bauer, 2010: Estimates of spatial and interchannel observation-
664 error characteristics for current sounder radiances for numerical weather prediction. II: Appli-
665 cation to AIRS and IASI data. *Quarterly Journal of the Royal Meteorological Society*, **136**,
666 1051–1063.

667 Clark, P., N. Roberts, H. Lean, S. Ballard, and C. Charlton-Perez, 2015: Convection-permitting
668 models: A step-change in rainfall forecasting. *Met. Apps.*, doi:10.1002/met.1538.

669 Courtier, P., J. Thepaut, and A. Hollingsworth, 1994: A strategy for operational implementation of
670 4D-var, using an incremental approach. *Quarterly Journal of the Royal Meteorological Society*,
671 **120**, 1367–1387.

672 Dance, S. L., 2004: Issues in high resolution limited area data assimilation for quantitative precip-
673 itation forecasting. *Physica D: Nonlinear Phenomena*, **196**, 1 – 27.

674 Dee, D. P., and A. M. Da Silva, 1999: Maximum-likelihood estimation of forecast and observation
675 error covariance parameters. Part I: Methodology. *Monthly Weather Review*, **127**, 1822–1843.

676 Desroziers, G., L. Berre, B. Chapnik, and P. Poli, 2005: Diagnosis of observation, background and
677 analysis-error statistics in observation space. *Quarterly Journal of the Royal Meteorological*
678 *Society*, **131**, 3385–3396.

679 Doviak, R. J., and D. S. Zrnic, 1993: *Doppler Radar and Weather Observations*. 2nd ed., Aca-
680 demic Press.

- 681 Fabry, F., 2010: Radial velocity measurement simulations: common errors, approximations, or
682 omissions and their impact on estimation accuracy. *In Proceedings of of the sixth European*
683 *conference on radar in meteorology and hydrology*.
- 684 Fabry, F., and A. Kilambi, 2011: The devil is in the details: Preparing radar information for its
685 proper assimilation. *In Proceedings of of the 35th Conference on Radar Meteorology*.
- 686 Ge, G., J. Gao, K. Brewster, and M. Xue, 2010: Impacts of beam broadening and earth curvature
687 on 3D variational radar data assimilation with two Doppler radars. *J. Atmos. Ocean Tech*, **27**,
688 617–636.
- 689 Hand, W. H., N. I. Fox, and C. G. Collier, 2004: A study of twentieth-century extreme rainfall
690 events in the united kingdom with implications for forecasting. *Meteorological Applications*,
691 **11 (1)**, 15 – 31, doi:10.1017/S1350482703001117.
- 692 Hawcroft, M. K., L. C. Shaffrey, K. I. Hodges, and H. F. Dacre, 2012: How much northern hemi-
693 sphere precipitation is associated with extratropical cyclones? *Geophysical Research Letters*,
694 **39 (24)**, doi:10.1029/2012GL053866, URL <http://dx.doi.org/10.1029/2012GL053866>.
- 695 Healy, S. B., and A. A. White, 2005: Use of discrete Fourier transforms in the 1D-Var retrieval
696 problem. *Quarterly Journal of the Royal Meteorological Society*, **131**, 63–72.
- 697 Hollingsworth, A., and P. Lönnberg, 1986: The statistical structure of short-range forecast errors
698 as determined from radiosonde data. Part I: The wind field. *Tellus*, **38A**, 111–136.
- 699 Janjic, T., and S. E. Cohn, 2006: Treatment of observation error due to unresolved scales in
700 atmospheric data assimilation. *Monthly Weather Review*, **134**, 2900–2915.
- 701 Kitchen, M., 1997: Towards improved radar estimates of surface precipitation rate at long range.
702 *Quarterly Journal of the Royal Meteorological Society*, **123**, 145163.

- 703 Lean, H., P. Clark, M. Dixon, N. Roberts, A. Fitch, R. Forbes, and C. Halliwell, 2008: Charic-
704 taristics of high-resolution versions of the Met Office Unified Model for forecasting convection
705 over the United Kingdom. *Monthly Waether Review*, **136**, 3408–3424.
- 706 Lindskog, M., H. Jarvinen, and D. B. Michelson, 2000: Assimilation of radar radial winds in
707 the HIRLAM 3D-Var. *Physics and Chemistry of the Earth - Part B: Hydrology, Oceans and*
708 *Atmosphere*, **25**, 1243–1249.
- 709 Lindskog, M., K. Salonen, H. Jaarvinen, and D. B. Michelson, 2004: Doppler radar wind assimi-
710 lation with HIRLAM 3DVAR. *Monthly Weather Review*, **132**, 1081–1092.
- 711 Lindskog, M., and Coauthors, 2001: Three-dimensional variational data assimilation for a limited
712 area model. Part II: Observation handling and assimilation experiments. *Tellus*, **53A**, 447–468.
- 713 Liu, Z.-Q., and F. Rabier, 2002: The interaction between model resolution observation resolution
714 and observation density in data assimilation: A one dimensional study. *Quarterly Journal of the*
715 *Royal Meteorological Society*, **128**, 1367–1386.
- 716 Liu, Z.-Q., and F. Rabier, 2003: The potential of high-density observations for numerical weather
717 prediction: A study with simulated observations. *Quarterly Journal of the Royal Meteorological*
718 *Society*, **129**, 3013–3035.
- 719 Lorenc, A. C., and Coauthors, 2000: The met. office global three-dimensional variational data
720 assimilation scheme. *Quarterly Journal of the Royal Meteorological Society*, **126**, 2991–3012.
- 721 Montmerle, T., and C. Faccani, 2009: Mesoscale assimilation of radial velocities from Doppler
722 radars in a preoperational framework. *Monthly Weather Review*, **137**, 1939–1953.
- 723 Park, S. K., and D. Zupanski, 2003: Four-dimensional variational data assimilation for mesoscale
724 and storm-scale applications. *Meteorology and Atmospheric Physics*, **82**, 173–208.

725 Piccolo, C., and M. Cullen, 2011: Adaptive mesh method in the Met Office variational data as-
726 simulation system. *Quarterly Journal of the Royal Meteorological Society*, **137**, 631–640, doi:
727 10.1002/qj.801.

728 Piccolo, C., and M. Cullen, 2012: A new implementation of the adaptive mesh transform in the
729 Met Office 3D-Var system. *Quarterly Journal of the Royal Meteorological Society*, **138**, 1560–
730 1570, doi:10.1002/qj.1880.

731 Rawlins, F., S. P. Ballard, K. J. Bovis, A. M. Clayton, D. Li, G. W. Inverarity, A. C. Lorenc, and
732 T. J. Payne, 2007: The Met Office global four-dimensional variational data assimilation scheme.
733 *Quarterly Journal of the Royal Meteorological Society*, **133**, 347–362.

734 Rennie, S. J., S. L. Dance, A. J. Illingworth, S. P. Ballard, and D. Simonin, 2011: 3D-Var assim-
735 ilation of insect-derived Doppler radar radial winds in convective cases using a high-resolution
736 model. *Monthly Weather Review*, **139**, 1148–1163.

737 Rennie, S. J., A. J. Illingworth, S. L. Dance, and S. P. Ballard, 2010: The accuracy of doppler
738 radar wind retrievals using insects as targets. *Meteorological Applications*, **17**, 419 – 432, doi:
739 10.1002/met.174.

740 Rihan, F. A., C. G. Collier, S. P. Ballard, and S. J. Swarbrick, 2008: Assimilation of Doppler radial
741 winds into a 3d-var system: Errors and impact of radial velocities on the variational analysis and
742 model forecasts. *Quarterly Journal of the Royal Meteorological Society*, **134**, 1701–1716.

743 Salonen, K., H. Jarvinen, R. Eresmaa, and S. Niemela, 2007: Bias estimation of Doppler radar
744 radial-wind observations. *Quarterly Journal of the Royal Meteorological Society*, **133**, 1501–
745 1507.

- 746 Salonen, K., H. Jarvinen, G. Haase, S. Niemela, and R. Eresmaa, 2009: Doppler radar radial winds
747 in HIRLAM. Part II: Optimizing the super-observation processing. *Tellus*, **61A**, 288–295.
- 748 Salonen, K., H. Jarvinen, S. Jarvenoja, S. Niemela, and R. Eresmaa, 2008: Doppler radar radial
749 wind data in nwp model validation. *Meteorological Applications*, **15**, 97–102.
- 750 Simonin, D., S. Ballard, Z. Li, and J. F. Caron, 2012: Doppler radar assimilation. Available at
751 <http://www.meteo.fr/cic/meetings/2012/ERAD/presentations/friday/14-2.pdf>, ERAD 201 27th
752 European Conference on Radar in Meteorology and Hydrology.
- 753 Simonin, D., S. P. Ballard, and Z. Li, 2014: Doppler radar radial wind assimilation using an
754 hourly cycling 3D-Var with a 1.5 km resolution version of the Met Office Unified Model for
755 nowcastings. *Quarterly Journal of the Royal Meteorological Society*, doi:10.1002/qj.2298.
- 756 Stewart, L. M., 2010: Correlated observation errors in data assimilation. Ph.D. thesis, University
757 of Reading, <http://www.reading.ac.uk/maths-and-stats/research/theses/maths-phdtheses.aspx>.
- 758 Stewart, L. M., J. Cameron, S. L. Dance, S. English, J. R. Eyre, and N. K. Nichols, 2009: Obser-
759 vation error correlations in IASI radiance data. Tech. rep., University of Reading. Mathematics
760 reports series, www.reading.ac.uk/web/FILES/maths/obs_error_IASI_radiance.pdf.
- 761 Stewart, L. M., S. L. Dance, and N. K. Nichols, 2008: Correlated observation errors in data
762 assimilation. *International Journal for Numerical Methods in Fluids*, **56**, 1521–1527.
- 763 Stewart, L. M., S. L. Dance, and N. K. Nichols, 2013: Data assimilation with correlated observa-
764 tion errors: experiments with a 1-D shallow water model. *Tellus A*, **65**, doi:[http://dx.doi.org/10.](http://dx.doi.org/10.3402/tellusa.v65i0.19546)
765 [3402/tellusa.v65i0.19546](http://dx.doi.org/10.3402/tellusa.v65i0.19546).

- 766 Stewart, L. M., S. L. Dance, N. K. Nichols, J. R. Eyre, and J. Cameron, 2014: Estimating inter-
767 channel observation-error correlations for IASI radiance data in the Met Office system. *Quar-*
768 *terly Journal of the Royal Meteorological Society*, **140**, 1236–1244, doi:10.1002/qj.2211.
- 769 Sun, J., 2005: Convective-scale assimilation of radar data: Progresses and challenges. *Quarterly*
770 *Journal of the Royal Meteorological Society*, **131**, 3439–3463.
- 771 Sun, J., and Coauthors, 2014: Use of NWP for nowcasting convective precipitation: Recent pro-
772 gresses and challenges. *Bulletin of the American Meteorological Society*, **95**, 409–426.
- 773 Tang, Y., H. W. Lean, and J. Bornemann, 2013: The benefits of the Met Office variable resolu-
774 tion NWP model for forecasting convection. *Meteorological Applications*, **20**, 417–426, doi:
775 10.1002/met.1300.
- 776 Toomay, J., and P. Hannen, 2004: *Radar Principles for the Non Specialist*. 3rd ed., SciTech Pub-
777 lishing.
- 778 Waller, J. A., 2013: Using observations at different spatial scales in data assimilation for en-
779 vironmental prediction. Ph.D. thesis, University of Reading, Department of Mathematics and
780 Statistics, <http://www.reading.ac.uk/maths-and-stats/research/theses/maths-phdtheses.aspx>.
- 781 Waller, J. A., S. L. Dance, A. S. Lawless, and N. K. Nichols, 2014a: Estimating corre-
782 lated observation error statistics using an ensemble transform Kalman filter. *Tellus A*, doi:
783 <http://dx.doi.org/10.3402/tellusa.v66.23294>, article number: 23294.
- 784 Waller, J. A., S. L. Dance, A. S. Lawless, N. K. Nichols, and J. R. Eyre, 2014b: Representativ-
785 ity error for temperature and humidity using the Met Office high-resolution model. *Quarterly*
786 *Journal of the Royal Meteorological Society*, **140**, 1189–1197, doi:10.1002/qj.2207.

- 787 Waller, J. A., S. L. Dance, and N. K. Nichols, 2016: Theoretical insight into diagnosing
788 observation error correlations using observation-minus-background and observation-minus-
789 analysis statistics. *Quarterly Journal of the Royal Meteorological Society*, **142**, 418–431, doi:
790 10.1002/qj.2661.
- 791 Wattrelot, E., T. Montmerle, and C. G. Guerrero, 2012: Evolution of the assimilation of radar data
792 in the arome model at convective scale. In *Proceedings of of the seventh European conference*
793 *on radar in meteorology and hydrology*.
- 794 Weston, P. P., W. Bell, and J. R. Eyre, 2014: Accounting for correlated error in the assimilation
795 of high-resolution sounder data. *Quarterly Journal of the Royal Meteorological Society*, **140**,
796 2420–2429, doi:10.1002/qj.2306.
- 797 Xiao, Q., Y. H. Kuo, J. Sun, W. C. Lee, E. Lim, Y. R. Guo, and D. M. Barker, 2005: Assimilation
798 of Doppler radar observations with a regional 3D-VAR system: Impact of Doppler velocities on
799 forecasts of a heavy rainfall case. *Journal of Applied Meteorology*, **44**, 768–788.
- 800 Xiao, Q., and Coauthors, 2008: Doppler radar data assimilation in KMAs operational forecasting.
801 *Bulletin of the American Meteorological Society*, **89**, 39–43.
- 802 Xu, Q., K. Naib, and L. Wei, 2007: An innovation method for estimating radar radial-velocity
803 observation error and background wind error covariances. *Quarterly Journal of the Royal Me-*
804 *teorological Society*, **133**, 407–415.
- 805 Xu, Q., and L. Wei, 2013: Prognostic equation for radar radial velocity derived by considering
806 atmospheric refraction and earth curvature. *J. Atmos. Sci.*, **70**, 3328–3338, doi:http://dx.doi.org/
807 10.1175/JAS-D-13-011.1.

808 Xue, M., M. Hu, and A. Schenkman, 2014: Numerical prediction of 8 May 2003 Oklahoma City
809 tornadic supercell and embedded tornado using ARPS with assimilation of WSR-88D radar
810 data. *Wea. Forecasting*, **29**, 39–62.

811 Xue, M., F. Kong, K. Thomas, J. Gao, Y. Wang, K. Brewster, and K. Droegemeier, 2013: Predic-
812 tion of convective storms at convection-resolving 1-km resolution over continental United States
813 with radar data assimilation: An example case of 26 May 2008 and precipitation forecasts from
814 spring 2009. *Adv. Meteor.*, doi:10.1155/2013/259052, article ID 259052.

815 **LIST OF TABLES**

816 **Table 1.** Summary of experimental design for different cases 44

817 **Table 2.** Horizontal and along-beam standard deviations calculated for Cases 1-4 using
818 all available data up to a height of 5km. 45

TABLE 1. Summary of experimental design for different cases

Case	B	Superobservations	Observation Operator
1	New	Yes	Old
2	Old	Yes	Old
3	New	No	Old
4	New	No	New

819 TABLE 2. Horizontal and along-beam standard deviations calculated for Cases 1-4 using all available data up
820 to a height of 5km.

Case	Horizontal standard deviation (ms^{-1})	Along-Beam standard deviation (ms^{-1})
1	1.97	1.95
2	1.57	1.59
3	1.96	1.99
4	1.82	1.89

819 **LIST OF FIGURES**

820 **Fig. 1.** A typical radar scan where each box is the location of a superobservation. The blue cells
821 show a group of observations, all at the same height, that would be compared to calculate
822 horizontal correlations. The red cells show observations that would be compared to calculate
823 the along-beam correlations. 48

824 **Fig. 2.** A typical radar beam at elevations 1° (black), 2° (blue), 4° (red) and 6° (cyan). 49

825 **Fig. 3.** All elevation horizontal observation error correlations for Case 1 (Control, squares), Case 2
826 (Alternate background error statistics, diamonds), Case 3 (Thinned raw data, triangles) and
827 Case 4 (New observation operator, circles) . Error correlations are deemed to be insignificant
828 below the horizontal line at 0.2. 50

829 **Fig. 4.** Horizontal observation error standard deviation for elevations 1° (black), 2° (blue), 4° (red)
830 and, 6° (cyan) for Case 1 (Control, squares), Case 2 (Alternate background error statistics,
831 diamonds), Case 3 (Thinned raw data, triangles) and Case 4 (New observation operator,
832 circles). 51

833 **Fig. 5.** Horizontal observation correlations for elevation 2° at height 1.1km (dot), 2.7km (dash),
834 3.5km (solid) and 4.3km (dot-dash) for Case 1 (control). Error correlations are deemed to
835 be insignificant below the horizontal line at 0.2. 52

836 **Fig. 6.** Horizontal correlations at height 2.5km for elevations 1° (black), 2° (blue), 4° (red) and,
837 6° (cyan) for Case 1 (Control). Error correlations are deemed to be insignificant below the
838 horizontal line at 0.2. 53

839 **Fig. 7.** All elevation along-beam observation error correlation for Cases 1 (Control, squares), 2
840 (Alternate background error statistics, diamonds), 3 (Thinned raw data, triangles) and 4
841 (New observation operator, circles) and those found previously by Météo-France (crosses).
842 Error correlations are deemed to be insignificant below the horizontal line at 0.2. 54

843 **Fig. 8.** Along-beam observation error standard deviation for elevations 1° (black), 2° (blue), 4° (red)
844 and, 6° (cyan) for Case 1 (Control, squares), Case 2 (Alternate background error statistics,
845 diamonds), Case 3 (Thinned raw data, triangles) and Case 4 (New observation operator,
846 circles). 55

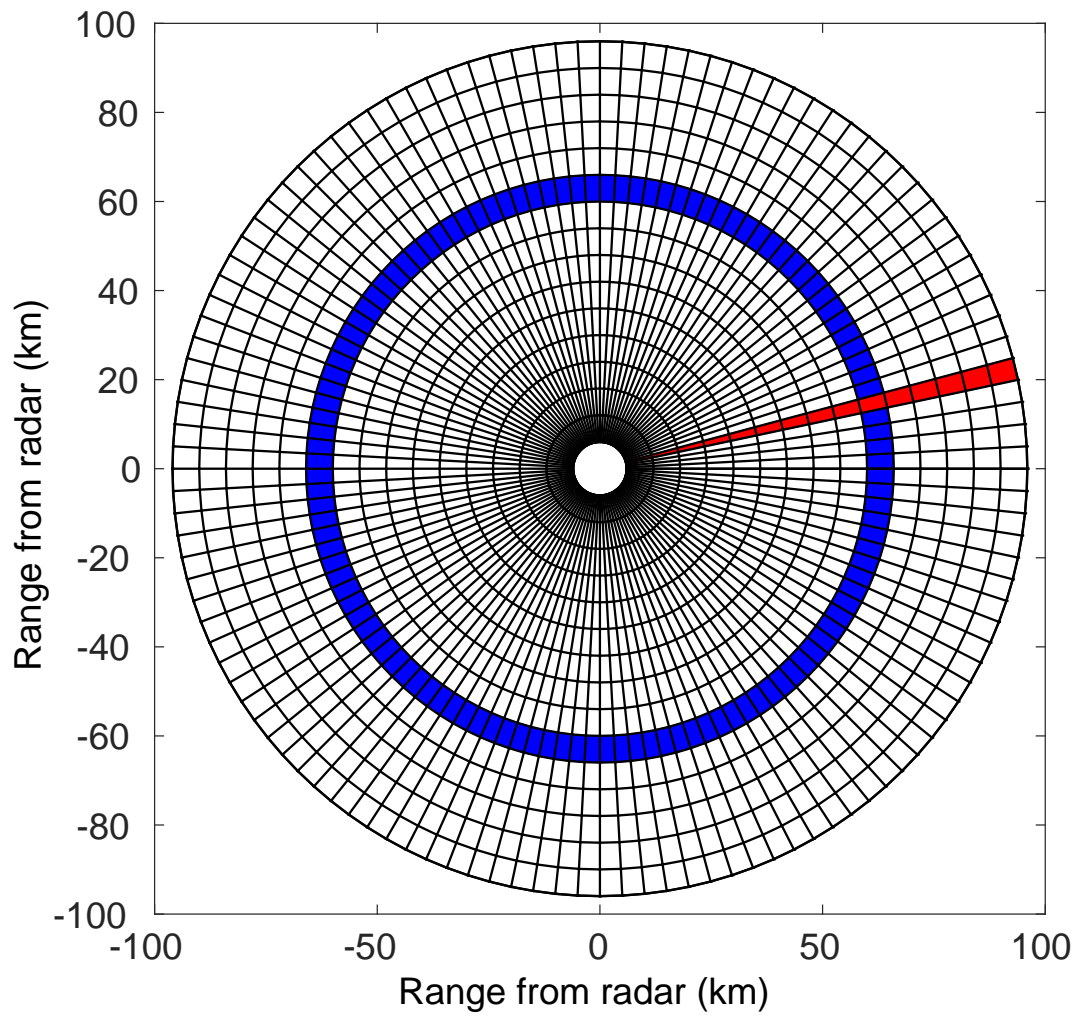
847 **Fig. 9.** Along-Beam observation correlations for elevation 2° at height 1.1km (dotted line), 3.0km
848 (dashed line) and 3.5km (solid line) for Case 1 (Control). 56

849 **Fig. 10.** Correlations along the beam at height 2.5km for elevations and approximate ranges $1^\circ \approx$
850 94km (black), $2^\circ \approx 64\text{km}$ (blue), $4^\circ \approx 35\text{km}$ (red) and , $6^\circ \approx 22\text{km}$ (cyan) for superobbed
851 data (squares/solid lines) and thinned raw data (triangles/dashed lines). Error correlations
852 are deemed to be insignificant below the horizontal line at 0.2. 57

853 **Fig. 11.** Correlations along the beam at range 40km for elevations and approximate heights $1^\circ \approx$
854 0.8km (black), $2^\circ \approx 1.5\text{km}$ (blue), $4^\circ \approx 3.0\text{km}$ (red) and , $6^\circ \approx 4.3\text{km}$ (cyan) for superobbed
855 data (solid lines) and thinned raw data (dashed lines). Error correlations are deemed to be
856 insignificant below the horizontal line at 0.2. 58

857 **Fig. 12.** Horizontal observation correlations for elevation 2° at a range of 24km (solid) and 90km
858 (dash) for Case 1 (control, squares) and Case 3 (Thinned raw data, triangles). Error correla-
859 tions are deemed to be insignificant below the horizontal line at 0.2. 59

860 **Fig. 13.** Horizontal observation correlations for elevation 1° at a range of 18km (solid) and 74km
861 (dash) for Case 3 (Thinned raw data, triangles) and Case 4 (New observation operator, cir-
862 cles). Error correlations are deemed to be insignificant below the horizontal line at 0.2.
863 60



864 FIG. 1. A typical radar scan where each box is the location of a superobservation. The blue cells show a
865 group of observations, all at the same height, that would be compared to calculate horizontal correlations. The
866 red cells show observations that would be compared to calculate the along-beam correlations.

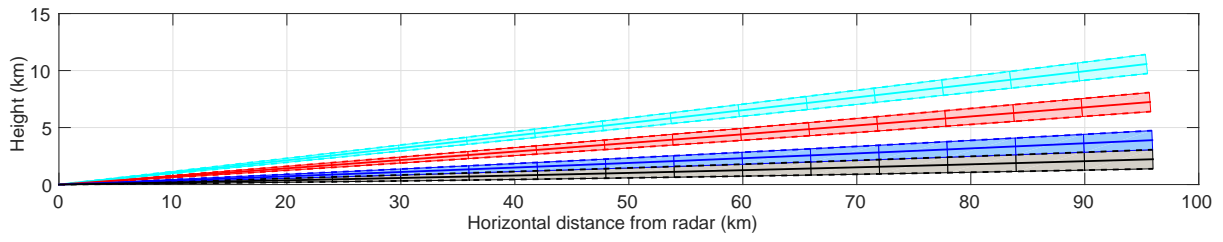
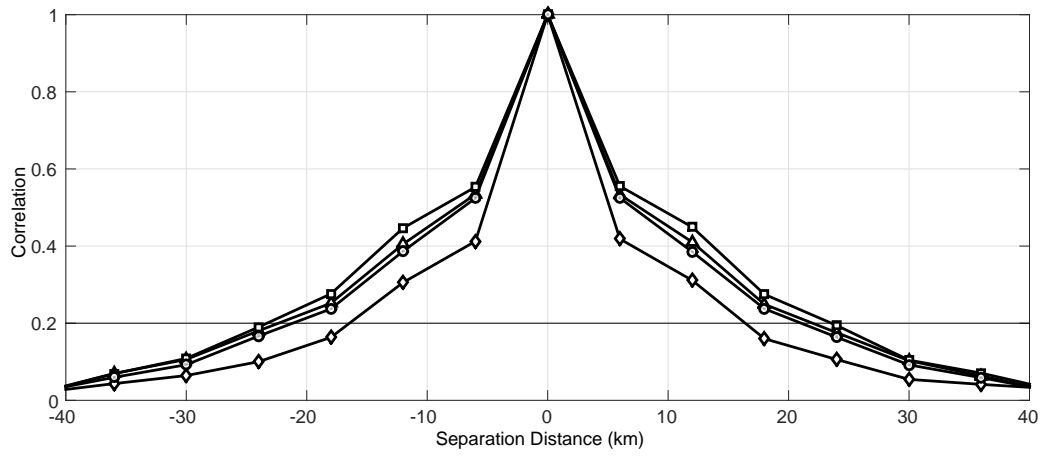
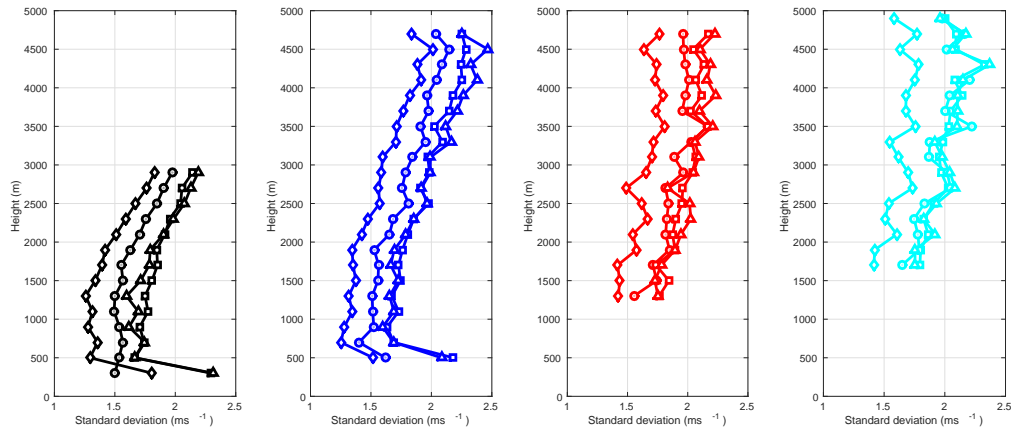


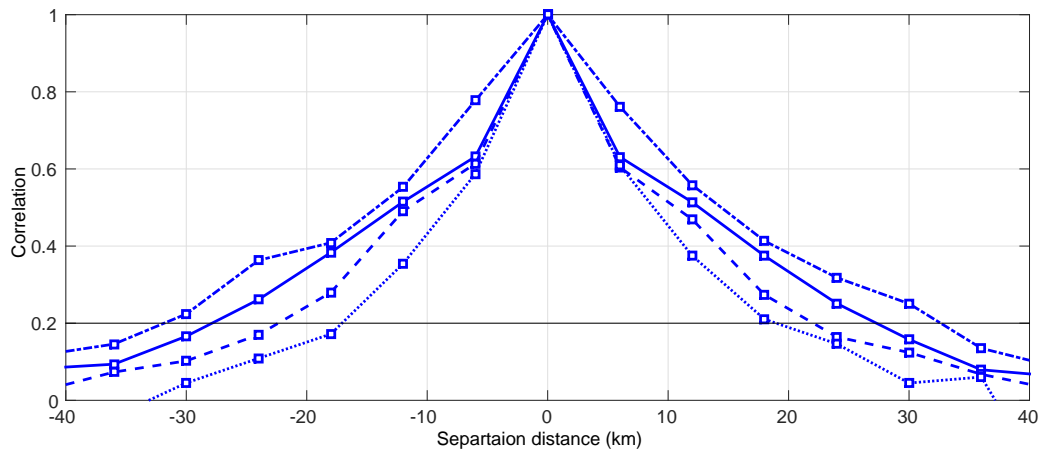
FIG. 2. A typical radar beam at elevations 1° (black), 2° (blue), 4° (red) and 6° (cyan).



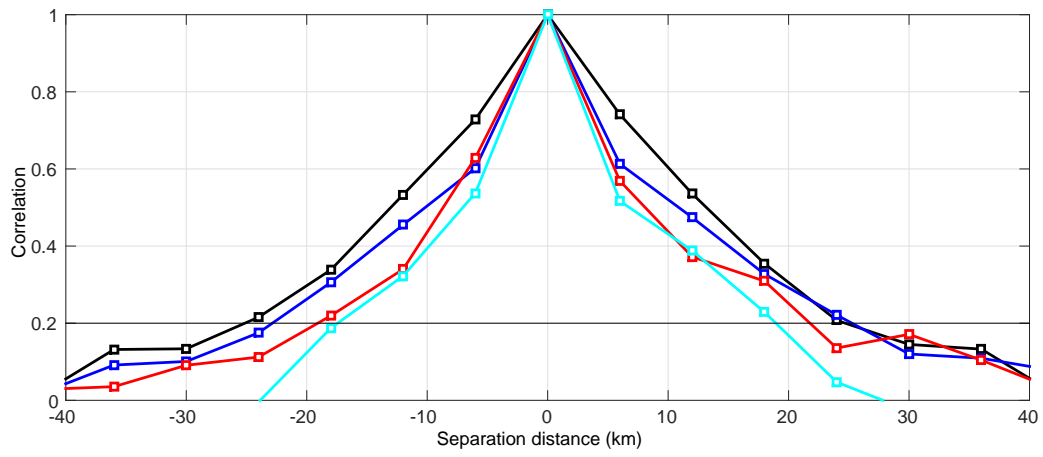
864 FIG. 3. All elevation horizontal observation error correlations for Case 1 (Control, squares), Case 2 (Alter-
 865 nate background error statistics, diamonds), Case 3 (Thinned raw data, triangles) and Case 4 (New observation
 866 operator, circles) . Error correlations are deemed to be insignificant below the horizontal line at 0.2.



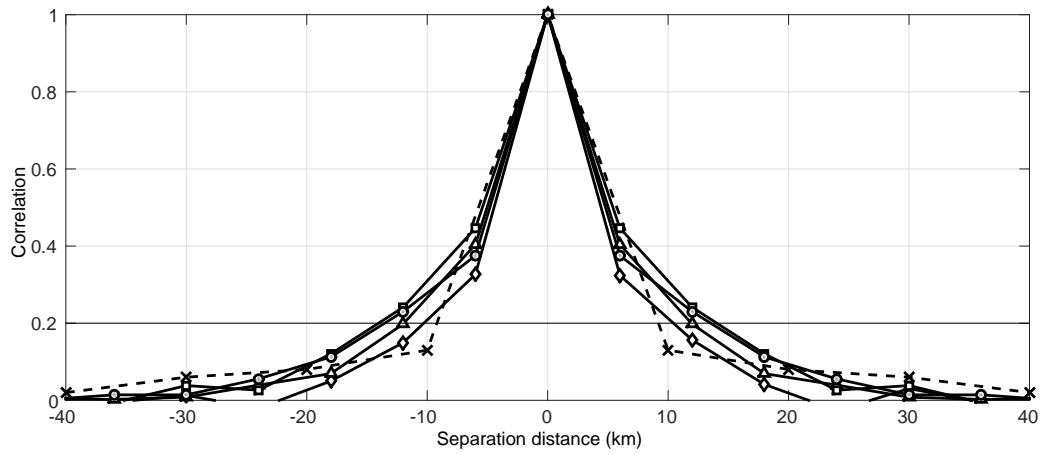
864 FIG. 4. Horizontal observation error standard deviation for elevations 1° (black), 2° (blue), 4° (red) and, 6°
 865 (cyan) for Case 1 (Control, squares), Case 2 (Alternate background error statistics, diamonds), Case 3 (Thinned
 866 raw data, triangles) and Case 4 (New observation operator, circles).



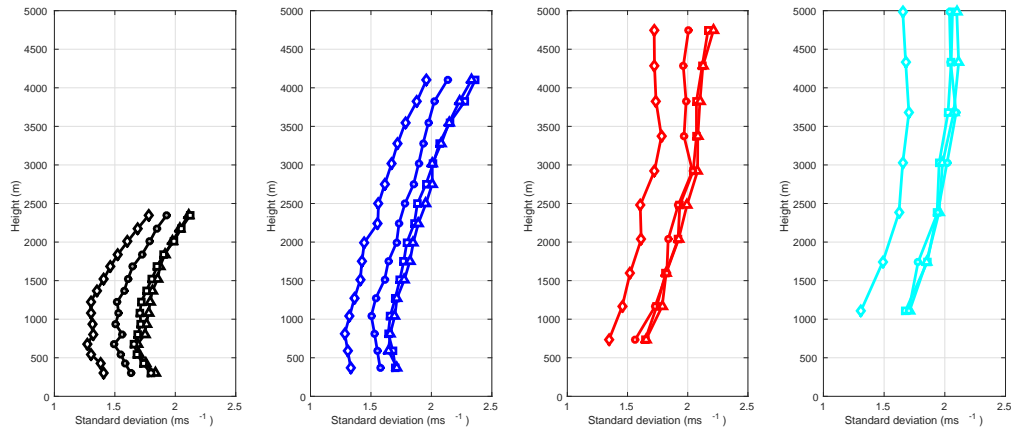
864 FIG. 5. Horizontal observation correlations for elevation 2° at height 1.1km (dot), 2.7km (dash), 3.5km (solid)
 865 and 4.3km (dot-dash) for Case 1 (control). Error correlations are deemed to be insignificant below the horizontal
 866 line at 0.2.



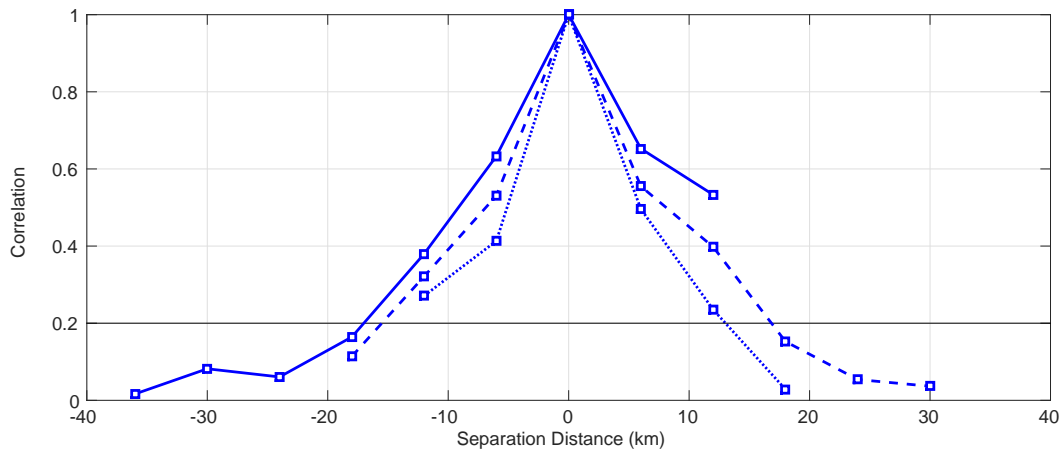
864 FIG. 6. Horizontal correlations at height 2.5km for elevations 1° (black), 2° (blue), 4° (red) and, 6° (cyan) for
 865 Case 1 (Control). Error correlations are deemed to be insignificant below the horizontal line at 0.2.



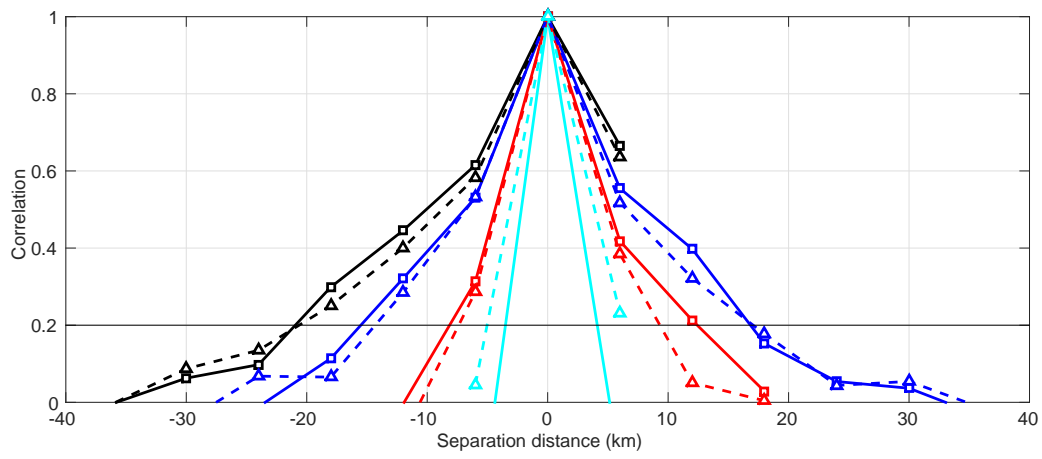
864 FIG. 7. All elevation along-beam observation error correlation for Cases 1 (Control, squares), 2 (Alternate
 865 background error statistics, diamonds), 3 (Thinned raw data, triangles) and 4 (New observation operator, circles)
 866 and those found previously by Météo-France (crosses). Error correlations are deemed to be insignificant below
 867 the horizontal line at 0.2.



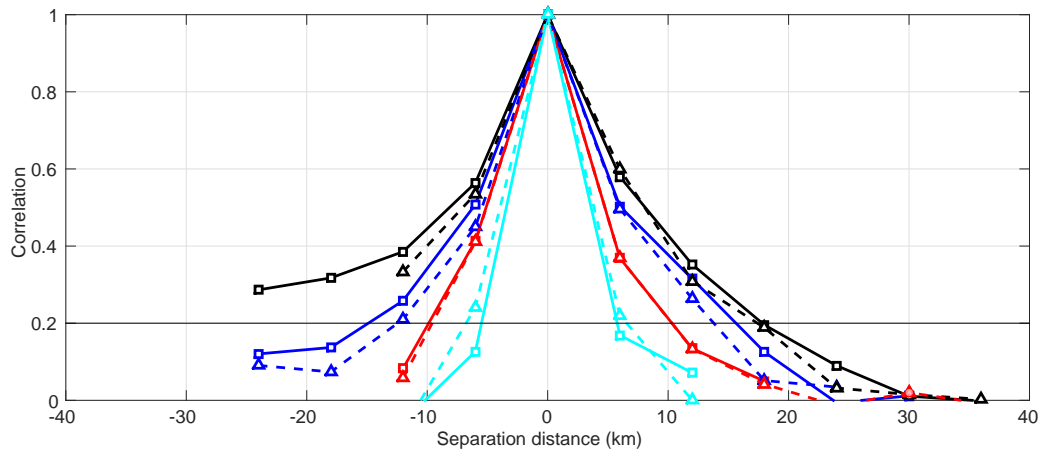
864 FIG. 8. Along-beam observation error standard deviation for elevations 1° (black), 2° (blue), 4° (red) and, 6°
 865 (cyan) for Case 1 (Control, squares), Case 2 (Alternate background error statistics, diamonds), Case 3 (Thinned
 866 raw data, triangles) and Case 4 (New observation operator, circles).



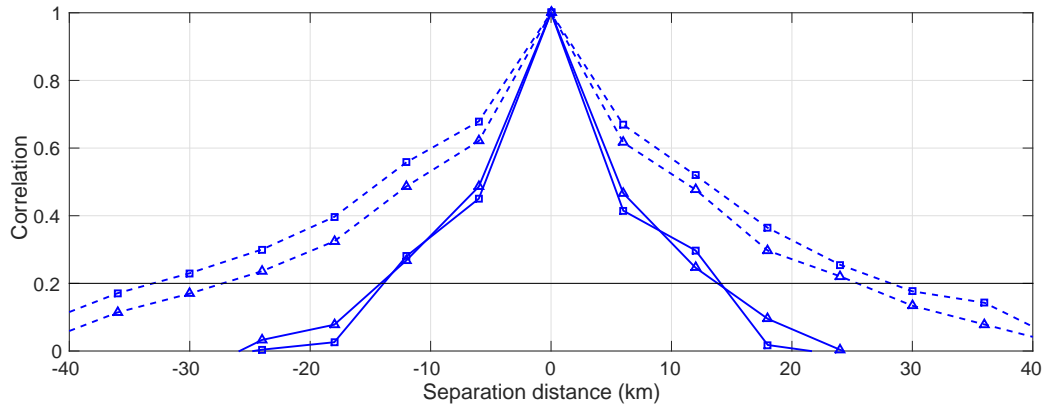
864 FIG. 9. Along-Beam observation correlations for elevation 2° at height 1.1km (dotted line), 3.0km (dashed
 865 line) and 3.5km (solid line) for Case 1 (Control).



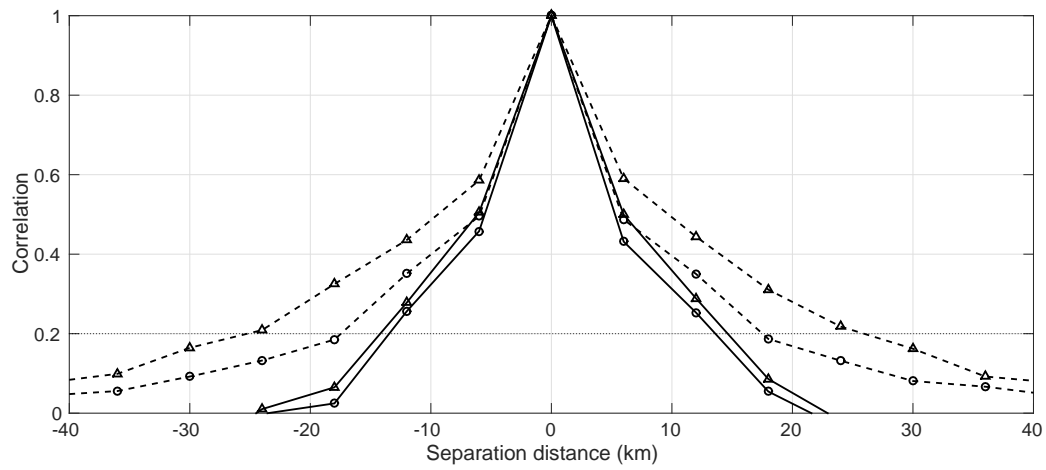
864 FIG. 10. Correlations along the beam at height 2.5km for elevations and approximate ranges $1^\circ \approx 94\text{km}$
 865 (black), $2^\circ \approx 64\text{km}$ (blue), $4^\circ \approx 35\text{km}$ (red) and $6^\circ \approx 22\text{km}$ (cyan) for superrobbed data (squares/solid lines) and
 866 thinned raw data (triangles/dashed lines). Error correlations are deemed to be insignificant below the horizontal
 867 line at 0.2.



864 FIG. 11. Correlations along the beam at range 40km for elevations and approximate heights $1^\circ \approx 0.8\text{km}$
 865 (black), $2^\circ \approx 1.5\text{km}$ (blue), $4^\circ \approx 3.0\text{km}$ (red) and $6^\circ \approx 4.3\text{km}$ (cyan) for superrobbed data (solid lines) and
 866 thinned raw data (dashed lines). Error correlations are deemed to be insignificant below the horizontal line at
 867 0.2.



864 FIG. 12. Horizontal observation correlations for elevation 2° at a range of 24km (solid) and 90km (dash)
 865 for Case 1 (control, squares) and Case 3 (Thinned raw data, triangles). Error correlations are deemed to be
 866 insignificant below the horizontal line at 0.2.



864 FIG. 13. Horizontal observation correlations for elevation 1° at a range of 18km (solid) and 74km (dash)
 865 for Case 3 (Thinned raw data, triangles) and Case 4 (New observation operator, circles). Error correlations are
 866 deemed to be insignificant below the horizontal line at 0.2.