High resolution ensemble analysis: linking correlations and spread to physical processes

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1. Introduction

"certain turbulent systems, possibly including the earth's atmosphere, possess for practical purposes a finite range of predictability" (Lorentz 1969)

Error growth is scale dependent, with errors growing faster at smaller scales . Hohenegger and Schär 2007 found error doubling times of several hours at grid lengths of 2.2km compared to several days at grid lengths of 80km. This has important implications for modelling convective storms:

- We need ensembles as part of a probabilistic framework
- Models should be evaluated on scales that are skilful. This may not be the grid scale.

Here we present a methodology for evaluating convective ensembles on scales that are believable, using correlations.

2. Methodology

Neighbourhood approach: instead of only considering members from a single grid point to be part of the ensemble, members from neighbouring grid points within a given distance of the original point were also included. A Gaussian weighting is applied to take account of the expected increase in similarity between members at small separations. This neighbourhood based method for increasing the ensemble size is shown schematically in **Figure 1** and:

- Is variable dependent
- Varies across the domain
- Allows evaluation on believable scales

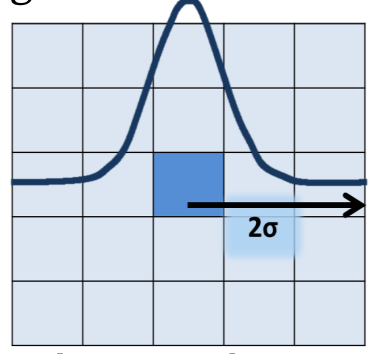

Figure 1: schematic showing neighbourhood method.

Believable scales selected using a metric based on the Fractions Skill score (Roberts and Lean 2008, Roberts 2008) given in **Equation 1**.

$$\frac{(A_{i,j}-B_{i,j})^2}{{A_{i,j}}^2+{B_{i,j}}^2} < 0.5 + \frac{W}{2W_{max}} \quad (1)$$

Weighting based on neighbourhood width W: criterion always met at the maximum width, W= W_{max}

Value when neighbourhood size is twice the spatial separation

$A_{i,j}, B_{i,j}$ - Total of values inside neighbourhood for fields A and B

W - total width of neighbourhood

Correlations were calculated to investigate the vertical structure of the ensemble. Different neighbourhood sizes were considered for three dimensional fields and instantaneous rain rates. Auto-correlations were considered between different vertical levels and cross-correlations between different variables.

3. Case study : 8th July 2011

A convective storm broke out in an area of instability within a decaying low pressure system. One particular storm occurred over Edinburgh and remained stationary for around 4 hours causing flooding. The domain of interest and ensemble mean instantaneous rain rates at 15:00 are given in **Figure 2**. Note how, due to spatial differences in the position of the storm between ensemble members, the ensemble mean is not physically representative of the storm.

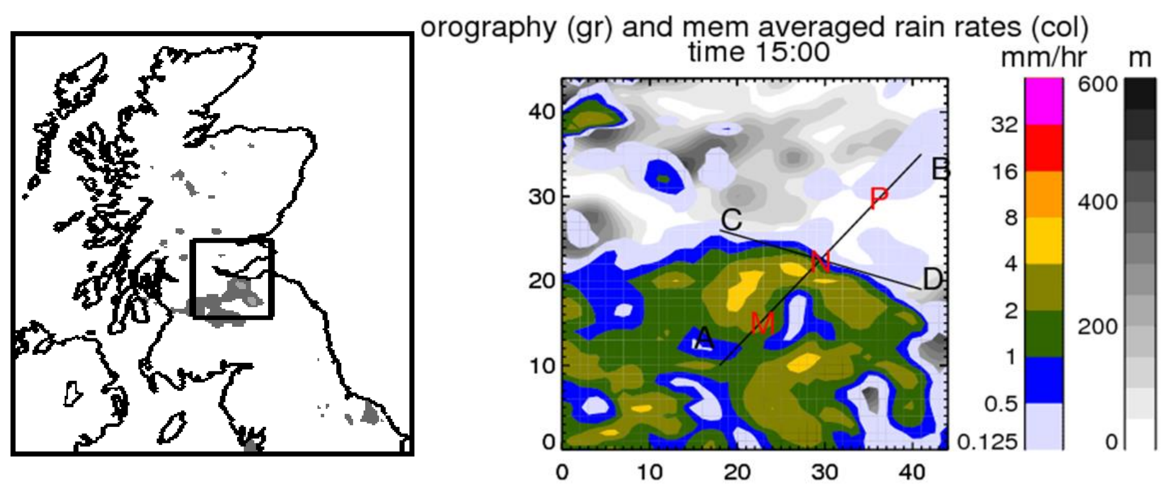

Figure 2: left- hourly radar accumulations and right- ensemble mean instantaneous rain rates at 15:00.

- Met office United Model 7.7
- Run over UK operational domain at 2.2km grid spacing.
- 11 members downscaled from global ensemble and unperturbed control.

4. Rain rate correlations

- Instantaneous rain rates correlated with horizontal divergence at horizontal point "N" (see **Figure 2** for location) and different vertical levels.
- Strong correlations during times of convection (12:00,15:00) and in the convective layer as shown in **Figure 3**.
- The development of convection results in physically meaningful correlations

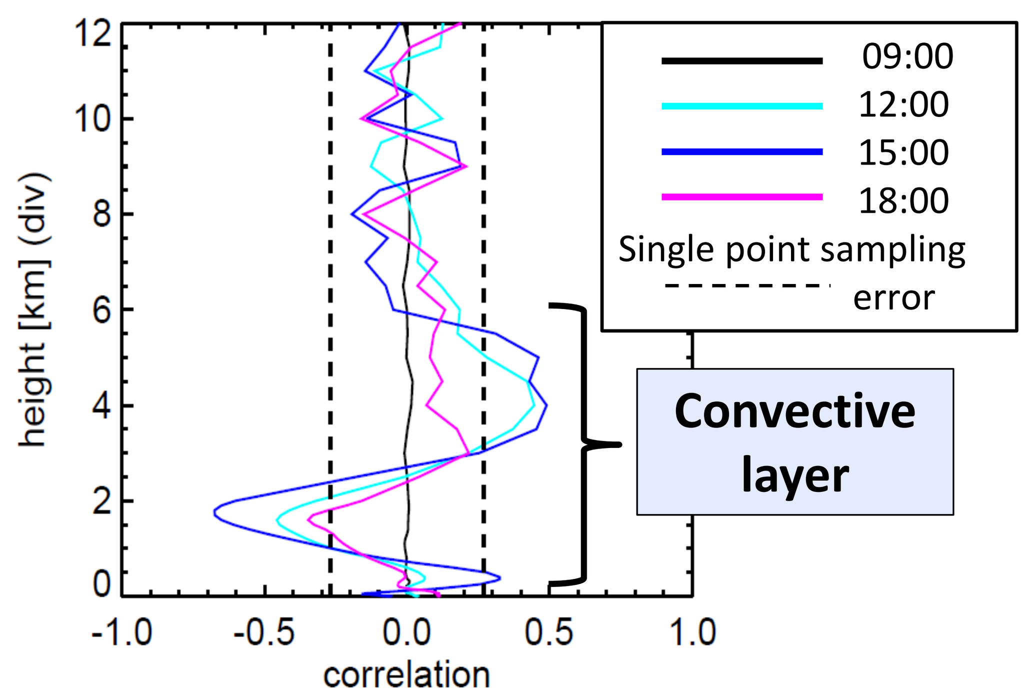

Figure 3: rain rate- horizontal divergence autocross-correlations for different times. The dashed lines show the expected sampling error if no neighbourhood was used.

5. Divergence vertical correlations

- Auto-correlations for horizontal divergence at point "N" and different vertical levels.
- Using a neighbourhood reduces correlations at large separations (further from diagonal) that may not be trustworthy.

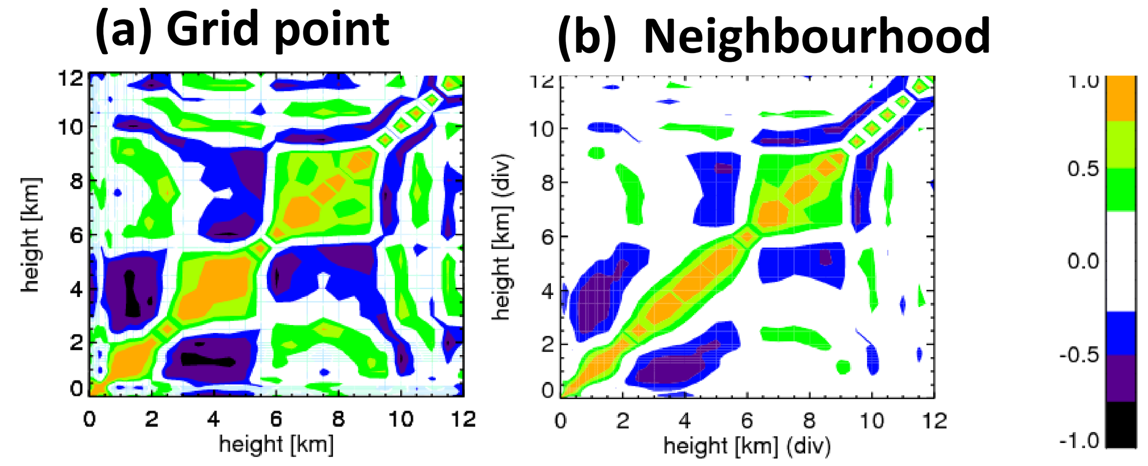

Figure 4: vertical auto-correlations for horizontal divergence calculated at (a) a single grid point and (b) over a neighbourhood.

- Change in sign of correlation at edges of convergent/divergent layers
- Correlations reflect convective structure
- Correlations change sign when members cross the ensemble mean

6. Divergence-cloud fraction vertical cross-correlations

- Physically, we expect horizontal divergence and cloud fraction to correlate as shown in **Figure 5**.
- This is indeed seen in **Figure 6**.
- Using a neighbourhood again removes noisy unphysical correlations
- Credible physical relationships are extracted from ensemble

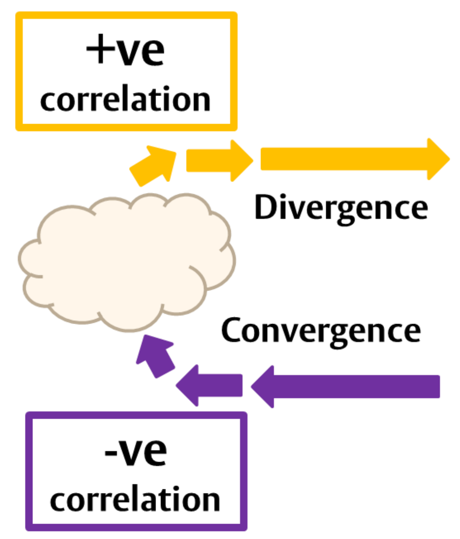

Figure 5: Schematic explaining cloud fraction-divergence correlations.

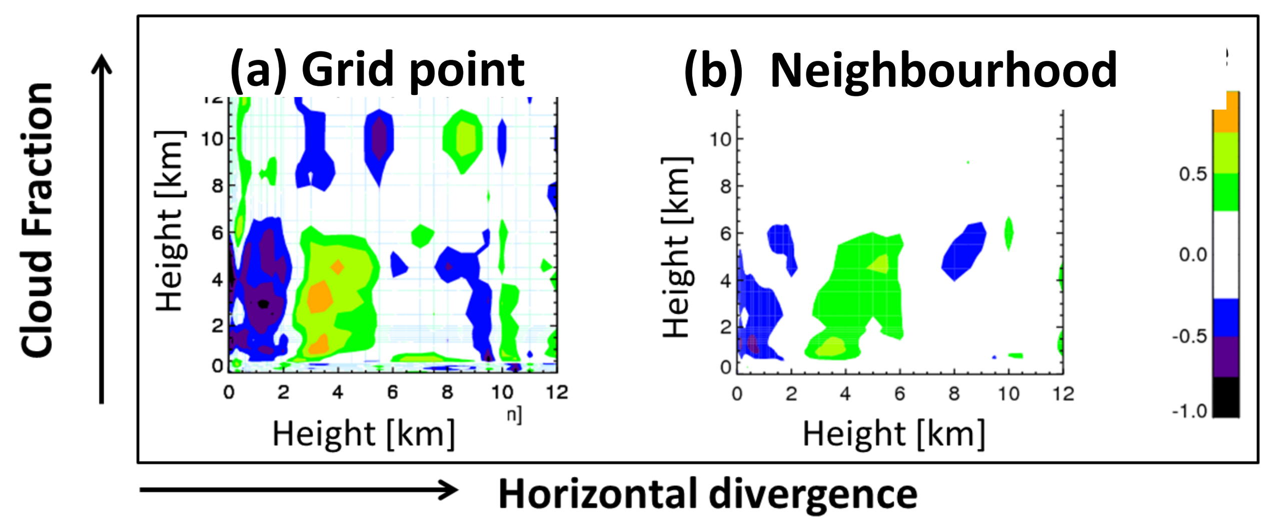

Figure 6: vertical autocross-correlations between cloud fraction and horizontal divergence calculated at (a) a single grid point and (b) over a neighbourhood.

7. Summary

1. Useful and robust information can be extracted from a convective scale ensemble using correlations.
2. Neighbourhood sampling is needed for analysis on meaningful scales.
3. Increasing the effective ensemble size also reduces sampling error, removing noisy correlations and increasing confidence in the results

8. Applications

This work is relevant to the evaluation of high resolution models and how those models represent physical processes. Another area of relevance is in data assimilation. To perform data assimilation it is necessary to know the background error covariance matrix **B** (Bannister 2008). Many estimates for **B** use climatological and balance relations that are not appropriate for the convective scale . By using information from an ensemble to estimate the correlations flow dependency, and information relevant to the convective scale can be included (e.g Lahoz et.al)

9. Next steps

Current work is apply ing the correlation and neighbourhood techniques to multiple cases. Six cases will be studied from the COnvective Precipitation Experiment (COPE). These cases show a range of different convective behaviour.

- What can be learnt about different convective structures using correlations?
- What is the most appropriate neighbourhood size to use and how does this relate to the meteorological situation?
- By considering temporal correlations is it possible to "predict the predictability "of the convection?

References

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