The spatial behaviour and evaluation of a convection-permitting ensemble

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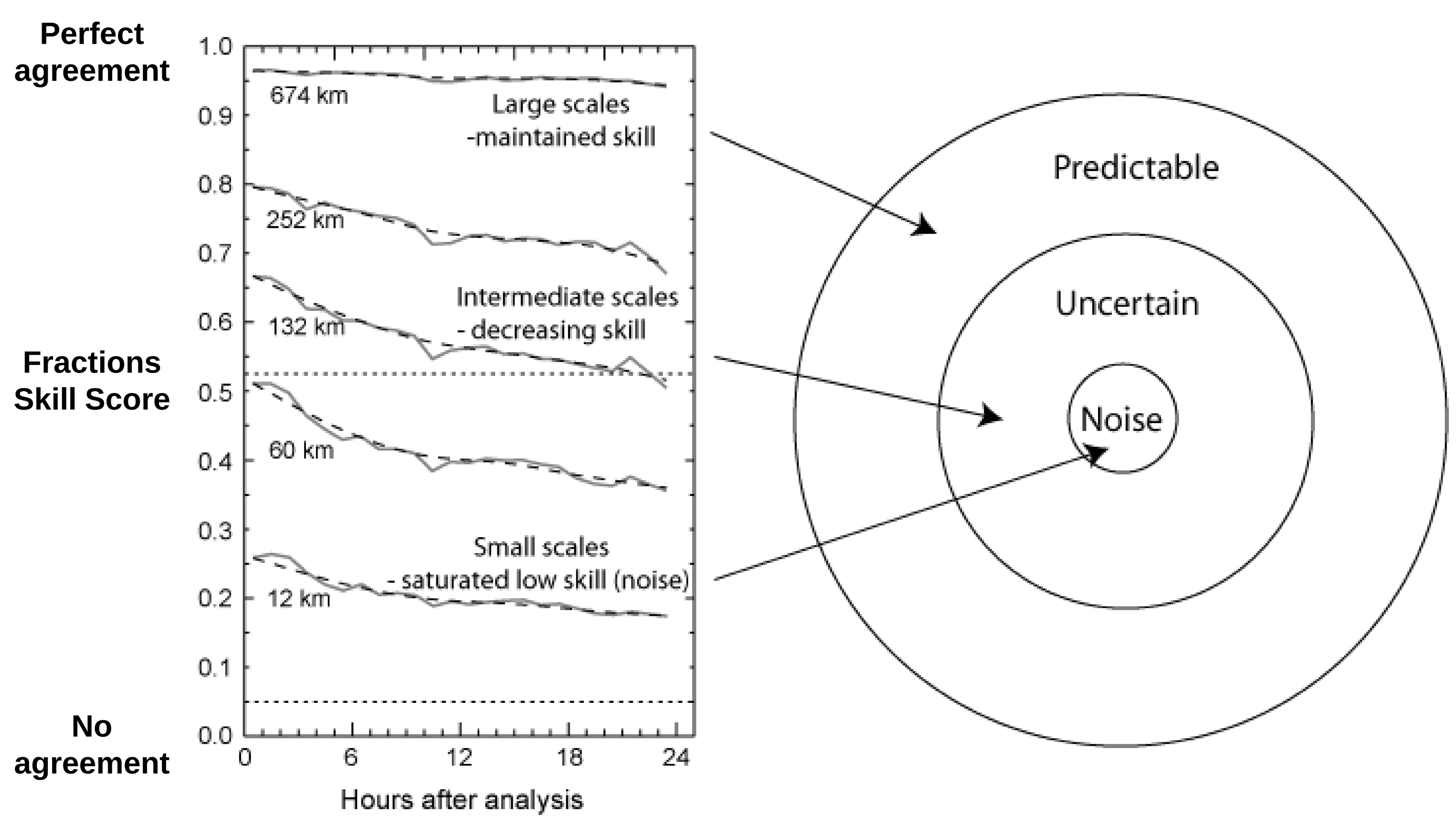
Introduction - MOGREPS-UK

The Met Office now runs a convection permitting ensemble - MOGREPS-UK. It has 12 members and runs 36-hour forecasts every 6 hours on a 2.2 km grid. The purpose is to provide probabilistic forecasts of local weather – especially high-impact weather such as flood-producing thunderstorms. This poster discusses the rationale behind this ensemble and spatial methods for using and evaluating the output.

The scale dependence of forecast skill

•Below (left) shows the average change of skill over 24h at different scales for a years worth of precipitation forecasts compared with radar for a 12 km model (taken from Roberts 2008) The forecasts can be partitioned into three spatial categories (right). The large scales maintain high skill throughout the forecasts and are therefore predictable. The small scales lose skill quickly then remain unskilful and can be treated as noise. The intermediate scales lose skill throughout the period and skill will depend on the meteorological situation. Convection permitting models behave in the same way.

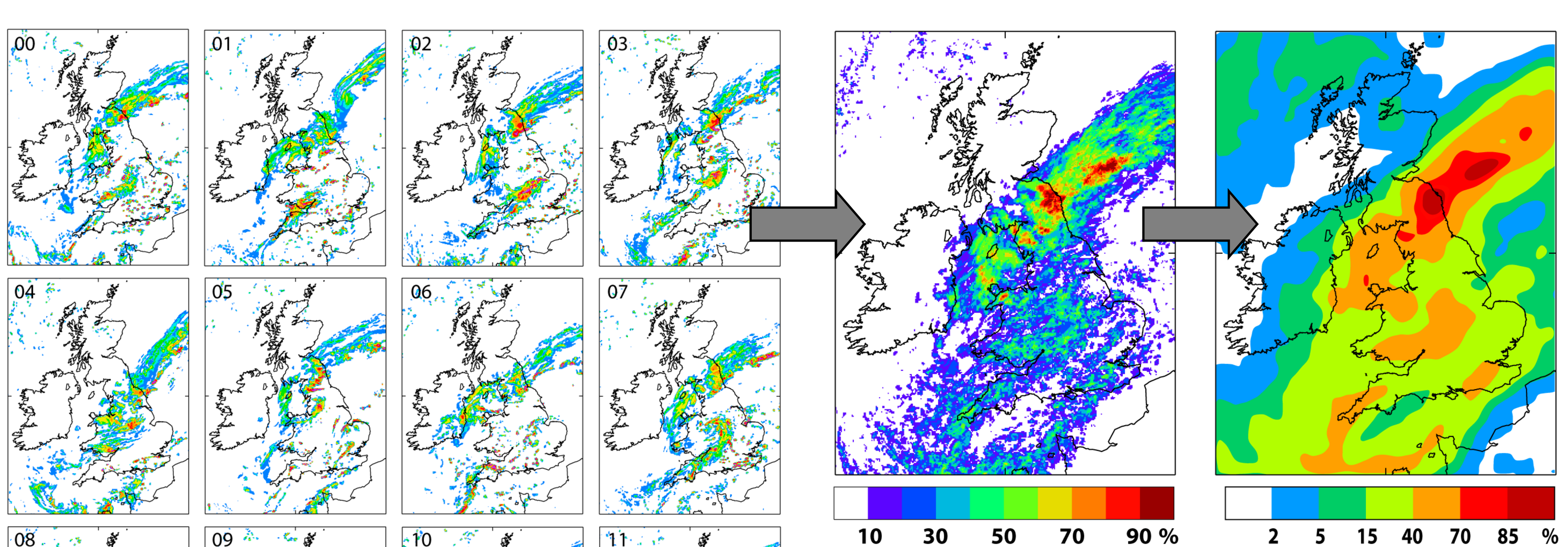


Implications for a convection-permitting ensemble

•A convection-permitting ensemble is needed but we can only afford a few members.
•Given a small ensemble we should target the intermediate uncertain scales.
•There are certainly not enough members to target the smaller unpredictable scales.
•Post-processing is needed to account for the under-sampling of small scales by a small ensemble. We use a 'neighbourhood' approach
•MOGREPS-UK takes initial and boundary conditions from a coarser-resolution ensemble (MOGREPS-R) and does therefore target the intermediate scales.

Spatial post processing

•An example of precipitation forecasts from MOGREPS-UK are shown below (left).
•The middle panel shows the probability of rain from those forecasts. Notice the speckled nature and gaps due to there being too few ensemble members.
•The right panel shows smooth probabilities after applying 'neighbourhood processing' to the middle panel. The probabilities at each pixel are averaged over squares (neighbourhoods) with some additional filtering. The width of the squares was ~30 km, but the optimal size should really vary over the domain and from forecast to forecast.



Probability of rain generated by the usual method. Reveals under-sampling (gaps) with 12 members

Probability of rain in a half-hour window smoothed using a neighbourhood approach. Same algorithm used for products for the Olympics

Finding spatial difference between ensemble members

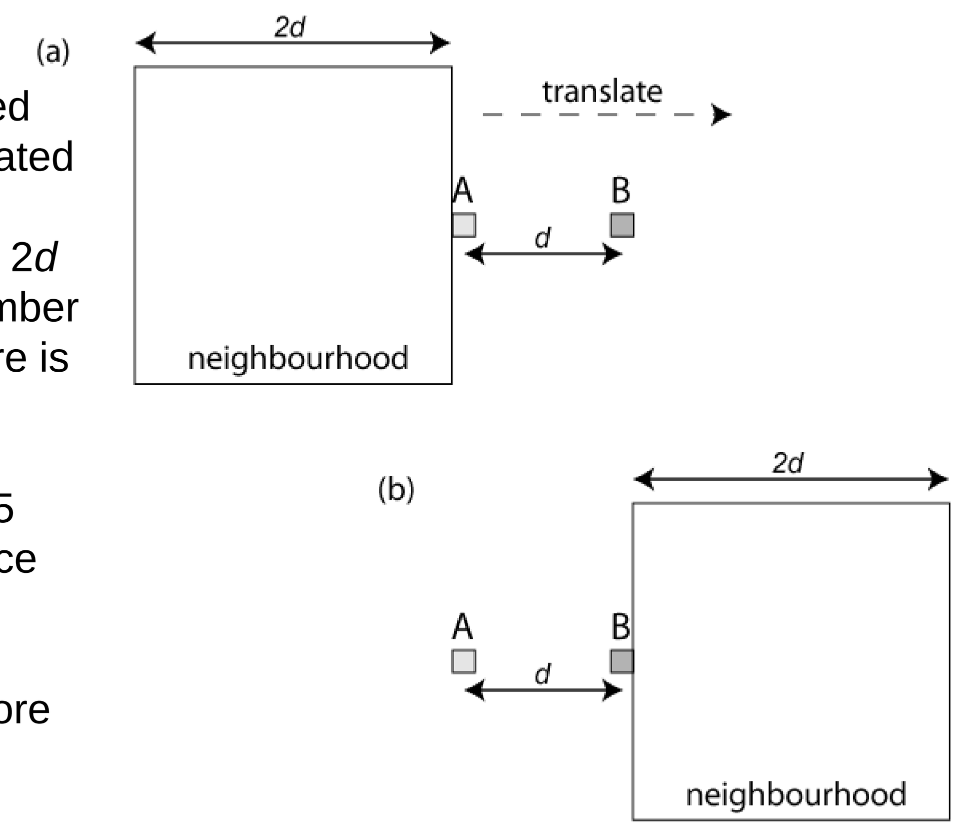
•The Fractions Skill Score (FSS) can be used to find the spatial difference between two binary fields. It can therefore be used to find spatial differences between ensemble members and an optimal neighbourhood size for a particular ensemble forecast.

$$FSS = 1 - \frac{\frac{1}{N}\sum_{j=1}^{N}(p_j - o_j)^2}{\frac{1}{N}\left[\sum_{j=1}^{N}(p_j)^2 + \sum_{j=1}^{N}(o_j)^2\right]}$$

$0 < p_j < 1$ forecast fractions
$0 < o_j < 1$ radar fractions
N number of points

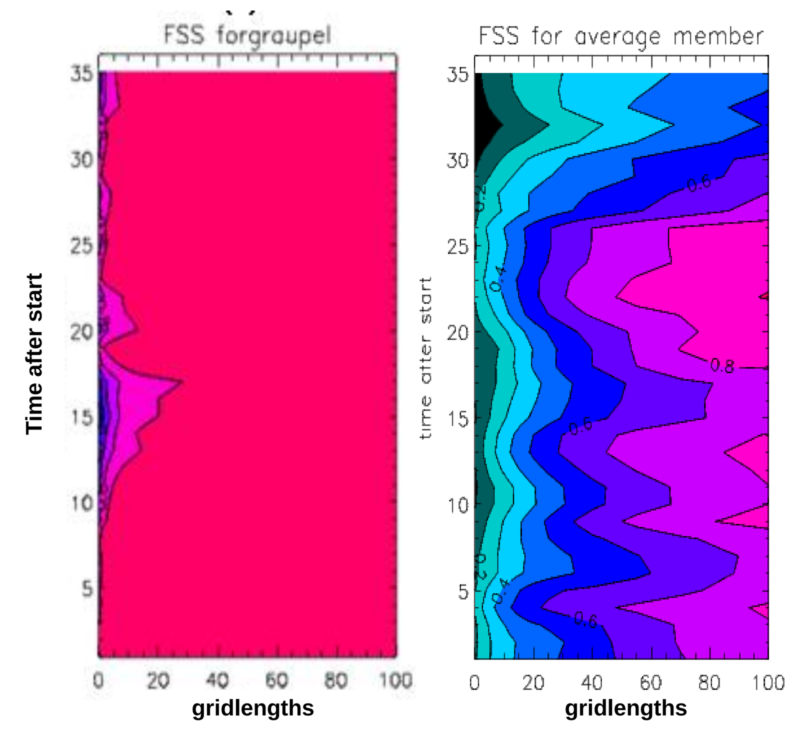
Fractions are the number of pixels in neighbourhood squares. The FSS is computed for different square neighbourhood sizes

•The schematic on the right shows an idealised situation with two binary pixels A and B separated by a distance *d*.
•When the neighbourhood square has length 2*d* and is placed in all possible locations, the number of locations in which A or B is inside the square is twice that of just A or just B.
•This gives FSS = 0.5 (numerator half denominator) and means that when FSS = 0.5 the length of the neighbourhood is always twice the separation of the pixels.
•This provides a way of computing the mean separation between binary pixels (even for more complex fields like rainfall forecasts).



Finding the spread across scales

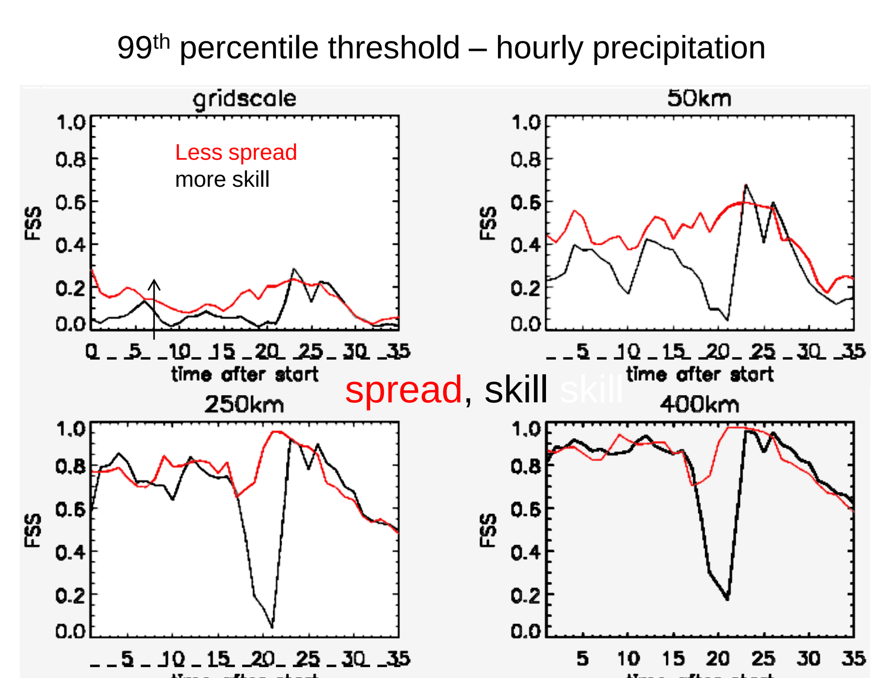
•The FSS can be used to find the mean spatial agreement between ensemble members.
•This is useful because traditional approaches focus on the grid-scale and do not show differences across scales. This method can reveal whether there is any upscale growth of spatial spread.



•The picture shows how the ensemble-mean FSS for hourly precipitation changes with forecast lead time and spatial scale for a 8-member convection-permitting ensemble forecast (right panel). The larger the FSS (more purple/red) the better the spatial agreement between the members. The left panel shows the impact of a small change to the physics formulation. The much higher FSS values in the left panel reveal that, in this instance, the physics change has little impact except at very small scales, and even then much less than the ensemble variability. The method is described in Dey et al 2014.

Spatial ensemble verification

•The FSS can also be used to find the skill-spread at different scales.
•Picture right shows a comparison of spatial differences between members (spread –red) and spatial differences from radar (skill – black) at four scales for a 36-hour forecast (single case).
•The ensemble has sufficient skill when the black line is above dashed black line.
•The ensemble has a good skill/spread relationship when red and black lines are on top of each other.
•The ensemble is under-spread and has poor skill at small scales (on this occasion).



References

Roberts, NM (2008). 'Assessing the spatial and temporal variation in the skill of precipitation forecasts from an NWP model', Meteorological Applications, Volume 15, Issue 1, pages 163–169

Dey SRA, G Leoncini, NM Roberts, RS Plant, S Migliorini. (2014). 'A Spatial View of Ensemble Spread in Convection Permitting Ensembles' Mon. Wea. Rev., 142, 4091–4107.

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