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Evaluation of the Plant–Craig stochastic convection scheme in an ensemble forecasting system

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Abstract

The Plant–Craig stochastic convection parameterization (version 2.0) is implemented in the Met Office Regional Ensemble Prediction System (MOGREPS-R) and is assessed in comparison with the standard convection scheme with a simple stochastic element only, from random parameter variation. A set of 34 ensemble forecasts, each with 24 members, is considered, over the month of July 2009. Deterministic and proba-

bilistic measures of the precipitation forecasts are assessed. The Plant–Craig parameterization is found to improve probabilistic forecast measures, particularly the results for lower precipitation thresholds. The impact on deterministic forecasts at the grid scale
 is neutral, although the Plant–Craig scheme does deliver improvements when forecasts are made over larger areas. The improvements found are greater in conditions of relatively weak synoptic forcing, for which convective precipitation is likely to be less predictable.

1 Introduction

- ¹⁵ Quantitative precipitation forecasting is recognized as one of the most challenging aspects of numerical weather prediction (Ebert et al., 2003; Montani et al., 2011; Gebhardt et al., 2011). While progress is continually being made in improving the accuracy of single forecasts – through improvements in the model formulation as well as increases in grid resolution – a complementary approach is the use of ensembles in
- order to obtain an estimate of the uncertainty in the forecast (Buizza et al., 2005, 2007; Montani et al., 2011; Bowler et al., 2008; Thirel et al., 2010; Yang et al., 2012; Zhu, 2005; Abhilash et al., 2013; Roy Bhowmik and Durai, 2008; Clark et al., 2011; Tennant and Beare, 2013). Of course, ensemble forecasting systems themselves remain imperfect, and one of the most important problems is insufficient spread in ensemble forecasts, where the forecast tends to cluster tends to strength, around minfell values that
- ²⁵ forecasts, where the forecast tends to cluster too strongly around rainfall values that turn out to be incorrect.



One reason for lack of spread in an ensemble is that model variability is constrained by the number of degrees of freedom in the model, which is typically much less than that of the real atmosphere. The members of an ensemble forecast may start with a good representation of the range of possible initial conditions, but running exactly

the same model for each ensemble member means that the range of possible ways of modelling the atmosphere – of which the model in question is one – are not fully considered. Two possible ways of accounting for model variability are running different models for each ensemble member (e.g. Mishra and Krishnamurti, 2007; Berner et al., 2011) and adding random perturbations to the tendencies produced by the parameter izations (e.g. Buizza et al., 1999; Bouttier et al., 2012).

Focusing on convective rainfall, and for model grid lengths where convective rainfall is parameterized, another way of accounting for model variability is to introduce random variability in the convection parameterization itself, ideally in a physically consistent way, so that the random variability causes the parameterization to sample from the range of possible convective responses on the grid scale (e.g. Lin and Neelin, 2003; Khouider et al., 2010; Plant and Craig, 2008; Ragone et al., 2014). A recent overview is given by Plant et al. (2015).

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Such "stochastic" convection parameterization schemes have been developed over the last 10 years, and are just beginning to be implemented and verified in operational forecasting setups, with some promise for the improvement of probabilistic ensemble forecasts (e.g Bengtsson et al., 2013; Kober et al., 2015). The purpose of the present study is to continue this pioneering work of verifying probabilistic forecasts using stochastic convection parameterizations, by investigating the performance of the Plant and Craig (2008) (PC) scheme in MOGREPS, the Met Office ensemble forecasting system (Bowler et al., 2008).

The PC scheme has been shown to produce rainfall variability in much better agreement with cloud resolving model results than for other non-stochastic schemes (Keane and Plant, 2012), and has been shown to add variability in a physically consistent way when the model grid spacing is varied (Keane et al., 2014). It has also been demon-



strated that the convective variability it produces, on scales of tens of kilometres, can be a major source of model variability (Ball and Plant, 2008) and further that its performance at large scales in a model intercomparison is similar to that of more traditional methods (Davies et al., 2013).

- These are encouraging results, albeit from idealized modelling setups, and it is important to establish whether or not they might translate into better ensemble forecasts in a fully-operational NWP setup. Groenemeijer and Craig (2012) examined seven cases using the COSMO ensemble system with 7 km grid spacing and found that the PC scheme produced 25–50 % of the total variance of hourly–accumulated rainfall on
- ¹⁰ a scale of 35 km. The present study investigates the behaviour of the scheme in a trial of 34 forecasts with the MOGREPS-R ensemble, using a grid length of 24 km. The mass-flux variance produced by the PC scheme is inversely proportional to the grid box area being used and so it is not obvious from the results of Groenemeijer and Craig (2012) whether the stochastic variations of PC will contribute significantly to variabil-
- ity within an ensemble system operating at the scales of MOGREPS-R. Nonetheless, MOGREPS-R has been shown, in common with most ensemble forecasting systems, to produce insufficient spread relative to its forecast error in precipitation (Tennant and Beare, 2013), suggesting that there is scope for the introduction of a stochastic convection parameterization to be able to improve its performance.

Although the version of MOGREPS used here has now been superseded, the present study represents the first time that the scheme has been verified in an operationally-used ensemble forecasting system for an extended verification period, and provides the necessary motivation for more extensive tuning and verification studies in a more current system. As well as this, the present study aims to learn more about the behaviour of the scheme itself, building on work referenced above, as well

as on recent work by Kober et al. (2015) which focused on individual case studies.

The paper compares the performance of the PC scheme with the default MOGREPS convection parameterization, based on Gregory and Rowntree (1990), in order to seek evidence that accounting for model variability by using a stochastic convection param-



eterization can lead to improvements in ensemble forecasts. Of course, the two parameterizations are fundamentally different, quite apart from the stochasticity of the PC scheme, so that it will be impossible to obtain unequivocal proof that the stochasticity is responsible for an improvement in performance. Nonetheless, the default MOGREPS scheme has benefitted from much experience in developing it alongside the Met Office

Unified Model (Lean et al., 2008, UM), whereas relatively modest efforts were made here to adapt the PC scheme to the host ensemble system: thus, any improvements that the PC scheme shows over the default scheme are of clear interest.

2 Methods

2.1 The Plant–Craig stochastic convection parameterization

The Plant and Craig (2008) scheme operates, at each model grid point, by reading in the vertical profile from the dynamical core, and calculating what convective response is required to stabilize that profile. It can be considered as a stochastic and spectral generalization of the Kain–Fritsch convection parameterization (Kain and Fritsch, 1990; Kain, 2004), since it adapts the plume model used there and also has a similar formulation for the closure, based on a dilute CAPE. Details of its implementation in an idealized configuration of the UM are given by Keane and Plant (2012); this would be regarded as Version 1.1. The important differences in the implementation for the present study, to produce Version 2.0, are presented here.

- ²⁰ The scheme allows for the vertical profile from the dynamical core to be averaged before it is input. This means that the input profile is more representative of the largescale (assumed quasi-equilibrium) environment, and is less affected by the stochastic perturbations locally induced by the scheme at previous time steps. It was decided in the present study to use different spatial averaging extents over ocean and over land,
- in order that orographic effects were not too heavily smoothed. The spatial averaging strategy implemented was to use a square of 7×7 grid points over the ocean and



 3×3 grid points over land; the temporal averaging strategy was to average over the previous 7 time steps (each of 7.5 min) and the current time step. The cloud lifetime was set to 15 min. As well as using the averaged profile for the closure calculation, the plume profiles were also calculated for ascent within the averaged environment.

- Initial tests showed that the scheme was yielding too small a proportion of convective precipitation over the domain. Two further parameters were adjusted from the study by Keane and Plant (2012), in order to increase this fraction: the mean mass flux per cloud $\langle m \rangle$ and the root mean square cloud radius $\sqrt{\langle r^2 \rangle}$. Similar changes were made for the same reason by Groenemeijer and Craig (2012) in their mid-latitude tests over land,
- ¹⁰ and reflect the fact that the original settings in Plant and Craig (2008) and Keane and Plant (2012) were chosen to match well with cloud-resolving model simulations of tropical oceanic convection. Specifically, the mean mass flux per cloud was reduced here from 2×10^7 to 0.8×10^7 kg s⁻¹ in order to increase the number of plumes produced by the scheme. The entrainment rates used in the scheme are inversely proportional to
- ¹⁵ cloud radius, and a pdf of cloud radius is used characterized by the root mean square cloud value $\sqrt{\langle r^2 \rangle}$. This was increased from 450 to 600 m, in order to produce less strongly entraining plumes. This had some impact on the convective precipitation fraction, but the scheme still yielded a relatively low proportion of convective rain: 12% in these tests, as compared with 50% for the standard scheme. There is no correct
- ²⁰ answer for this proportion which is both model and resolution dependent in current operational practice. For example, the current ECMWF model has a global average of about 60% (Bechtold, 2015). Doubtless the convective precipitation fraction produced by the Plant–Craig scheme in MOGREPS-R could be increased further with stronger changes to parameters and we remark that Groenemeijer and Craig (2012) set $\sqrt{\langle r^2 \rangle}$
- to 1250 m for their tests, which would likely have such an effect. We attempted only minimal tuning here and were deliberately rather conservative about the parameter choices made, with the intention that the results can reasonably be considered to represent a lower limit of the possible impact of a more thoroughly adapted scheme.



2.2 Description of MOGREPS

The Met Office Global and Regional Ensemble Prediction System (MOGREPS) has been developed to produce short-range probabilistic weather forecasts (Bowler et al., 2008). It is based on the UM (Davies et al., 2005) with 24 ensemble members, and

- ⁵ is comprised of global and regional ensembles. In the present study, the regional ensemble MOGREPS-R was used, with a resolution of 24 km and 38 vertical levels. This covers a North Atlantic and European (NAE) domain, which is shown in Fig. 1. The model was run on a rotated latitude-longitude grid, with real latitude and longitude locations of the north pole and the corners of the domain given in Table 1. The regional
- ensemble was driven by initial and boundary conditions from the global ensemble, as described by Bowler et al. (2008). The operational system has been upgraded since these tests and so the present study represents a "proof of concept" for a stochastic convection scheme in a full-complexity regional or global ensemble prediction system, rather than a detailed technical recommendation for the latest version of MOGREPS.
- Stochastic physics is already included in the regional MOGREPS, in the form of a random parameters scheme, where a number of selected parameters are stochastically perturbed during the forecast run (Bowler et al., 2008). This scheme was retained for the present study, given that the Plant–Craig scheme is intended to account only for the variability in the convective response for a given large-scale state, and as such its
- design does not conflict with the inclusion of a method to treat parameter uncertainty within other parameterization schemes. The MOGREPS random parameter scheme does introduce variability in parameters that appear within the standard UM convection scheme, which is based on the Gregory and Rowntree (1990) scheme with subsequent developments as described by Martin et al. (2006). No stochastic parameter variation
- is applied for any of the parameters appearing in the Plant–Craig scheme. Thus, there is no "double counting" of parameterization uncertainty in these tests but rather we are comparing different methods of accounting for convective uncertainties in a framework



which also includes a simple stochastic treatment of uncertainties in other aspects of the model physics.

The forecasts using the Plant-Craig scheme were obtained by rerunning the regional version of MOGREPS, with the standard convection scheme replaced by the

⁵ Plant–Craig scheme, and driven by initial and boundary conditions taken from the same archived data that were used for the operational forecasts. These are compared with the forecasts produced operationally during the corresponding period, so that the only difference between the two sets of forecasts is in the convection parameterization scheme. The study used the UM at version 7.3. The model timestep was 7.5 min, within which the convection scheme was called twice.

2.3 Time period investigated

The time period investigated was from 10–30 July 2009. This length of time was chosen as being sufficient to obtain statistically meaningful results, but without requiring a more lengthy experiment that would only be justified by a more mature system. The particular

¹⁵ month was chosen partly for convenience and partly as a period that subjectively had experienced plentiful convective rain over the UK, therefore providing a good test of a convective parameterization scheme.

Experimental forecasts with the Plant–Craig scheme were generated twice daily (at 06:00 and 18:00 UTC) for comparison with the operational forecast which was taken from the archive. On some days the archive forecast was missing and so no experimental forecast was generated. In total 34 forecasts were generated, with start times shown in Table 2.

2.4 Verification

A detailed verification was carried out against Nimrod radar rainfall data (Harrison et al.,

²⁵ 2000; Smith et al., 2006). This observational data set is only available over the UK (as shown in Fig. 1), and so most of the verification in the following focuses on this region.



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The forecasts were assessed on the basis of 6 hourly rainfall accumulations, every 6 h, for lead times from 0 to 54 h.

2.4.1 Fractions skill score

This score (denoted FSS) was developed by Roberts and Lean (2008), and was used ⁵ by Kober et al. (2015) to assess the quality of deterministic forecasts produced using the Plant–Craig scheme for two case studies. Note that we use the term "deterministic", in this manuscript, to refer to forecasts providing a single quantity (for example, a single-member forecast, or the ensemble mean), and "probabilistic" to refer to forecasts providing a probabilistic distribution (or, at the very least, a deterministic forecast, with, in addition, an assessment of its uncertainty). The FSS is determined, at a given grid point *X*, by comparing the fractions of observed, *O*, and forecast, *F*, grid points exceeding a specific rainfall threshold, within a specific spatial window centred at *X*. Here we define:

$$FSS = 1 - \frac{\langle (F - O)^2 \rangle}{\langle F^2 \rangle + \langle O^2 \rangle}$$

where the angled brackets $\langle ... \rangle$ indicate averages over the grid points *X* for which observations are available, and also over the different forecast initialization times. The score is positively oriented, and ranges between 0 and 1.

2.4.2 Brier scores

In order to determine whether or not the variability introduced by the Plant–Craig scheme is added where it is most needed, the Brier skill score (Wilks, 2006) was applied to both forecast sets, using the same observational data, to assess the respective quality of the probabilistic forecasts. The Brier score is a threshold-based probabilistic verification score, and is given by the mean difference between the forecast probability of exceeding a given threshold (this probability is here simply taken to be the fraction

(1)

of ensemble members which forecast precipitation greater than the threshold) and the observed probability (i.e 1 if the observed precipitation is above the threshold and 0 if it is below). To obtain the Brier skill score, BSS, this is compared with a reference score; the reference score is here taken to be that calculated from always forecast-⁵ ing a probability taken from the observation data set (i.e. the proportion of times the observed precipitation is above the threshold). Thus,

$$BSS = 1 - \frac{\langle (f - o)^2 \rangle}{\langle (\langle o \rangle - o)^2 \rangle}$$

where *f* is the forecast probability, *o* is the observation (0 or 1) and $\langle o \rangle$ is the "climatological" probability based on the observation set. The angle brackets denote an average over the entire forecast set. Although $\langle o \rangle$ is only available a posteriori to the event, it does provide a useful "base" for comparison: if the forecast issued is no better than one given by simply always issuing a climatological average (i.e. if BSS < 0) then the forecast can be said to have no skill.

2.4.3 Ensemble added value

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¹⁵ This measure aims to assess the benefit of using an ensemble, as against a single forecast randomly selected from the ensemble. It was recently developed and described in detail by Ben Bouallègue (2015) and a brief outline is given here. The score is of particular interest to the present study, as this measure should highlight the advantages and disadvantages of using the stochastic Plant–Craig methodology, and provides an assessment that is less affected by structural differences between the Plant– Craig scheme and the Gregory–Rowntree (GR) scheme.

The ensemble added value (EAV) is based on the quantile score (QS) (Koenker and Machado, 1999; Gneiting, 2011), which is used to assess probabilistic forecasts at a given probability level (equivalently, the Brier score assesses probabilistic forecasts at a given value threshold). If a quantile forecast ϕ_{τ} of the τ th quantile of a meteorological



variable is given, then the quantile score for that quantile is interpreted as

 $q_\tau = \big\langle (\omega - \phi_\tau) (\tau - I\{ \omega < \phi_\tau\}) \big\rangle$

where ω is the observed value, the function I(x) is defined as 1 if x is true and 0 if x is false and the angle brackets denote an average over all forecasts, as for the Brier skill

⁵ score. In this way, a forecast for a low quantile is penalized more heavily if it is above the observed value, than if it is below the observed value, and vice-versa for a forecast for a high quantile (note that the score is negatively oriented). The score for the 50% quantile is simply the mean absolute error.

The QS can, like the Brier score, be decomposed into a reliability and a resolution component (Bentzien and Friederichs, 2014). In order to calculate the EAV, a potential QS Q_{τ} is defined as the total QS minus its reliability component. The QS is here evaluated by first sorting the ensemble members, and interpreting the *m*th sorted ensemble member as the (m - 0.5)/24 quantile forecast. The EAV is then given by summing the potential QSs Q_m over the 24 members, and comparing with an equivalent sum over reference potential QSs:

$$\mathsf{EAV} = 1 - \frac{\sum_m Q_m}{\sum_m Q_m^{\mathrm{ref}}}.$$

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The reference forecast is created by defining the quantile as simply a randomlyselected member of the ensemble, so that the reference forecast represents the score which could have been obtained with only one forecast (a single member is randomly selected, with replacement, once for the entire period, but separately for each quantile).

The EAV thus measures the quality of the ensemble forecast, relative to the quality of the individual members of the ensemble.

2.5 Separation into weakly- and strongly-forced cases

Groenemeijer and Craig (2012) applied the Plant–Craig scheme in an ensemble forecasting system for seven case studies, with various synoptic conditions, and showed



(3)

(4)

that the proportion of ensemble variability arising from the use of the stochastic scheme (as against that arising from variations in the initial and boundary conditions) depends on the strength of the large-scale forcing, as measured by the large-scale vorticity maximum. In particular, the stronger the large-scale forcing, the lower the proportion of the variability that comes from the stochastic scheme.

Kober et al. (2015) investigated two of the case studies further, by verifying forecasts using the Plant–Craig scheme and using a non-stochastic convection scheme. They found that the improvement in forecast quality from using the Plant–Craig scheme was significantly higher for the more weakly-forced of the two cases, since the additional grid-scale variability introduced by the stochastic scheme is more important.

As part of the present study, we extend the work of Kober et al. (2015) by separating our verification period into dates for which the synoptic forcing is relatively weak or strong. We then compare any improvement in the forecasts using the Plant–Craig scheme, over those using the Gregory–Rowntree scheme, for the two sets of forecasts, to assess over an extended period whether the benefit of using a stochastic scheme is

indeed greater when the synoptic forcing is weaker.

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The separation into weakly- and strongly-forced cases was carried out a posteriori to the event based on surface analysis charts. The aim here is not to develop an adaptive forecasting system, but rather to develop understanding of the behaviour of the

- Plant–Craig scheme. Nonetheless, the results may also be interpreted as providing evidence that such a system may be feasible if the strength of the synoptic forcing could be predicted in advance (using, for example, the convective adjustment time scale as discussed by Keil et al., 2014). The period was divided into 12 h sections, centred on 00:00 or 12:00 UTC, and a surface analysis chart valid at the respective centre-time
- ²⁵ was used to determine whether to categorize the section as weakly- or strongly-forced. The 00:00 UTC analyses were taken from Wetterzentrale (2009) and the 12:00 UTC analyses from Eden (2009).

The separation was conducted by assigning periods with discernible cyclonic and/or frontal activity over or close to the UK as strongly-forced and the rest as weakly-forced,



with some additional adjustment of the preliminary categorization based on the written reports by Eden (2009). The periods were categorized as in Table 3.

3 Results

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3.1 Fractions skill score

- ⁵ The quality of the respective deterministic forecasts using Gregory–Rowntree (GR) and Plant–Craig (PC) is assessed using Figs. 2 and 3. The performance of the schemes is overall similar, with PC being superior for low thresholds (in contrast to the findings of Kober et al., 2015) and short lead times. With averaging (Fig. 3), the differences between the schemes become more scattered across the plots, with the performance of both schemes improving for higher thresholds, which is in broad agreement with
- 10 of both schemes improving for higher thresholds, which is in broad agreement with the results of Kober et al. (2015). In general, the difference in the scores between the two schemes does not reach such high values as those seen in Kober et al. (2015), although this could be due to the fact that they investigated individual case studies which were specifically selected to test the impact of the stochastic scheme, whereas 15 our results are scores averaged over an extended period.

In general, then, the schemes perform similarly overall, and the impact of using a stochastic scheme on the FSS is modest. Indeed, the fact that there is no skill for the highest threshold, for either scheme, is more important. This lack of skill could be simply due to the fact that the case study period was too short to obtain a statistically significant sample of extreme rain events. However, it is also true that MOGREPS

20 cally significant sample of extreme rain events. However, it is also true that MOGREP significantly overforecasts heavy rain over the UK for this period (see Fig. 10).

3.1.1 Separation into weakly- and strongly-forced cases

Figure 4 shows the difference in FSS between PC and GR, for forecasts separated into weakly- and strongly-forced cases, as described in Sect. 2. It can be seen that, with no averaging, PC is better for the smallest thresholds but worse for the moderate



thresholds, while with upscaling this becomes less dependent on threshold, as was seen in Figs. 2 and 3.

PC generally performs better than GR for weakly-forced cases, and worse for strongly-forced cases. While both schemes benefit from upscaling the score, this ben-⁵ efit is greater for PC. The results agree well with those of Kober et al. (2015) for two example cases, where the Plant–Craig scheme benefits more from the upscaling than the non-stochastic scheme, and performs relatively better for the weakly-forced than for the strongly-forced case. Note that the upscaling required for the Plant–Craig scheme to show better results is a function of number of grid boxes and rather independent of the actual physical scale – the PC scheme works on the scale of the grid box, whatever that may be, and the key is to average over a sufficient number of calls to the scheme. Moreover, it is clear that the upscaling is more beneficial to the PC scheme (relative

to the GR scheme) for the weakly-forced cases than for the strongly-forced cases. The interpretation is that the PC scheme provides a better statistical description of smallscale, weakly-forced convection than a non-stochastic scheme. This will not provide any improvement to the FSS evaluated at the grid scale, since the convection is placed randomly, but it does improve the FSS when it is evaluated over a neighbourhood of grid points, so that it becomes a more statistical evaluation of the guality of the scheme.

3.2 Brier score

The quality of the probabilistic forecasts is assessed using Brier skill scores, plotted in Fig. 5. While neither scheme has skill for high thresholds, PC performs substantially better for medium and low thresholds, for all lead times. In particular, PC has skill in predicting whether or not rain will occur (zero threshold), while GR does not. Further analysis shows that this is also the case for thresholds between 0 and 0.05 (not shown).



3.2.1 Separation into weakly- and strongly-forced cases

Figure 6 shows the Brier skill scores as a function of threshold, separated into stronglyand weakly-forced cases. The forecasts are improved using PC for both sets of cases, and the difference is considerably greater for weakly-forced cases, where GR has al-

⁵ most no skill. This can be interpreted in terms of the fact that small-scale variability is relatively more important for the weakly-forced cases, and ensemble members using the Plant–Craig scheme differ from each other more than for the strongly-forced cases, where initial and boundary condition variability is relatively more important (Groene-meijer and Craig, 2012). Our result is similar to what was found by Kober et al. (2015),
¹⁰ where the Plant–Craig scheme was found to perform better than a non-stochastic scheme for a weakly-forced case, and at low thresholds, but worse than the non-stochastic Tiedtke (1989) scheme for a strongly-forced case.

3.3 Ensemble added value (EAV)

The EAV is plotted in Fig. 7. The PC scheme performs substantially better for this score across lead times, and the improvement is of a similar magnitude to that of the Brier score. This suggests that the improvement in the probabilistic forecast from using PC comes from the stochasticity of the scheme, since the EAV is measured against individual forecasts from the same ensemble and should, therefore, be "normalized" against differences in the underlying convection scheme which are not related to the

stochasticity. The interpretation here is that while structural differences between two convection schemes will lead to differences in the quality of the ensemble forecasts, this will mainly be due to differences in the quality of individual members of the ensemble. The stochastic character of the PC scheme may or may not improve the quality of the individual members, but it is primarily designed to improve the quality of the ensemble as a whole.

Note that the ensemble forecasts using the GR scheme also have a positive EAV, representing the value added by the multiple initial and boundary conditions provided



by the global model, and by the stochasticity coming from the random parameters scheme. Since these factors are also present in the ensemble forecasts using the PC scheme, it can be interpreted that the fractional difference between the two EAVs represents the value added by the stochastic character of the PC scheme as a fraction of the value added by all the ensemble generation techniques in MOGREPS.

Ben Bouallègue (2015) suggests that the resolution component of a skill score represents a more fundamental assessment of its quality than the reliability, as the latter can be reduced to zero by applying statistical calibration to the forecast. Therefore, because the EAV is based on the resolution component of the quantile score, the fact that the

¹⁰ PC scheme improves this quantity provides some evidence that it improves the forecast beyond what could be achieved by a simple statistical calibration or downscaling of the forecast.

3.4 General climatology

Although Nimrod radar observations were only available over a restricted part of the forecast domain, it is also of interest to compare the forecasts over the whole domain. Figure 8 shows the convective fraction (that is, the amount of rainfall which came from the convection scheme divided by the total amount of rain from the convection scheme and grid-scale precipitation). Both schemes produce more convective rain over land, and the difference between the fractions over land and sea is in proportion to the frac-

tion over the whole domain; the fractions are fairly constant with forecast lead time. As discussed in Sect. 2.1, the convective fraction is much lower for PC than for GR, suggesting that adjusting parameters to increase this fraction would further increase the PC influence on the forecast (for example, Groenemeijer and Craig, 2012, used a reduced closure time scale to increase the activity of the PC scheme), although it is important to reiterate that there is no correct value for the convective fraction.

The ensemble spread is shown as a function of lead time in Fig. 9, over the whole domain and separately over land and over ocean. Both schemes produce more spread over land, but the difference between PC and GR is also much greater over land. This



is presumably due to the fact that PC has a higher convective fraction over land, and is therefore more able to influence the spread. The spread increases with forecast lead time, and does so more quickly with PC than with GR.

Figure 10 shows density plots of rainfall from the two schemes, and from the observations, over the UK part of the domain. It is clear that the model produces too many instances of heavy rainfall for this period, and that this is exacerbated by the extra variability introduced by the PC scheme. However, as shown earlier in this Section, neither scheme has any skill for large thresholds, and it is clear from Fig. 10 that this is due to over-production of heavy rain.

Figure 11 shows that the PC scheme also produces more heavy rainfall than the GR scheme over ocean. This suggests that one possible approach to tuning the PC scheme could be to apply less input averaging over the ocean, since Keane et al. (2014) have shown that applying more input averaging increases the variability and, therefore, the tails of the distribution.

¹⁵ Although a lead time of 30 to 36 h was chosen for Figs. 10 and 11, similar conclusions could be drawn for the plots for other lead times (not shown). The exception to this statement is that for the first 6 h, for which the forecasts had not developed sufficiently for the curves to lie significantly apart from each other.

3.4.1 Verification over the whole NAE domain

- Routine verification was also performed for the two setups, covering land areas over the whole forecast domain. This calculates various forecast skill scores, by comparing against SYNOP observations at the surface and at a height of 850 hPa, and yielded a mixed assessment of the performance of the PC scheme against the GR scheme. For example, the continuous ranked probability score, which assesses both the fore-
- cast error and how well the ensemble spread predicts the error (Hersbach, 2000), was improved by roughly 10% on using the PC scheme for rainfall, but degraded by about 10% for temperature and pressure. The impact on the wind forecast was broadly neutral.



This shows that, while the improvements demonstrated in this Section hold for other areas outside the UK, this has come at a cost to the quality of the forecast for some of the other variables. An important advantage of using a stochastic convection scheme, over a statistical downscaling procedure, is its feedback on the rest of the model, and it is important that this feedback is of benefit. The recent analysis by Selz and Craig (2015a) is very encouraging in this regard, demonstrating the processes of upscale error growth from convective uncertainties can be well reproduced by the PC scheme, in good agreement with the behaviour of large-domain simulations in which the convection is simulated explicitly Selz and Craig (2015b).

10 4 Conclusions

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A physically-based stochastic scheme for the parameterization of deep convection has been evaluated by comparing probabilistic rainfall forecasts produced using the scheme in an operational ensemble system with those from the same ensemble system with its standard deep convection parameterization. The impact of using a stochastic scheme on deterministic forecasts is broadly neutral, although there is some improvement when larger areas are assessed. This is relevant to applications such as hydrology, where rainfall over an area larger than a grid box can be more relevant than rainfall on the grid box scale.

The Plant–Craig scheme has been shown to have a positive impact on probabilistic
forecasts for light and medium rainfall, while neither scheme is able to skillfully forecast heavy rainfall. The impact of the scheme is greater for weakly-forced cases, where subgrid-scale variability is more important. Keil et al. (2014) studied a convection-permitting ensemble without stochastic physics, and found that deterministic forecast skill was poorer during weak than during strong forcing conditions. They developed a convective adjustment time-scale to measure the strength of the forcing conditions. This quantity can be calculated from model variables and could therefore be used in advance to determine how predictable the convective response will be for a given



forecast. This could potentially be useful in an adaptive ensemble system using two convection parameterizations (see, for example, Marsigli et al., 2005), one of which is stochastic and is better suited to providing an estimate of the uncertainty in weaker forcing cases.

- Although the Plant–Craig scheme clearly produces improved probabilistic forecasts, it is not certain whether this is due to its stochasticity, or to different underlying assumptions between it and the standard convection scheme. In order to make a clean distinction, further studies could be performed in which the performance of the Plant– Craig scheme is compared against its own non-stochastic counterpart, which can be
- ¹⁰ constructed by using the full cloud distribution and appropriately normalizing, instead of sampling randomly from it (cf. Keane et al., 2014). Nonetheless, the results from applying the recently-developed ensemble added value metric do provide some relevant information for this question. This metric aims to assess the quality of the ensemble in relation to the underlying member forecasts, and the Plant–Craig scheme has been
- shown to increase it. This indicates that the stochastic aspect of the scheme can increase the value added to a forecast by using an ensemble, since other aspects of the scheme would be expected (broadly) to affect the performance of the ensemble as a whole, and of the individual members, equally.

The results of this study justify further work to investigate the impact of the Plant– ²⁰ Craig scheme on ensemble forecasts. Since the version of MOGREPS used in this study has been superseded, it is not feasible to carry out more a more detailed investigation beyond the proof-of-concept carried out in the present study. Interestingly, the resolution used in this study is now becoming more widely used in global ensemble forecasting, and so future work could involve implementing the scheme in a global

NWP system, for example the global version of MOGREPS. This would enable assessments to be made as to whether the scheme provides benefits for the representation of tropical convection, in addition to those aspects of mid-latitude convection that were demonstrated here.



Code availability

The source code for the Plant–Craig parameterization, as it was used in this study, can be made available on request, by contacting r.s.plant@reading.ac.uk.

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References

10

- Abhilash, S., Sahai, A. K., Pattnaik, S., Goswami, B. N., and Kumar, A.: Extended range prediction of active-break spells of Indian summer monsoon rainfall using an ensemble prediction system in NCEP Climate Forecast System, Int. J. Climatol., 34, 98–113, doi:10.1002/joc.3668, 2013. 10200
- Ball, M. A. and Plant, R. S.: Comparison of stochastic parameterization approaches in a singlecolumn model, Philos. T. Roy. Soc. A, 366, 2605–2623, 2008. 10202

Bechtold, P.: Convection in global numerical weather prediction, in: Parameterization of Atmospheric Convection, Volume 2: Current Issues and New Theories, edited by: Plant, R. S., and

- spheric Convection, Volume 2: Current Issues and New Theories, edited by: Plant, R. S., and Yano, J.-I., World Scientific, Imperial College Press, New Jersey, USA, 5–45, 2015. 10204 Ben Bouallègue, Z.: Assessment and added value estimation of an ensemble approach with a focus on global radiation, Mausam, Q. J. Meteor. Hydrol. Geophys., 66, 541–550, 2015. 10208, 10214
- Bengtsson, L., Steinheimer, M., Bechtold, P., and Geleyn, J.-F.: A stochastic parametrization for deep convection using cellular automata, Q. J. Roy. Meteor. Soc., 139, 1533–1543, doi:10.1002/qj.2108, 2013. 10201
 - Bentzien, S. and Friederichs, P.: Decomposition and graphical portrayal of the quantile score, Q. J. Roy. Meteor. Soc., 140, 1924–1934, doi:10.1002/qj.2284, 2014. 10209
- Berner, J., Ha, S.-Y., Hacker, J. P., Fournier, A., and Snyder, C.: Model uncertainty in a mesoscale ensemble prediction system: stochastic versus multiphysics representations, Mon. Weather Rev., 139, 1972–1995, doi:10.1175/2010MWR3595.1, 2011. 10201



Bouttier, F., Vié, B., Nuissier, O., and Raynaud, L.: Impact of stochastic physics in a convection-permitting ensemble, Mon. Weather Rev., 140, 3706–3721, doi:10.1175/MWR-D-12-00031.1, 2012. 10201

Bowler, N. E., Arribas, A., Mylne, K. R., Robertson, K. B., and Beare, S. E.: The MOGREPS

- short-range ensemble prediction system, Q. J. Roy. Meteor. Soc., 134, 703–722, 2008. 10200, 10201, 10205
 - Buizza, R., Miller, M., and Palmer, T. N.: Stochastic representation of model uncertainties in the ECMWF Ensemble Prediction System, Q. J. Roy. Meteor. Soc., 125, 2887–2908, 1999. 10201
- ¹⁰ Buizza, R., Houtekamer, P. L., Toth, Z., Pellerin, G., Wei, M., and Zhu, Y.: A comparison of the ECMWF, MSC, and NCEP global ensemble prediction systems, Mon. Weather Rev., 133, 1076–1097, 2005. 10200
 - Buizza, R., Bidlot, J.-R., Wedi, N., Fuentes, M., Hamrud, M., Holt, G., and Vitart, F.: The new ECMWF VAREPS (Variable Resolution Ensemble Prediction System), Q. J. Roy. Meteor.
- ¹⁵ Soc., 133, 681–695, doi:10.1002/qj.75, 2007. 10200

30

- Clark, A. J., Kain, J. S., Stensrud, D. J., Xue, M., Kong, F., Coniglio, M. C., Thomas, K. W., Wang, Y., Brewster, K., Gao, J., Wang, X., Weiss, S. J., and Du, J.: Probabilistic precipitation forecast skill as a function of ensemble size and spatial scale in a convection-allowing ensemble, Mon. Weather Rev., 139, 1410–1418, doi:10.1175/2010MWR3624.1, 2011. 10200
- Davies, L., Jakob, C., Cheung, K., Genio, A. D., Hill, A., Hume, T., Keane, R. J., Komori, T., Larson, V. E., Lin, Y., Liu, X., Nielsen, B. J., Petch, J., Plant, R. S., Singh, M. S., Shi, X., Song, X., Wang, W., Whitall, M. A., Wolf, A., Xie, S., and Zhang, G.: A single-column model ensemble approach applied to the TWP-ICE experiment, J. Geophys. Res., 118, 6544–6563, 2013. 10202
- ²⁵ Davies, T., Cullen, M. J. P., Malcolm, A. J., Mawson, M. H., Staniforth, A., White, A. A., and Wood, N.: A new dynamical core for the Met Office's global and regional modelling of the atmosphere, Q. J. Roy. Meteor. Soc., 131, 1759–1782, 2005. 10205
 - Ebert, E. E., Damrath, U., Wergen, W., and Baldwin, M. E.: The WGNE assessment of short-term quantitative precipitation forecasts, B. Am. Meteorol. Soc., 84, 481–492, doi:10.1175/BAMS-84-4-481. 2003. 10200
 - Eden, P.: July 2009, A hot start, then very unsettled with several heavy falls of rain, Weather, 64, i–iv, doi:10.1002/wea.496, 2009. 10210, 10211

Gebhardt, C., Theis, S., Paulat, M., and Ben Bouallègue, Z.: Uncertainties in COSMO-DE precipitation forecasts introduced by model perturbations and variation of lateral boundaries, Atmos. Res., 100, 168–177, doi:10.1016/j.atmosres.2010.12.008, 2011. 10200

Gneiting, T.: Making and evaluating point forecasts, J. Am. Stat. Assoc., 106, 746–762, doi:10.1198/jasa.2011.r10138, 2011. 10208

5

30

Gregory, D. and Rowntree, P. R.: A mass flux convection scheme with representation of cloud ensemble characteristics and stability-dependent closure, Mon. Weather Rev., 118, 1483–1506, 1990. 10202, 10205

Groenemeijer, P. and Craig, G. C.: Ensemble forecasting with a stochastic convective parametrization based on equilibrium statistics, Atmos. Chem. Phys., 12, 4555–4565,

- doi:10.5194/acp-12-4555-2012, 2012. 10202, 10204, 10209, 10213, 10214
 Harrison, D. L., Driscoll, S. J., and Kitchen, M.: Improving precipitation estimates from weather radar using quality control and correction techniques, Meteorol. Appl., 7, 135–144,
- doi:10.1017/S1350482700001468, 2000. 10206
 ¹⁵ Hersbach, H.: Decomposition of the Continuous Ranked Probability Score for Ensemble Prediction Systems, Weather Forecast., 15, 559–570, doi:10.1175/1520-0434(2000)015<0559:DOTCRP>2.0.CO;2, 2000. 10215
 - Kain, J. S.: The Kain–Fritsch convective parameterization: an update, J. Appl. Meteorol., 43, 170–181, 2004. 10203
- Kain, J. S. and Fritsch, J. M.: A one-dimensional entraining/detraining plume model and its application in convective parameterization, J. Atmos. Sci., 47, 2784–2802, 1990. 10203
 - Keane, R. J. and Plant, R. S.: Large-scale length and time-scales for use with stochastic convective parametrization, Q. J. Roy. Meteor. Soc., 138, 1150–1164, doi:10.1002/qj.992, 2012. 10201, 10203, 10204
- Keane, R. J., Craig, G. C., Zängl, G., and Keil, C.: The Plant–Craig stochastic convection scheme in ICON and its scale adaptivity, J. Atmos. Sci., 71, 3404–3415, doi:10.1175/JAS-D-13-0331.1, 2014. 10201, 10215, 10217
 - Keil, C., Heinlein, F., and Craig, G. C.: The convective adjustment time-scale as indicator of predictability of convective precipitation, Q. J. Roy. Meteor. Soc., 140, 480–490, doi:10.1002/gj.2143, 2014. 10210, 10216
 - Khouider, B., Biello, J., and Majda, A. J.: A stochastic multicloud model for tropical convection, Commun. Math. Sci., 8, 187–216, 2010. 10201

- Kober, K., Foerster, A. M., and Craig, G. C.: Evaluation of a stochastic and deterministic convection parameterization in the COSMO model, Mon. Weather Rev., 143, 4088–4103, doi:10.1175/MWR-D-15-0012.1, 2015. 10201, 10202, 10207, 10210, 10211, 10212, 10213
 Koenker, R. and Machado, J. A. F.: Goodness of fit and related inference processes for guan-
- tile regression, J. Am. Stat. Assoc., 94, 1296–1310, doi:10.1080/01621459.1999.10473882, 1999. 10208
 - Lean, H. W., Clark, P. A., Dixon, M., Roberts, N. M., Fitch, A., Forbes, R., and Halliwell, C.: Characteristics of high-resolution versions of the Met Office Unified Model for forecasting convection over the United Kingdom, Mon. Weather Rev., 136, 3408–3424, doi:10.1175/2008MWR2332.1. 2008. 10203
- Lin, J. W.-B. and Neelin, J. D.: Toward stochastic deep convective parameterization in general circulation models, Geophys. Res. Lett., 30, 11, doi:10.1029/2002GL016203, 2003. 10201
 Marsigli, C., Boccanera, F., Montani, A., and Paccagnella, T.: The COSMO-LEPS mesoscale ensemble system: validation of the methodology and verification, Nonlin. Processes Geophys., 12, 527–536, doi:10.5194/npg-12-527-2005, 2005, 10217

10

- Martin, G. M., Ringer, M. A., Pope, V. D., Jones, A., Dearden, C., and Hinton, T. J.: The physical properties of the atmosphere in the new Hadley Centre Global Environmental Model (HadGEM1), Part I: Model description and global climatology, J. Climate, 19, 1274–1301, doi:10.1175/JCLI3636.1, 2006. 10205
- ²⁰ Mishra, A. and Krishnamurti, T.: Current status of multimodel superensemble and operational NWP forecast of the Indian summer monsoon, J. Earth Syst. Sci., 116, 369–384, doi:10.1007/s12040-007-0037-z, 2007. 10201
 - Montani, A., Cesari, D., Marsigli, C., and Paccagnella, T.: Seven years of activity in the field of mesoscale ensemble forecasting by the COSMO-LEPS system: main achievements
- ²⁵ and open challenges, Tellus A, 63, 605–624, doi:10.1111/j.1600-0870.2010.00499.x, 2011. 10200
 - Plant, R. S. and Craig, G. C.: A stochastic parameterization for deep convection based on equilibrium statistics, J. Atmos. Sci., 65, 87–105, 2008. 10201, 10203, 10204
 - Plant, R. S., Bengtsson, L., and Whitall, M. A.: Stochastic aspects of convective parameteri-
- zation, in: Parameterization of Atmospheric Convection, Volume 2: Current Issues and New Theories, edited by: Plant, R. S., and Yano, J.-I., World Scientific, Imperial College Press, New Jersey, USA, 135–172, 2015. 10201

- 10222
- 1-12. doi:10.1007/s13351-012-0101-8. 2012. 10200 Zhu, Y.: Ensemble forecast: a new approach to uncertainty and predictability, Adv. Atmos. Sci., 22. 781-788. doi:10.1007/BF02918678. 2005. 10200
- Wilks, D.: Statistical Methods in the Atmospheric Sciences: An Introduction, International Geophysics Series, Elsevier Academic Press, 2006. 10207 Yang, C., Yan, Z., and Shao, Y.: Probabilistic precipitation forecasting based on ensemble output

using generalized additive models and Bayesian model averaging, Acta Meteorol. Sin., 26,

- in large-scale models, Mon. Weather Rev., 117, 1779-1800, doi:10.1175/1520-0493(1989)117<1779:ACMFSF>2.0.CO;2, 1989. 10213 Wetterzentrale: UK Met Office surface analysis, available at: http://www.wetterzentrale.de/ topkarten/fsfaxbra.html, last access: 12 November 2014, 2009. 10210
- drological ensemble forecasts over France, Atmos. Sci. Lett., 11, 72-77, doi:10.1002/asl.254, 2010. 10200 Tiedtke, M.: A comprehensive mass flux scheme for cumulus parameterization
- Tennant, W. and Beare, S.: New schemes to perturb sea-surface temperature and soil moisture 15 content in MOGREPS, Q. J. Roy. Meteor. Soc., 140, 1150–1160, doi:10.1002/gi.2202, 2013. 10200, 10202 Thirel, G., Regimbeau, F., Martin, E., Noilhan, J., and Habets, F.: Short- and medium-range hy-
- Smith, R. N. B., Blyth, E. M., Finch, J. W., Goodchild, S., Hall, R. L., and Madry, S.: Soil state and surface hydrology diagnosis based on MOSES in the Met Office Nimrod nowcasting system, Meteorol, Appl., 13, 89–109, doi:10.1017/S1350482705002069, 2006, 10206
- scheme, Geophys. Res. Lett., 42, 3056–3062, doi:10.1002/2015GL063525, 2015a. 10216 Selz, T. and Craig, G. C.: Upscale error growth in a high-resolution simulation of a summertime 10 weather event over Europe, Mon. Weather Rev., 143, 813-827, 2015b. 10216
- resolution forecasts of convective events, Mon. Weather Rev., 136, 78-97, 2008. 10207 5 Roy Bhowmik, S. K., and Durai, V. R.: Multi-model ensemble forecasting of rainfall over Indian monsoon region, Atmósfera, 21, 225-239, 2008. 10200

Soc., 141, 37-51, doi:10.1002/gj.2331, 2014. 10201

20

25

30

- Selz, T. and Craig, G. C.: Simulation of upscale error growth with a stochastic convection

Ragone, F., Fraedrich, K., Borth, H., and Lunkeit, F.: Coupling a minimal stochastic lattice gas

model of a cloud system to an atmospheric general circulation model, Q. J. Roy. Meteor.

Roberts, N. M. and Lean, H. W.: Scale-selective verification of rainfall accumulations from high-

Discussion

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The Plant–Craig scheme in an ensemble system

R. J. Keane et al.

Table 1. Locations of the north pole and the corners of the domain of the NAE rotated grid, in terms of real latitude and longitude.

Location	latitude (° N)	longitude (° E)
north pole	37.5	177.5
bottom-left	16.3	-19.8
top-left	72.7	-80.0
bottom-right	16.5	14.2
top-right	73.2	74.1

Table 2. Start times of forecasts investigated in this study (all dates in July 2009).

10 Jul, 18:00 UTC	16 Jul, 18:00 UTC	21 Jul, 06:00 UTC	27 Jul, 18:00 UTC
11 Jul, 06:00 UTC	17 Jul, 06:00 UTC	21 Jul, 18:00 UTC	28 Jul, 06:00 UTC
11 Jul, 18:00 UTC	17 Jul, 18:00 UTC	22 Jul, 06:00 UTC	28 Jul, 18:00 UTC
12 Jul, 06:00 UTC	18 Jul, 06:00 UTC	23 Jul, 06:00 UTC	29 Jul, 06:00 UTC
12 Jul, 18:00 UTC	18 Jul, 18:00 UTC	23 Jul, 18:00 UTC	29 Jul, 18:00 UTC
13 Jul, 06:00 UTC	19 Jul, 06:00 UTC	24 Jul, 18:00 UTC	30 Jul, 06:00 UTC
14 Jul, 06:00 UTC	19 Jul, 18:00 UTC	25 Jul, 06:00 UTC	30 Jul, 18:00 UTC
15 Jul, 18:00 UTC	20 Jul, 06:00 UTC	25 Jul, 18:00 UTC	
16 Jul, 06:00 UTC	20 Jul, 18:00 UTC	26 Jul, 06:00 UTC	

Table 3. Categorization of 12 h periods (centred at the time given) investigated in this study, into weak and strong synoptic forcing (all dates in July 2009).

10 Jul, 00:00 UTC Weak	17 Jul, 12:00 UTC Strong	25 Jul, 00:00 UTC Weak
10 Jul, 12:00 UTC Strong	18 Jul, 00:00 UTC Strong	25 Jul, 12:00 UTC Weak
11 Jul, 00:00 UTC Strong	18 Jul, 12:00 UTC Weak	26 Jul, 00:00 UTC Strong
11 Jul, 12:00 UTC Strong	19 Jul, 00:00 UTC Strong	26 Jul, 12:00 UTC Strong
12 Jul, 00:00 UTC Strong	19 Jul, 12:00 UTC Weak	27 Jul, 00:00 UTC Strong
12 Jul, 12:00 UTC Strong	20 Jul, 00:00 UTC Weak	27 Jul, 12:00 UTC Weak
13 Jul, 00:00 UTC Weak	20 Jul, 12:00 UTC Weak	28 Jul, 00:00 UTC Strong
13 Jul, 12:00 UTC Weak	21 Jul, 00:00 UTC Strong	28 Jul, 12:00 UTC Strong
14 Jul, 00:00 UTC Strong	21 Jul, 12:00 UTC Strong	29 Jul, 00:00 UTC Strong
14 Jul, 12:00 UTC Strong	22 Jul, 00:00 UTC Strong	29 Jul, 12:00 UTC Strong
15 Jul, 00:00 UTC Weak	22 Jul, 12:00 UTC Strong	30 Jul, 00:00 UTC Weak
15 Jul, 12:00 UTC Weak	23 Jul, 00:00 UTC Weak	30 Jul, 12:00 UTC Weak
16 Jul, 00:00 UTC Weak	23 Jul, 12:00 UTC Weak	31 Jul, 00:00 UTC Weak
16 Jul, 12:00 UTC Weak	24 Jul, 00:00 UTC Weak	31 Jul, 12:00 UTC Strong
17 Jul, 00:00 UTC Strong	24 Jul, 12:00 UTC Weak	

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Figure 2. Fractions skill score computed for grid-scale data for the Gregory-Rowntree scheme (top), the Plant-Craig scheme (centre) and the difference between the two schemes (bottom).

Figure 3. Fractions skill score for the Gregory-Rowntree scheme (top), the Plant-Craig scheme (centre) and the difference between the two schemes (bottom). The neighbourhood area is (120 km)², corresponding to the central grid box and two grid boxes in each direction.

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Figure 4. Fractions skill score for the Plant–Craig scheme, minus that for the Gregory– Rowntree scheme, for strongly forced cases (full lines) and weakly forced cases (dashed lines), with no averaging (top), with a neighbourhood area of two grid boxes in each direction (centre) and with a neighbourhood area of four grid boxes in each direction (bottom). The score shown is the average over all lead times.

Figure 5. Brier skill score for the Gregory-Rowntree scheme (top), the Plant-Craig scheme (centre) and the difference between the two schemes (bottom). For the difference plot, instances where both skill scores are lower than zero are not plotted.

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Figure 6. Brier skill score for the Gregory–Rowntree scheme (green lines) and the Plant–Craig scheme (red lines), averaged over all lead times, for cases with strong forcing (full lines) and weak forcing (dashed lines), as a function of threshold. The axes have been chosen to focus on where the skill score is above zero.

Figure 7. Ensemble added value (EAV) for the Gregory-Rowntree scheme (green line) and the Plant-Craig scheme (red line) as a function of forecast lead time.

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