The elicitation of distributions of parameters in HadGEM3 versions GA4 and GA7 for use in perturbed parameter ensembles

Hadley Centre Technical Note 101

David M. H. Sexton[1], Ambarish Karmalkar[1 now at 2], James Murphy[1], Ben Booth[1], Leighton Regayre[3], Jill Johnson[3]

[1] Hadley Centre, Met Office, UK

[2] Northeast Climate Science Center, and Department of Geosciences, University of Massachusetts Amherst, Amherst Massachusetts, USA

[3]Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds

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1. **Introduction**

Climate models are imperfect representations of the real climate system either due to limitations in our understanding or because the processes are either approximated or not represented at all. This means that there is uncertainty about the way in which climate models simulate the responses to any given scenario of concentrations of radiatively-active species like greenhouse gases and aerosols. This ”modelling” uncertainty can be sampled by collections of climate simulations which typically fall into one of two types. The first type is the multimodel ensemble which samples so-called ”structural” modelling uncertainty that arises from variations in the way the different international climate centres construct their models to approximate the real system. One use of multimodel ensembles is to find emergent relationships between climate variables that can be observed and ones that we want to predict e.g. Hall and Qu (2006). However, the multimodel ensemble is not designed, so there are a many ad hoc differences between the ensemble members, and it is often hard to determine what is driving the variations across the ensemble. In contrast, the second type is the perturbed parameter ensemble (PPEs), which is based on a single model and only samples modelling uncertainty related to the fact that there is a range of plausible values for each of the model parameters that control the strength of processes unresolved at the grid scale. PPEs have been found to under-represent the structural uncertainty (Yokohata et al, 2013) but the extent to which this happens can vary with the underlying model and choice of parameters. For instance, PPEs based on HadCM3 explore a reasonably large fraction of the multimodel range for several variables (Collins et al, 2011) whilst one based on NCAR only sampled a narrow range of climate sensitivities (Sanderson, 2011). However, PPEs are designed and can be used to estimate the sensitivity of a variable to each parameter (Lee et al, 2013). Therefore, the strengths and limitations of these two types of ensemble nicely complement each other, and there are benefits in synthesising information from both ensembles (Sexton et al, 2012).

PPEs have been applied to a wide range of simulators from different scientific fields, and are often used to focus on understanding a particular feature of the mode. An example of this in Climate Science is by Carslaw et al (2013) targeted their PPE to explore the sensitivity of the indirect aerosol forcing to parameters in an aerosol model. However, the original PPE with a climate model (Murphy et al, 2004) was used to sample responses for a wide range of variables in HadCM3, so that it could be used to underpin climate projections e.g. the 2009 UK Climate Projections (UKCP09; Murphy et al (2009)). Here, we aim to generate PPEs for the current family of Hadley Centre climate models, called HadGEM3. These PPEs will also be used to underpin climate projections for a range of variables for different worldwide regions.

The application of the PPE to some extent determines the choice of parameters to be perturbed. Here, we describe the elicitation process involving experts to identify these parameters and their plausible ranges for two versions of the HadGEM3 climate model - GA4 with the 5A GWD scheme (Walters et al, 2017), and GA7. Although these two model versions come under the umbrella term HadGEM3, there has been a lot of model development from GA4 to GA7, most notably upgrades to a new dynamic core, ENDGAME, the PC2 cloud scheme, and the UKCA-MODE aerosol scheme. Despite this many of the parameters are common to both model versions, and it is advantageous to document both elicitations together, especially as the GA7 one benefitted from lessons learnt with GA4.

In section 2, we list and describe the parameters to perturb, present their plausible ranges, and describe the process to elicit this information from the parameterisation experts. Sections 3 and 5 show the final parameter distributions and section 4 and 6 describe the parameters in GA4 and GA7 scheme by scheme.

Please note that the distributions are only plotted here. The precise definitions can be requested from David Sexton (david.sexton@metoffice.gov.uk) or John Rostron (john.rostron@metoffice.gov.uk) and are available in CSV files which can easily be viewed as spreadsheets. This is done to minimise errors in copying the definitions and has the added advantage that the CSV files also store the parameter perturbations used for the GA4 and GA7 ensembles.

2. The elicitation process

Elicitation is the process of capturing expert knowledge about one or more uncertain quantities, either as a plausible range or more typically a probability distribution. Statisticians, who practise elicitation to analyse uncertainties in the output of simulators, generally have no prior expertise in the simulators themselves. Here we provide insights from the perspective of climate scientists who have adopted best practice advocated by the statisticians but who have a deeper understanding of the simulator and the science that surrounds it. We also had the benefit of experience from the elicitation of parameters to perturb in HadSM3 from Murphy et al (2004).

We used an off the shelf package called The SHeffied ELicitation Framework (SHELF; Oakley, J. E., O' Hagan (2010)), designed for formally eliciting probability distributions, as our guide to best practice. The SHELF process involves identifying the simulator (climate model in our case) and the parameterisation experts, pre-brief the experts about their role in the elicitation process, and finally interviewing the experts to find out the required information. We ran a workshop in June 2012 to inform the experts of our initial project plans with the GA4 model version, and to explain the elicitation exercise and guidelines. The key guidelines focussed on how to select which parameters to perturb, their plausible range, and the associated probability distributions. The interview process that followed was expedited by providing a pro forma to be completed in advance of the interview. This asked for information on the role of the parameter, its signature effect in the model, any explicit resolution dependence, and any relevant references. Some of this is presented in Tables 1 and 2. SHELF also allows for the elicitation to be completed after the meeting as long as the experts understand what is required of them and have experience with one example of a parameter already. There were a couple of aspects of SHELF that we did not use. First, SHELF requires specification of a set of the simulator outputs, whereas our elicitation is aimed at parametric uncertainty that could be related to a wide variety of historic and future model outputs. These outputs cannot be precisely specified in advance as we are interested in understanding a wide range of regional biases, responses and feedbacks for multiple climate variables. Secondly, we did not use the SHELF software which enables the distributions to be updated live during the meeting according to the experts' judgement. This was mainly because our previous experience suggested that most climate modelling experts lack evidence for complexity, and are comfortable with simpler probability distributions. However, for some parameters there was a need for more complex distributions (see section 2.3), which were determined through more detailed discussions with the parameterisation experts.

2.1 Selection of parameters to perturb

It is not feasible to perturb all the parameters in a climate model, and statistical methods for exploiting PPEs require the ensemble size to be at least several times the number of parameters. Therefore, we produced a set of guidelines adapted from SHELF to help the experts prioritise the key parameters to perturb. We suggested splitting the atmosphere model into the main schemes and the experts suggested five for this trial: gravity wave drag

(GWD), convection, boundary layer (BL), microphysics, clouds/radiation, land and surface, and aerosol. Within a scheme, we asked the experts to identify a few key parameters. Only the first five schemes were explored in GA4 (Walters et al, 2014). As explained in section 1, the potential uses for this PPE are wide ranging so we advocated that the experts consider the key complementary processes and pick a parameter that represents each process.

Both the aerosol and land surface schemes have already undergone systematic PPE-based sensitivity analysis. Lee et al (2013) and Carslaw et al (2013) perturbed the GLOMAP aerosol scheme to investigate the sensitivity of indirect aerosol forcing. The GLOMAP model is the basis of the UKCA-MODE aerosol in HadGEM3 GA7, with differences arising from the way the aerosol scheme has been adapted to integrate it into the HadGEM3 model. Sensitivity analyses based on PPEs have been done for the JULES land surface scheme but these have been focussed on a few global mean variables. However, because of our focus on worldwide regions and many climate variables, we emphasised the importance of considering complementary processes.

2.2 Plausible ranges

To elicit the plausible range for each parameter, the most important aspect is to explain to the experts that the simulations will be evaluated against a wide range of observational metrics so that so that (i) PPE members can be ruled out as implausible and (ii) the final uncertainty quantification can be based on constrained parameter ranges. During the elicitation exercise, results from Williamson et al (2013) and Sexton et al (2012) to show how these could be achieved. The latter provides an example of a constraint on the entrainment rate, where multi-annual means of several climate variables constrained the original range of 0.6 - 9 down to roughly 2 - 5. This example was used to encourage the experts to avoid suggesting overly narrow ranges, with the reassurance that the ranges could be constrained a posteriori using observations. We advised the experts to base their ranges on their own sensitivity analyses, theoretical understanding, or empirical evidence excluding any knowledge they had of the effects of the parameters in climate simulations. Consequently many parameter ranges were based on the experts' own analyses of very high resolution process models such as Large Eddy Simulations or Cloud Resolving Models. These process studies cover a range of regional analyses revealing a wide variation in values for the parameter under discussion. However, we were specifically interested in a global number as used in a climate model, that represented average behaviour over a range of regional scenarios. In practice, it is very difficult for an expert to be able to make the distinction between a range of global values and the range of values from their regional sensitivity analyses, some of which can be extreme. Therefore, for some of the parameters, the expert ranges will reflect parametric uncertainty that falls somewhere between the two cases, potentially making the ranges wider than they should be for a global number. However, this is not a problem as observations will be used to screen out or downweight parts of parameter space. For GA7, we added a new guideline that we are interested in globally representative parameter values.

2.3 Prior probability distributions

For the probability distributions (see Fig. 1), we explained that once a range (X, Y) has been established for the parameter, it is not simply of specifying a uniform distribution U(X, Y). Such distributions are criticised for the instantaneous jump in probability from zero to a non-zero value either at X or Y, and a steady reduction to zero probability at X or Y is favoured. An exception is made where X or Y are at some physical limit, where an immediate drop to zero probability is justified. In Sexton et al (2012), trapezoidal distributions were used, and these were often used by the experts.

Not all distributions were straightforward to elicit, and the longer discussions generally focussed around distributions which were highly asymmetric about the value used in the standard (unperturbed) version of the model. Using a trapezoidal distribution in such a case places a large fraction of the samples to one side of the standard value, and in several cases the experts were not comfortable with this. We then discussed whether the parameter uncertainty was seen in terms of a multiplicative factor which should have a mode around the standard value or the possibility of using distributions based on log(parameter). Using logarithms did not work well as the experts considered the resultant distributions to be overly skewed towards lower values. We also tried beta distributions, which are part of the SHELF software, but found it difficult to find suitable beta distributions which simultaneously reconciled the minimum and maximum values and the asymmetry implied by the modal value. We found that the truncated gamma distribution worked best as we could fix the minimum, modal, and maximum value and vary the shape. Sometimes this led to a small but tolerable step change at one or both of the extreme values (e.g. see parameters M_CI or AIC in Fig. 1). At the end of the process we asked the experts to double check the probability distributions.

2.4 Dependencies

We also asked the experts to consider if the parameters could be sampled a priori independently or not. Note, this is a question about whether the parameters are targeting independent processes, and not whether they ultimately impact the same climate variables. In our HadGEM3-GA4 experiment below, the stability function parameter, G0, and the critical Richardson number, in the boundary layer scheme were the only parameters to be considered interdependent with a reciprocal relationship.

2.5 Final prioritisation

A successful application of statistical tools used to analyse PPEs e.g. the emulators used by Lee et al (2013), requires amongst other things, that the ensemble size is at least six times (preferably ten times or more) the number of parameters. PPEs are limited by available supercomputing resource and for both GA4 and GA7, the number of parameters had to be reduced by prioritisation. Indeed for the GA7 exercise, the experts were aware of this from the outset. This generally involved another discussion about priorities with the experts, although the aerosol experts had already listed their parameters in order of importance. Two other reasons for not including a parameter were: (i) difficulty to implement the parameter in a quality assured way, especially given time constraints of the project; and (ii) if the experiments in the PPE are considered to be inadequate at providing a constraint on the parameter. For instance, the non-orographic GWD scheme was also considered and two parameters, LSTAR and USSP_LAUNCH_FACTOR, were elicited as these affect the amplitude and periodicity of the Quasi-Biennial Oscillation (QBO). However, the QBO periodicity is observed to be about 28 months and our PPEs, which are based on 5 or 10 year AMIP simulations, would have inadequately sampled a number of QBO cycles.

3. The GA4 Parameters

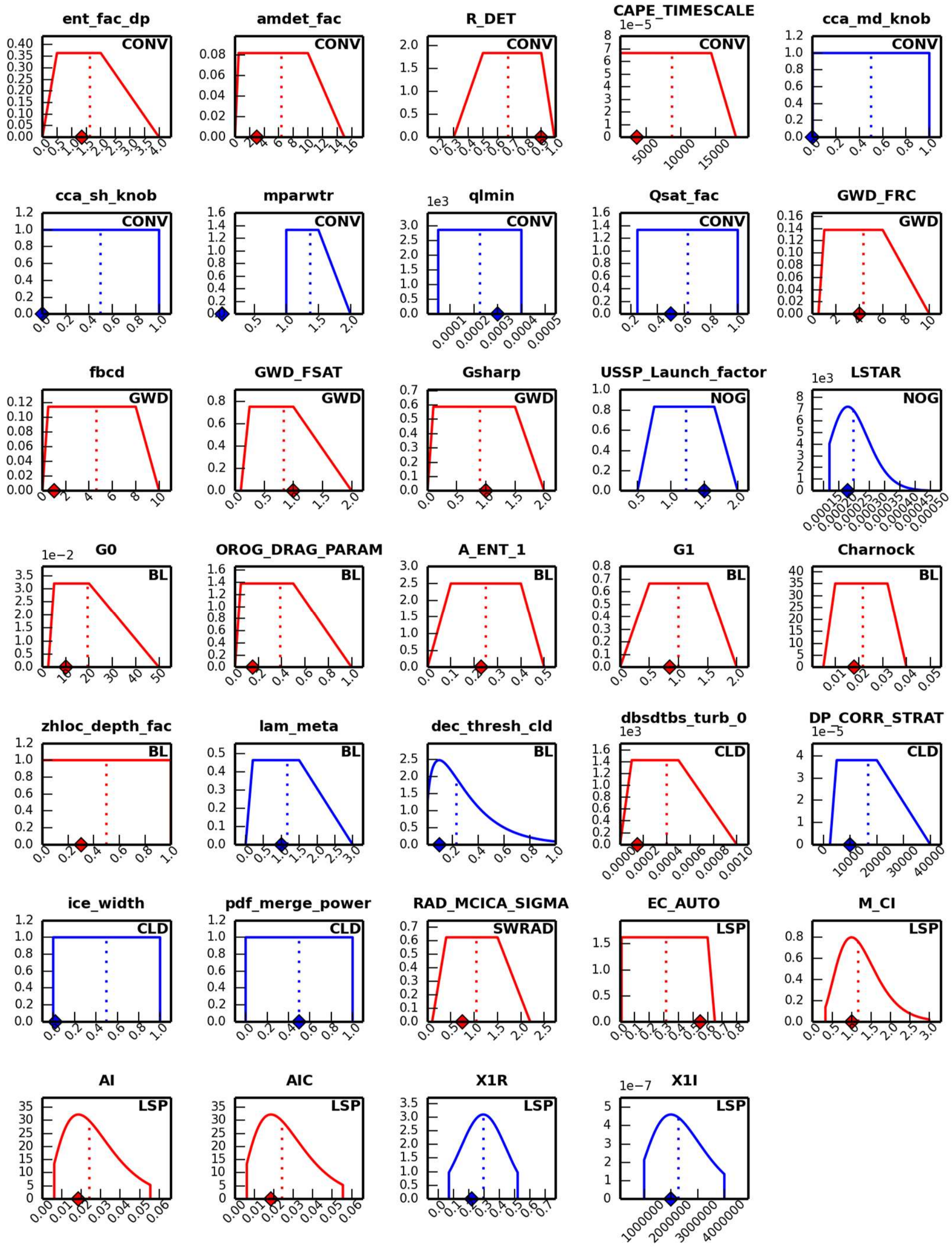

Figure 1: The distributions for the continuous parameters elicited during the elicitation exercise. Parameters with red PDFs were used to generate the PPE discussed in this study and are described in Table 1. One parameter, NITER_BS, is not shown as it had a discrete distribution with five equiprobable values 1, 2, 5, 10, and 20. Another parameter, critical Richardson number is also not shown and was calculated as 10.0/G0. Dotted lines show the median, and diamonds show the value of that parameter in the standard model variant.

Table 1: Summary of GA4 parameters by scheme and their role and signature effect.

Parameter/Scheme	Role	Signature Effect
Convection		
Entrainment amplitude (ent_fac_dp)	Controls the shape of the mass flux and the sensitivity of convection to relative humidity	Increased values lead to the reduction of convection depth and to some extent suppression of active precipitating convection
Mixing detrainment (amdet_fac)	Controls the rate of humidification of the atmosphere, and the shape of convective heating profile	Increases large-scale humidity and temperature profiles
Coefficient for adaptive detrainment (R_DET)	Active when there is decreasing parcel buoyancy with height. Tends to oppose this buoyancy reduction and thus raises the termination height of the convection	Larger R_DET gives deeper convection but also changes the height distribution.
CAPE timescale (CAPE_TIMESCALE)	Determines how fast the deep/mid-level convection scheme removes instability, short values remove instability faster	Shorter values give better representations of tropical cyclones in weather forecasts and climate simulations, and more spatially and temporally intermittent convection
Gravity Wave Drag and Orography		
Critical Froude number (GWD_FRC)	Determines the cut-off mountain height and the depth of the blocked flow layer around sub-grid mountains.	Affects tropospheric and stratospheric winds and mean sea level pressure (PSL). Increases in GWD_FRC will slow low-level winds and increase PSL.
Flow blocking drag coefficient (fbcd)	Determines the size of the low-level drag associated with flow blocking effects by sub-grid mountains.	Affects tropospheric winds and PSL.
Inverse critical Froude number for wave saturation (GWD_FSAT)	Determines the amplitude at which mountain waves generated by sub-grid orography will break, and exert a drag on the flow. As GWD_FSAT is reduced, smaller amplitude waves will break, typically leading to wave breaking (and drag) at lower altitudes.	Affects tropospheric and stratospheric winds and PSL.
Mountain wave amplitude (Gsharp)	Determines the amplitude of the mountain waves	Affects tropospheric and stratospheric winds and

	generated by sub-grid orography, and hence the size of the orographic gravity wave stress.	PSL. Increases in Gsharp lead to slower winds in the upper troposphere and above, and changes to temperature biases (through thermal wind balance).
Cloud and Cloud Radiation		
Cloud erosion rate (dbsdtbs_turb_0)	Determines the rate with which unresolved sub-grid motions mix clear and cloudy air and hence remove liquid condensate and evaporate liquid cloud fraction.	Modifies the radiative properties of the cloud (especially in regions of liquid-only cloud, e.g. sub-tropical maritime stratocumulus) and also affects the in-cloud liquid water content and hence how the precipitation formation processes will evolve.
Normalised cloud condensate standard deviation (RAD_MCICA_SIGMA)	Fractional standard deviation of the sub-grid cloud condensate as seen by radiation.	Will alter the cloud radiative effect. High values will mean the cloud is more inhomogeneous and its radiative effect will be reduced. Impacts are most clearly seen in stratocumulous regions.
Boundary layer (BL)		
Stability function parameter (G0)	Used in the definition of stability functions for stable boundary layers	Increasing implies smaller stability function, less BL mixing, e.g. less wind turning, shallower BL
Critical Richardson number (Ricrit)		Reducing lowers stable BL top, smaller mixing length, less BL mixing
Entrainment parameter (A_ent_1)	Parameter used in boundary layer top entrainment rate calculation	Increasing gives larger entrainment rate at BL top, deeper and warmer mixed layer, potentially quicker breakup of cloud
Parameter to control cloud-top diffusion (G1)	Parameter in cloud top-driven turbulent diffusion calculation	Increasing gives larger top-down diffusivity profile, better mixed cloud layer, possibly less decoupling and more stratocumulus
Charnock (Charnock)	Charnock parameter used in sea-surface roughness calculation	Reducing implies smoother sea surface, less mixing, wind turning etc.
Threshold fraction of the cloud layer depth (zhloc_depth_fac)	Fractional height into cloud layer for which Ri based BL	Higher value leads to more cumulus-capped BLs and fewer shear-dominated

	depth can diagnose shear dominated layer	BLs, lower cloud fraction in cold air outbreaks.
Turbulent Orographic Form Drag (OROG_DRAG_PARAM)	Determines the size of the form drag exerted on flow by small-scale sub-grid hills.	Affects boundary-layer winds and PSL. Larger values of OROG_DRAG_PARAM will give slower boundary layer winds.
Cloud microphysics		
Autoconversion efficiency (Ec_auto)	Controls autoconversion of cloud water to rain	Reducing will decrease rain rate
Ice fall speed scaling (M_CI)	Used to change the ice fall speed by a factor	Increasing fall speed will decrease ice water content
Aggregate mass scaling (AI) and Crystals mass scaling (AIC)	Control the breadth of the size distribution of snow for a fixed ice water content	Increasing the mean size impacts the process rates for sedimentation, riming, diffusional growth and melting, affecting the amount of ice cloud.
Number of sub-step iterations in microphysics (NITER_BS)		Setting lower will lead to increased light rain

4. The GA7 parameters

The following parameters in GA4 are not used in GA7: CAPE_TIMESCALE, Charnock, RAD_MCICA_SIGMA, Ec_auto and AIC.

The UKCA-MODE aerosol scheme is the name given to the aerosol model, GLOMAP as it is integrated into the Unified Model (UM). The bulk of the experts came from the academic community, mainly Leeds University where GLOMAP was developed. Carslaw et al (2013) had already perturbed this model and so unlike the other schemes, there was already a lot of information about the key parameters. As with the other schemes, there were too many parameters to perturb and the experts prioritised the parameters. One issue was that UKCA-MODE has necessarily diverged from GLOMAP to integrate it into a 3-D atmosphere model. Therefore, some of the GLOMAP parameters do not have a direct UKCA-MODE counterpart. For instance, SIGW in GLOMAP is a spatially fixed parameter that relates the activation of aerosol to the standard deviation of the updraught velocity. In UKCA-MODE, this has been replaced so that the standard deviation of the updraught velocity is diagnosed from the turbulent KE in the Boundary Layer Scheme. So to perturb this process in UKCA-MODE we included a scaling factor in this relationship.

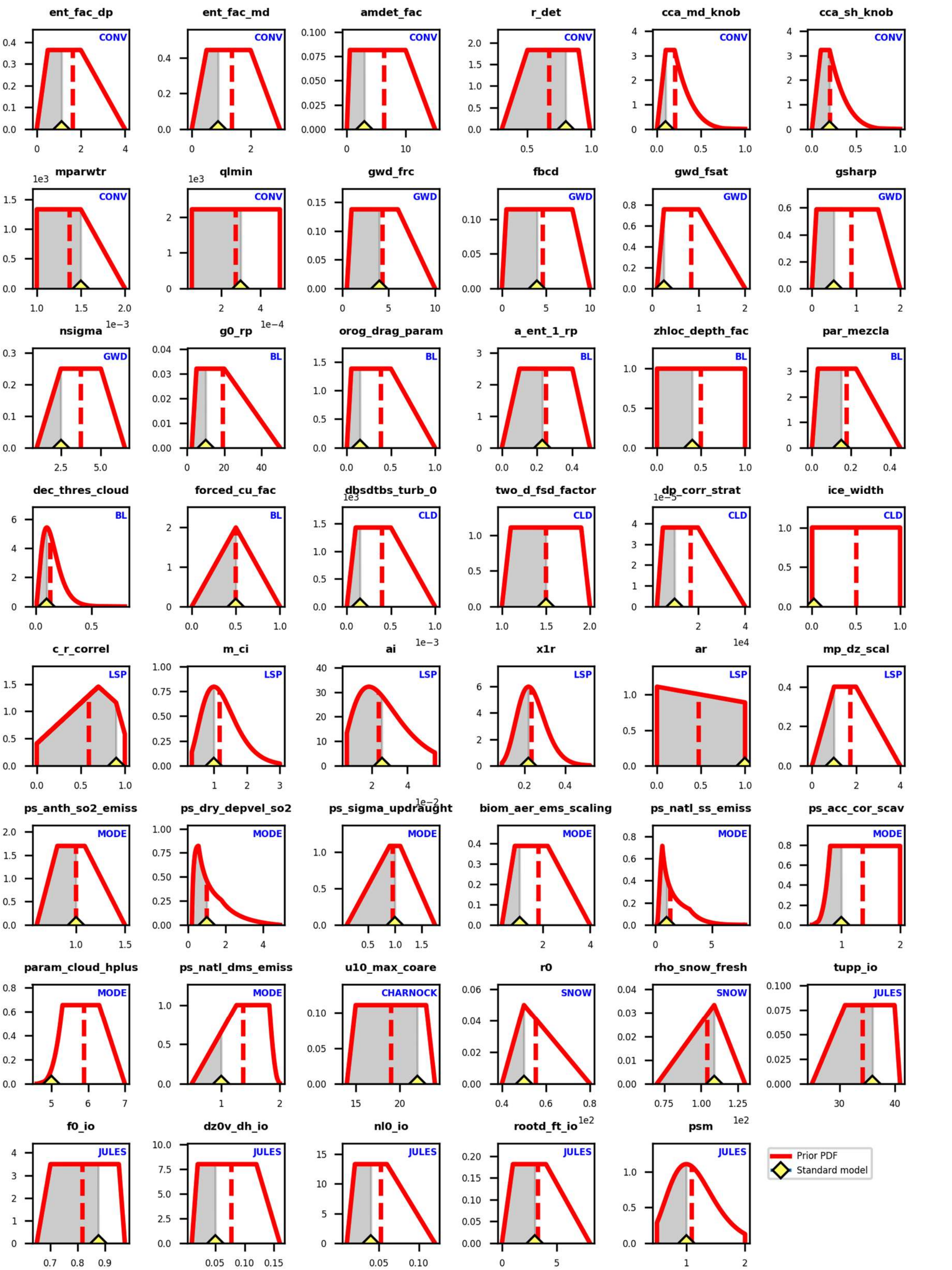

Figure 2: The distributions of GA7 parameters described in Table 2. Red dashed lines show the median, yellow diamonds are the standard value and the grey shading shows the area to the left of the standard value.

Table 2: Summary of GA7 parameters by scheme and their role and signature effect.

Parameter	Role	Signature Effect
CONVECTION		
Deep entrainment amplitude (ent_fac_dp)	Controls the shape of the mass flux and the sensitivity of deep convection to relative humidity to deep entrainment	Increased values lead to the reduction of convection depth and to some extent suppression of active precipitating convection
Mid entrainment amplitude (ent_fac_md)	Controls the shape of the mass flux and the sensitivity of mid-level convection to relative humidity to mid-level entrainment	Increased values lead to the reduction of convection depth and to some extent suppression of active precipitating convection
Mixing detrainment (amdet_fac)	Controls the rate of humidification of the atmosphere, and the shape of convective heating profile	Increases large-scale humidity and temperature profiles
Coefficient for adaptive detrainment (r_det)	Decrease of mass flux with height under decreasing parcel buoyancy. Tends to oppose this buoyancy reduction and thus raises the termination height of the convection	Larger rdet gives deeper convection but also changes the height distribution.
Convective core radiative effects (cca_md_knob, cca_dp_knob = cca_md_knob	Control how much deep and mid-level convective core gets seen by radiation	Increasing the values will mean convective cores have more of a radiative impact (i.e. more reflection of SW and more LW emission from a cold cloud top).
Shallow convective core radiative effects (cca_sh_knob)	Control how much shallow convective core gets seen by radiation	Increasing the values will mean convective cores have more of a radiative impact (i.e. more reflection of SW and more LW emission from a cold cloud top).
Maximum condensate (mparwtr)	The maximum condensate a convective parcel can hold before it is converted to precipitation.	
Minimum critical cloud condensate (qlmin)	The minimum value of the function that defines the maximum amount of condensate a convective parcel can hold before it is converted to precipitation.	Reducing it cools the troposphere, increasing it warms the troposphere presumably by decreasing/increasing the amount of high cloud.
GRAVITY WAVE DRAG (GWD)		
Critical Froude number (gwd_frc)	Determines the cut-off mountain height and the depth of the blocked flow layer around sub-grid mountains.	Affects tropospheric and stratospheric winds and MSLP. Increases in gwd_frc will slow low-level winds and increase MSLP.
Flow blocking drag coefficient (fbcd)	Determines the size of the low-level drag associated with flow	Affects tropospheric winds and MSLP.

	blocking effects by sub-grid mountains.	
Inverse critical Froude number for wave saturation (gwd_fsat)	Determines the amplitude at which mountain waves generated by sub-grid orography will break, and exert a drag on the flow. As gwd_fsat is reduced, smaller amplitude waves will break, typically leading to wave breaking (and drag) at lower altitudes.	Affects tropospheric and stratospheric winds and MSLP.
Mountain wave amplitude (gsharp)	Determines the amplitude of the mountain waves generated by sub-grid orography, and hence the size of the orographic gravity wave stress.	Affects tropospheric and stratospheric winds and MSLP. Increases in Gsharp will lead to slower winds in the upper troposphere and above, and changes to temperature biases (through thermal wind balance).
Drag coefficient for turbulent form drag (orog_drag_param)	Determines the size of the form drag exerted on flow by small-scale sub-grid hills.	Affects boundary-layer winds and MSLP. Larger values of Cd will gives lower boundary layer winds.
Scaling factor applied to sigma, the standard deviation of sub-grid mountain heights (nsigma)	Multiplies sigma(x,y) to determine the local assumed sub-grid orography height which is used in the GWD scheme. This effects the calculation of the Froude number, which then influences the magnitude of the parameterized flow blocking and mountain wave drag	Larger (smaller) values of nsigma will result in increases (decreases) in the drag. The relative changes in flow blocking and mountain wave drag will be regionally dependent.
BOUNDARY LAYER (BL)		
Flux profile parameter (g0)	Used in the definition of stability functions	Increasing implies smaller stability function, less BL mixing, e.g. less wind turning, shallower BL
Critical Richardson number (ricrit = 10.0 / g0)		Reducing lowers stable BL top, smaller mixing length, less BL mixing
Cloud-top entrainment rate (a_ent_1)	Parameter used in entrainment rate calculation	Increasing gives larger entrainment rate at boundary layer top, deeper and warmer mixed layer, potentially quicker break up of cloud.
Cloud-top diffusion (g1 = 0.85 * a_ent_1 / 0.23	Parameter in cloud top diffusion coefficient calculation	Increasing gives larger top-down diffusivity profile, better mixed cloud layer, possibly less decoupling and more stratocumulus
Threshold fraction of the cloud layer depth (zhloc_depth_fac)	Fractional height into cloud layer for which Ri based BL depth can diagnose shear dominated layer	Higher value leads to more cumulus capped BLs and less shear dominated BLs, lower cloud fraction in cold air outbreaks etc

Neutral mixing length (par_mezcla)		Reducing implies smaller stability function, less BL mixing, e.g. less wind turning, shallower BL
Minimum value of mixing length (lambda_min = 40 * par_mezcla / 0.15)		Reducing implies smaller stability function, less BL mixing, e.g. less wind turning, shallower BL.
Decoupling threshold for cloudy BLs (dec_thres cld, dec_thres_cloud2cu = 0.5 * dec_thres_cld)		Larger value makes decoupling less likely, shifts to more well-mixed boundary layers
Mixing factor applied to the in-cloud water content of forced cumulus clouds (forced_cub_fac)	Determines the fraction of the diagnosed adiabatic water content of forced cumulus clouds which is allowed to remain. 0 means no forced cumulus clouds, 1 means maximum possible water content based on an adiabatic parcel ascent, within 0-1 means mixing between clear and cloudy air.	Increasing the value will give more water in shallow convective regions, increased reflected SW etc.
Cloud and Cloud Radiation		
Cloud erosion rate (dbsdtbs_turb_0)	Determines the rate with which un-resolved sub-grid motions mix clear and cloudy air and hence remove liquid condensate and evaporate liquid cloud fraction.	Modifies the radiative properties of the cloud (especially in regions of liquid only cloud e.g. sub-tropical maritime Sc) and also affects the in-cloud liquid water content and hence how the precipitation formation processes will evolve.
Scaling to make sub-grid cloud condensate variance to cloud cover and convective activity two dimensional (two_d_fsd_factor)	Makes the cloud water variability around the grid box mean a two dimensional relationship based on a 1-d empirical relationship based on CloudSat observations.	This changes the cloud-radiation interaction and hence the LW, SW radiative balance. Increasing this parameter from 1.4 to 1.5 reduced the amount of outgoing SW at TOA by around 1.2 Wm-2 and increases the OLR by 0.4 Wm^{-2}.
Decorrelation scale pressure (dp_corr_strat)	Determines the vertical overlap between clouds in the sub-column in the cloud generator used to calculate the radiative impact of clouds.	Will alter the cloud radiative effect. High values will mean the cloud is more maximally overlapped and its radiative effect will be reduced. Impacts are most clearly seen in convective regions.
Ice width (ice_width)	Determines the amount of ice water content (as a fraction of qsat-liquid) that corresponds to a factor of two reduction in the width of the vapour distribution in the liquid-free part of the gridbox.	Changes the ice water content and ice cloud fraction, hence impacting SW and LW properties. Hence modifying the radiative balance.
Cloud Microphysics		

Cloud-rain correlation coefficient (c_r_correl)	Determines the sub-grid correlation between cloud and precipitation, i.e. a high value means that regions of high cloud water are correlated with regions of high precipitation, a small or negative number means they are un- or anti-correlated	Increasing the value will result in more warm rain, reducing the water content of stratocumulus clouds, reducing the reflected SW etc
Ice fallspeed (m_ci)	Scaling factor for the ice fallspeed	Increasing fallspeed will decrease ice water content
Precursor coefficient in the mass-diameter relationship for ice (m = ai × Dbi) (ai)	Changing ai has the effect of changing the density of the ice.	Increasing ai will produce a narrower PSD and so the mass weighted fallspeed will be lower and hence the cloud ice content should increase.
x1r	Controls rain PSD shape	Increasing X1R will decrease rainrate
Aspect ratio of ice particles(ar)	Used to calculate the depositional Capacitance of ice crystals which effects how efficiently they grow by depleting water vapour. Ice particles are assumed to be spheroidal for the purposes of calculating deposition rates. Capacitance is maximal for spheres (Ar=1) and reduces for oblate (ar1) and prolate (ar1) spheroids.	Higher capacitance will lead to a lower relative humidity. The ice water contents will only be weakly effected. In mixed-phase regions, the liquid water contents will increase.
Vertical scale in mixed phase turbulent production of supercooled liquid water (mp_dz_scal)	Vertical length scale over which the turbulence acts to produce supercooled water	Increasing mp_dz_scal will lead to an increase in liquid water path
Aerosols		
Anthropogenic SO2 emission flux (ps_anth_so2_emiss)	Direct scaling of emissions flux	Increasing this leads to higher aerosol concentrations in source regions.
Dry deposition rate of SO2 (ps_dry_so2_veloc)	Scaling factor for dry deposition rate calculated in the model which removes SO2 from lowest levels through deposition according to land surface type and prevailing wind speed	Increasing this will reduce low level SO2 concentrations
Scaling of the standard deviation used to define the pdf of updraft velocity (ps_sigma_updraught)	Relates the activation of aerosols to CDNC to the standard deviation used to define the pdf of updraft velocity	Increasing this produces more CDNC
Scaling of emission flux from biomass burning (biom_aer_ems_scaling)	Direct scaling of emissions flux	Increasing this directly affects BC/OC aerosol concentrations proportionately
Scaling of emission flux from sea spray (ps_natl_ss_emiss)	Direct scaling of emissions flux	Increasing this directly affects hygroscopic aerosol concentrations.

Scavenging rate in the coarse and accumulation modes (ps_acc_cor_scav)	Scaling of the scavenging rate calculated in the model	Increasing this will reduce concentrations of aerosols in coarse and accumulation mode
pH of cloud drops (ps_cloud-ph)	This controls in-cloud SO4 production dependent on SO2 availability	An increase in cloud pH leads to faster SO2 oxidation by ozone in cloud water, so more SO4 production.
Dimethyl-sulphide emission flux (ps_natl_dms_emiss)	Direct scaling of emissions flux	DMS is a precursor gas for sulphate production via oxidisation.
Land surface and snow		
Maximum wind speed used in COARE algorithm (u10_max_coare)	This is the highest windspeed used in calculating Charnock's coefficient in the COARE algorithm.	Higher values allow the sea surface to become rougher in strong winds.
Grain size of fresh snow (r0)	The grain size of fresh snow is set to this value, which affects the albedo of snow.	Higher values make the snow less reflective
Fresh snow density (rho-snow_fresh)	The density of fresh snow	Lower densities reduce the thermal conductivity of snow, leading to colder surface temperatures.
Upper value about 4K above Topt, the optimal temperature for photosynthesis (tupp io)	Topt determines the turn-over point for temperature, above which further increases in temperature will drive a decline in photosynthesis.	In tropical and sub-tropical regions the optimal temperature would be expected to have the biggest impact on plant functioning, with low values for this parameter leading to greater temperature dependence of photosynthesis.
Maximum ratio of internal to external CO2 (f0_io)	Controls the gradient of CO2 between plant stomata and the ambient air.	
Top leaf Nitrogen concentration in kg N kg C (nl0-io)	Defines the top leaf ratio of nitrogen to carbon. Plant photosynthesis (Vcmax) is defined in the model to be proportional to the Leaf Nitrogen. concentration	Higher ratios are associated with higher photosynthesis.
Root depth (rootd_ft_io)	Controls the depth (in model soil levels) that soil moisture is available.	Larger values equate to deeper depths in the soil, and subsequently greater resilience to short timescale droughts.
Scaling factor for critical and saturation levels for soil moisture towards wilt level (psm)	This pair of parameters control the critical and saturated volumetric soil moisture thresholds. The critical threshold controls the level above which evapotranspiration is no longer soil moisture dependent.	Higher values lead to larger soil moisture regimes where soil moisture limits this evapotranspiration, with its consequent implications for moisture and surface energy fluxes.

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Met Office
FitzRoy Road
Exeter
Devon
EX1 3PB
United Kingdom