Skill and independence weighting for multi-model assessments

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1 Abstract

We present a weighting strategy for use with the CMIP5 multi-model archive in the 4th National Climate Assessment which considers both skill in the climatological performance of models over North America as well as the interdependency of models arising from common parameterizations or tuning practises. The method exploits information relating to the climatological mean state of a number of projection-relevant variables as well as metrics representing long term statistics of weather extremes. The weights, once computed can be used to simply compute weighted means and significance information from an ensemble containing multiple initial condition members from potentially co-dependent models of varying skill. Two parameters in the algorithm determine the degree to which model climatological skill and model uniqueness are rewarded; these parameters are explored and final values are defended for the Assessment. The influence of model weighting on projected temperature and precipitation changes is found to be moderate, partly due to a compensating effect between model skill and uniqueness. However, more aggressive skill weighting and weighting by targeted metrics is found to have a more significant effect on inferred ensemble confidence in future patterns of change for a given projection.

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2 Introduction

The CMIP5 archive [1] is the most comprehensive collection of climate simulations produced to date. The archive contains simulations from over 25 institutions, some of which submit multiple models - bringing the total number of models in the archive to potentially more than 100 (although many of these are minor variants or initial condition members, and not all models conduct all experiments). Using this dataset to produce assessments of future climate change involves a number of conceptual challenges. Previous assessments of both the IPCC [2] and the National Climate Assessment in the United States [3] have considered the archive to represent model democracy [4], in that simulations of the future from each model are considered to be equally likely, without accounting for any variation in model skill or for the fact that some models are very similar to other models in the archive, bringing into question the assumption that their simulations can be considered to be independent samples of future behavior.

These underlying assumptions have been challenged by a number of studies over recent years. Various studies [5, 6, 7, 8], have pointed out that the ensemble contains demonstrable inter-dependence, where similarities in the spatial biases in model simulations correspond well to expected relationships which one might expect from models from the same institution, or those sharing significant amounts of code. As such, the number of effective models in the archive is likely to be significantly smaller than the number of simulations [9, 10, 7]. The weights should also be representative of the question at hand: skill is not a property of the model *per se*, but indicative of the ability of a model to project a certain change [11].

In addition, the models that are present in the archive are not equally skillful in representing the present day or past climate [12, 5]. A number of studies have attempted to weight models in a way which represents their skill alone; Bayesian Model Averaging [13] describes a set of approaches which collectively produce model weights which correspond to a posterior model probability representing truth given some data constraints. Giorgi and Mearns (2002) [14] proposed an ensemble averaging scheme which increased the weight of models which exhibited low observational biases but the method potentially discounts outlier projections [15]. However, these methods do not provide a mechanism for reducing the effect of model replication. An identical model submitted twice to the ensemble would still produce a different result - an issue which we address below. Furthermore, it is notably difficult to produce an overall ranking of model performance, given that the conclusion is conditional on both the region and metrics considered [16].

Some studies have suggested methodologies which might be able to address some of these complexities: Bishop and Abramowitz (2013) [17] proposed a method which produced a set of statistically independent meta models from the original archive, and applied this method to CMIP5 projections in Abramowitz and Bishop (2015) [18]. The technique calculates the optimal combination of models, such that a linear combination of models minimizes the error of a particular field against an observed target. While the bias of the combined product is by definition optimal, the coefficients of each model can be positive or negative. With the view that negative weights are unphysical, the authors transform the original model output such that all weights are positive, and such that the variance of the ensemble is rescaled to equal the natural variability of the observations themselves, with a solution that preserves the optimal combined model result from their initial regression.

While this 'replicate Earth' produces a product which significantly reduces the mean bias of the combined model product (a 30 percent reduction in RMSE compared to a simple multi-model mean [18]), there remain some issues of interpretation for the transformed ensemble members, which can no longer be directly interpreted as physical entities which conserve mass or energy. It is also not fully understood how the issue of independence of models in the original archive influences the results. And though the technique reduces errors in out-of-sample perfect model tests, the out-of-sample test presented in Bishop and Abramowitz (2013) [17] does not remove the effect of persistence of present day bias, which is directly solved-for in the regression - therefore not definitively demonstrating that prediction of future anomalies would be improved beyond the simple multi-model means for out-of-sample projections, which were not bias corrected.

In this study, we present a weighting scheme for use in the Climate Science Special Report (CSSR), which informs the 4th National Climate Assessment for the United States (NCA4). The requirements for this application are somewhat unique - in that a method from the literature cannot be simply taken 'out of the box' from an existing study. Traceability and simplicity are paramount for this application, where the derived weights are defined in this paper, but then form the basis of a number of varied analyses performed by the author team for the CSSR. Hence, the use of statistical meta-models as in Bishop and Abramowitz (2013) [17] would not be manageable because each individual application would have to be reconsidered in terms of the paradigm, where the details of statistical significance, model independence and individual model interpretation are not fully understood, and would be difficult to convey to the public audience for NCA4. As such, the request for the CSSR was to produce a single set of weights which reflected to some degree both model skill and model independence in the CMIP5 archive, which could be simply integrated into the existing workflow of the report.

Our methodology is based on the concepts outlined by Sanderson *et al* (2015) [7], a comparatively simple method for sub-sampling models the original archive, keeping models which were maximally independent and skillful in reproducing past climate. Another recent study [19] outlined an adaption of this approach for constraining a specific future change (future sea ice area, in that case). However, in this study, instead of deriving a subset or studying a single aspect of future change, the objective is to produce a single set of model weights which can be used to combine projections for a range of quantities into a weighted mean result, with significance estimates which also treat the weighting appropriately.

Ideally, the method would seek to have two fundamental characteristics.

Table 1: Observational Datasets used as observations.

Field	Description	Source	Reference
tas	Surface Temperature (seasonal)	Livneh, Hutchinson	[22, 22]
pr	Mean Precipitation (seasonal)	Livneh, Hutchinson	[22, 22]
rsut	TOA Shortwave Flux (seasonal)	CERES-EBAF	[23]
rlut	TOA Longwave Flux (seasonal)	CERES-EBAF	[23]
ta	Vertical Temperature Profile (seasonal)	AIRS*	[24]
hur	Vertical Humidity Profile (seasonal)	AIRS	[24]
psl	Surface Pressure (seasonal)	ERA-40	[25]
tnn	Coldest Night	Livneh, Hutchinson	[22, 22]
txn	Coldest Day	Livneh, Hutchinson	[22, 22]
tnx	Warmest Night	Livneh, Hutchinson	[22, 22]
txx	Warmest day	Livneh, Hutchinson	[22, 22]
rx5day	seasonal max. 5-day total precip.	Livneh, Hutchinson	[22, 22]

First, if a duplicate of one ensemble member is added to the archive, the resulting mean and significance estimate for future change computed from the ensemble should change as little as possible. Secondly, if a relatively poor (for the metrics considered) model is added to the archive, the resulting mean and significance estimates should also change as little as possible.

3 Method

3.1 Data pre-processing

Our analysis differs in a number of ways from that originally proposed by [7]

- The analysis region contains on the counterterminous United States (CONUS) and most of Canada, constrained by available high resolution observations of daily surface air temperature and precipitation.
- Inter-model distances are computed as simple root mean square differences here, in contrast to the multi-variate PCA used by [7].
- The weights for skill and independence are the final product in this analysis, whereas they only inform the subset choice in the study by [7].

We utilize data for a number of mean state fields, and a number of fields which represent extreme behaviour - these are listed in Table 1. All fields are masked to only include information from the combined CONUS/Canada region. Extreme indices are calculated using the ETCCDI protocols [20, 21]. We also consider a selection of models from the CMIP5 archive, listed in Table 2.

3.2 Inter-model distance matrix

For each variable, a distance matrix δ_v is computed between each pair of N total models and between each model and the observed field (such that the observa-

Table 2: Submodel components for the 38 CMIP5 models considered in this study.

Model	Atmosphere	Land	Ocean	Ice	Source
NorESM1-ME	CAM4	CLM4	MICOM-HAMOCC	CICE	https://verc.enes.org/ISENES2/models/earthsystem-models/ncc/noresm
NorESM1-M	CAM4	CLM4	MICOM-HAMOCC	CICE	https://verc.enes.org/ISENES2/models/earthsystem-models/ncc/noresm
MRI-CGCM3	MRI-AGCM3	HAL	MRI.COM3		http://www.mri-jma.go.jp/Publish/Technical/DATA/VOL_64/index_en.html
MPI-ESM-MR	ECHAM6	JSBACH	MPIOM		http://www.mpimet.mpg.de/en/science/models/mpi-esm.html
MPI-ESM-LR	ECHAM6	JSBACH	MPIOM		https://www.enes.org/models/system-models/mpi-m/mpi-esm
MIROC5	FRCGC-AGCM	MATSIRO	CCSR-COCO	Bitz/Lipscomb	http://journals.ametsoc.org/doi/full/10.1175/2010JCLI3679.1
MIROC4h	FRCGC-AGCM	MATSIRO	CCSR-COCO	Bitz/Lipscomb	http://journals.ametsoc.org/doi/full/10.1175/2010JCLI3679.1
MIROC-ESM-CHEM	FRCGC-AGCM	MATSIRO	CCSR-COCO	Bitz/Lipscomb	http://www.wcrp-climate.org/wgcm/WGCM15/presentations/21Oct/KIMOTO_Japan.pdf
MIROC-ESM	FRCGC-AGCM	MATSIRO	CCSR-COCO	Bitz/Lipscomb	http://www.wcrp-climate.org/wgcm/WGCM15/presentations/21Oct/KIMOTO_Japan.pdf
IPSL-CM5B-LR	LMDZ (CM4)	ORCHIDEE	NEMO-OPA	NEMO-LIM	http://icmc.ipsl.fr/index.php/icmc-models/icmc-ipsl-cm5
IPSL-CM5A-MR	LMDZ	ORCHIDEE	NEMO-OPA	NEMO-LIM	http://icmc.ipsl.fr/index.php/icmc-models/icmc-ipsl-cm5
IPSL-CM5A-LR	LMDZ	ORCHIDEE	NEMO-OPA	NEMO-LIM	http://icmc.ipsl.fr/index.php/icmc-models/icmc-ipsl-cm5
BCC-CSM1-1-M	BCC_AGCM 2.1	CLM3	MOM4	SIS	http://link.springer.com/article/10.1007%2Fs13351-014-3041-7
BCC-CSM1-1	BCC_AGCM 2.1	CLM3	MOM4	GFDL SIS	http://link.springer.com/article/10.1007%2Fs13351-014-3041-7
HadGEM2-ES	HadGAM2 (N96L38)	TRIFFID	HadGOM2		http://cms.ncas.ac.uk/wiki/UM/Configurations/HadGEM2
HadGEM2-CC	HadGAM2(N96L60)	TRIFFID	HadGOM2		http://cms.ncas.ac.uk/wiki/UM/Configurations/HadGEM2
HadGEM2-AO	HadGAM2 (N96L38)	MOSES2	HadGOM2		http://cms.ncas.ac.uk/wiki/UM/Configurations/HadGEM2
GISS-E2-R	GISS	GISS	Russell	Russell	http://data.giss.nasa.gov/modelE/ar5/
GISS-E2-H	GISS	GISS	HYCOM	HYCOM	http://data.giss.nasa.gov/modelE/ar5/
GFDL-ESM2M	GFDL-AM2.1	LM3	MOM4.1	SIS	http://cms.ncas.ac.uk/wiki/UM/Configurations/HadGEM2
GFDL-ESM2G	GFDL-AM2.1	LM3	GOLD	SIS	http://www.gfdl.noaa.gov/earth-system-model
GFDL-CM3	GFDL-AM3	LM3	MOM4.1	SIS	http://www.gfdl.noaa.gov/earth-system-model
FGOALS-g2	GAMIL 2.0	CLM3	LICOM2	CICE4_LASG	http://link.springer.com/article/10.1007%2Fs00376-012-2140-6
CanESM2	AGCM4	CLASS	NCAR		http://journals.ametsoc.org/doi/pdf/10.1175/JCLI-D-11-00715.1
CSIRO-Mk3-6-0	Gordon	CABLE	MOM2.2	SIS	http://www.bom.gov.au/amoj/docs/2013/jeffrey_hres.pdf
CNRM-CM5	ARPEGE-Climate	ISBA	NEMO-OPA	GELATO	http://www.cnrm-game.fr/spip.php?article126&lang=en
CMCC-CMS	ECHAM5	SILVA	OPA8.2	LIM	http://www.wcrp-climate.org/wgcm/WGCM16/Bellucci_CMCC.pdf
CMCC-CM	ECHAM5	SILVA	OPA8.2	LIM	http://www.cmcc.it/models/cmcc-cm
CMCC-CESM	ECHAM5	SILVA	OPA8.2	LIM	http://www.cmcc.it/models/cmcc-cm
CESM1-CAM5	CAM5	CLM4	POP2	CICE4	https://www2.cesm.ucar.edu/models
CESM1-FASTCHEM	CAM5	CLM4	POP2	CICE4	https://www2.cesm.ucar.edu/models
CESM1-BGC	CAM4	CLM4	POP2	CICE4	https://www2.cesm.ucar.edu/models
CCSM4	CAM4	CLM4	POP2	CICE4	https://www2.cesm.ucar.edu/models
BNU-ESM	CAM3.5	CLM/BNU	MOM4.1	CICE4.1	http://www.wcrp-climate.org/wgcm/WGCM15/presentations/21Oct/WANG_WGCM.pdf
BCC-CSM1-1-M	BCC_AGCM 2.1	CLM3	MOM4	SIS	http://link.springer.com/article/10.1007%2Fs13351-014-3041-7
BCC-CSM1-1	BCC_AGCM 2.1	CLM3	MOM4	GFDL SIS	http://link.springer.com/article/10.1007%2Fs13351-014-3041-7
ACCESS1-3	UKMO GA1.0	CABLE v1.8	MOM4.1	CICE4.1	https://wiki.csiro.au/display/ACCESS/Home
ACCESS1-0	HadGEM2 r1.1	MOSES	MOM4.1	CICE4.1	http://www.cawcr.gov.au/publications/technicalreports/CTR_059.pdf

tions are treated as an $N+1^{th}$ model). Data from each model is taken from the first available initial condition member of each model's historical contribution to CMIP5. Data from years 1976-2005 are used from each model, averaging all years to form a monthly climatology. Data from the observations are monthly climatologies averaged from all available years within the 1976-2005 window.

Distances are evaluated as the area-weighted root mean square difference over the domain. The matrix is then normalized by the mean inter-model distance, such that for each field in Table 1, there is a $(n_{model}+1)$ by$(n_{model}+1)$ matrix representing the pairwise distance between each model (and the observations).

These normalized matrices are then linearly combined, with each line in Table 1 taking equal weight,

$$\delta = \sum_{v} \delta_v, \tag{1}$$

to produce the multi-variate distance matrix δ illustrated in Figure 1.

3.3 Model Skill

The RMSE between observations and each model can be used to produce an overall ranking for model simulations of the CONUS/Canada climate (which is illustrated by the overall model-observation distance in Figure 1). Figure 2 shows how this metric is influenced by different component variables.

3.4 Independence weights

The inter-model distance matrix is also computed from the inter-model distance matrix δ. For a pair of models i and j, we first compute a similarity score $S(\delta_{ij})$ from their pairwise distance δ_{ij}:

$$S(\delta_{ij}) = e^{-\left(\frac{\delta_{ij}}{D_u}\right)^2}, \tag{2}$$

where D_u is the radius of similarity [7], which is a free parameter which determines the distance scale over which models should be considered similar (and thus down-weighted for co-dependence). We show below how an appropriate value can be chosen given prior knowledge about models with known dependencies in the archive.

In limits, two identical models will produce a value of $S(\delta_{ij})$ of 1, and $S(\delta_{ij}) \to 0$ as $\delta_{ij} \to \infty$. A given model i's effective repetition $R_u(i)$ can be calculated by summing the models close by:

$$R_u(i) = 1 + \sum_{j \neq i}^{n} S(\delta_{ij}), \tag{3}$$

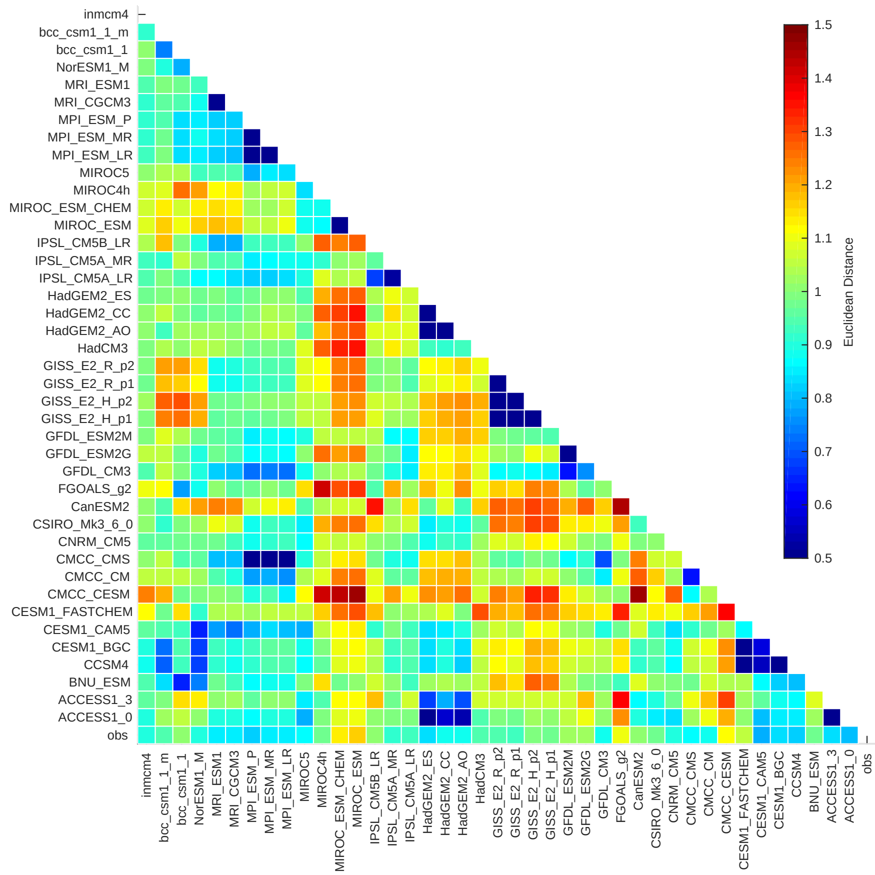

Figure 1: A graphical representation of the inter-model distance matrix for CMIP5 and a set of observed values. Each row and column represents a single climate model (or observation). All scores are aggregated over seasons (individual seasons are not shown). Each box represents a pair-wise distance, where warm colors indicate a greater distance. Distances are measured as a fraction of the mean inter-model distance in the CMIP5 ensemble. Smaller distances mean the datasets are in closer agreement than larger distances

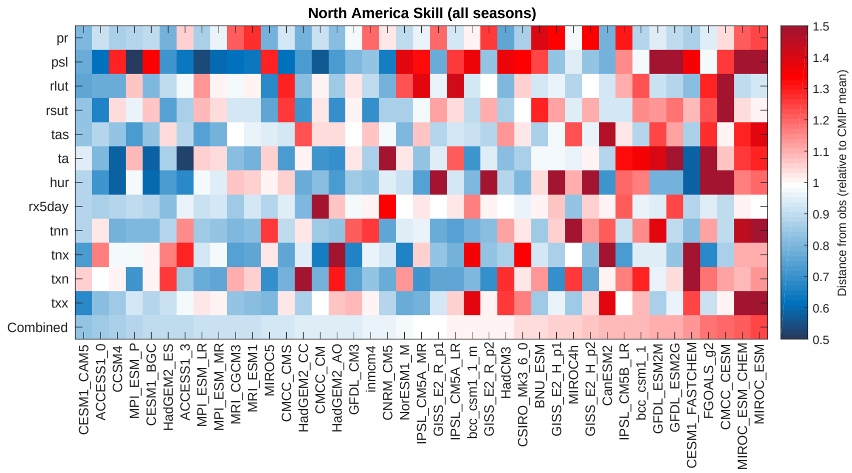

Figure 2: A graphical representation of the model-observation distance matrix for a number of variables, illustrating how different biases combine to produce the overall model-observation distance in Figure 1. Each column represents a single climate model, and rows represent the different observation types in Table 1. Distances along each row are normalized, such that the mean model has a distance of 1 to the observations. CMIP5 Models are sorted by their combined skill as shown in the bottom row.

where n is the total number of models. Finally, we calculate the independence weight for model i as the inverse of its repetition:

$$w_u(i) \quad = \quad (R_u(i))^{-1}\,. \tag{4}$$

Figure 3 shows the dependence of the independence weights on D_u for a number of different models. D_u is sampled by considering the distribution of inter-model distances δ, and sampling by percentiles σ_u the smallest inter-model distances in the archive.

As points of reference, we consider some models from the archive known to have no obvious duplicates (HadCM3 and INMCM), which should not be significantly down-weighted by the method. We also consider some models where there are numerous known closely related variants submitted from MIROC, MPI and GISS. It is desirable to choose a value of D_u which produces a weight of approximately $1/n$ where n is the number of variants submitted.

Hence, by inspection of Figure 3, we take D_u as 0.48 times the distance between the best performing model and observations in the CMIP5 archive, which produces approximately the desired weighting characteristics in these cases where we have a reasonable expectation of what the true model replication is in the archive.

The methodology described above assumes each model has submitted only

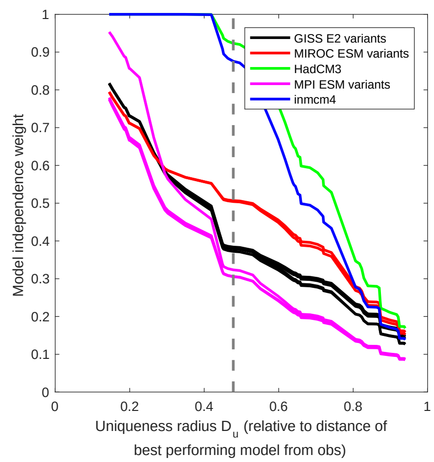

Figure 3: Model independence weights (w_u) as a function of the radius of interdependence D_u, plotted for a number of models and groups of models in the CMIP5 archive. The vertical line shows the value used in the Climate Science Special Report.

one simulation to the archive, but the method is robust to the inclusion of multiple initial condition members from each model. If D_u is chosen such that structurally similar ensemble members are treated as duplicates, then w_u will appropriately allocate a fractional weight to each initial condition ensemble member. In the case of NCA4, extreme value statistics were only available for a single instance of each model, hence initial condition ensembles were not considered.

3.5 Skill weights

The RMSE distances between each model and the observations are used to calculate skill weights for the ensemble. The skill weights represent the climatological skill of each model in simulating the CONUS/Canada climate, both in terms of mean climatology and extreme statistics. The skill weighting $w_q(i)$ for model i is calculated as in [7]:

$$w_q(i) = e^{-\left(\frac{\delta^{20c}_{i(obs)}}{D_q}\right)^2}, \qquad (5)$$

where $\delta^{20c}_{i(obs)}$ is the sum of the normalized RMSE differences over all variables, between each model and the observations, and D_q is the radius of model quality [7] which determines the degree to which models with a poor climatological simulation should be downweighted. As such, a very small value of D_q will allocate a large fraction of weight to the single best performing model in the archive (as assessed by the climatological skill). Equally, as $D_q \to \infty$, the multi-model average will tend to the non skill-weighted solution.

An overall weight is then computed as the product of the skill weight and the independence weight.

$$w(i) \quad = \quad A w_u(i) w_q(i), \tag{6}$$

where A is a normalization constant such that $w(i)$ satisfies:

$$\sum_{1}^{n} w(i) = 1, \tag{7}$$

where n is the total number of models. We determine an appropriate value for D_q by considering both the skill of the weighted average in reproducing observations, and also by conducting perfect model simulations with the CMIP5 ensemble. In Figure 4(a), we use the uniqueness parameter D_u determined in Section 3.4 and sample a range of D_q. The figure shows that the use of relatively strong weighting (where the D_q is approximately 40 percent of the distance between the best performing model and the observations) produces the weighted climatological average with the lowest in-sample error. However, in-sample score is not the only consideration.

A more skillful representation of the present-day state does not necessarily translate to a more skillful projection in the future. In order to assess whether our metrics improve the skill of future projections at all, we consider a perfect model test where a single model is withheld from the ensemble and then treated as truth.

However, such a test can be over-confident because when some models are treated as truth, there remain close relatives of that model in the archive which would be given a high skill weight and would inflate the apparent skill of the metric in predicting future climate evolution. To partly address this, we conduct our perfect model study with a subset of the CMIP5 archive which excludes obvious near relatives of the chosen 'truth' model. We achieve this by excluding any model which lies closer to the 'truth' model than the distance between the best performing model and the observations in the inter-model distance matrix δ. The excluded model pairs for the perfect model test are illustrated in Figure 5.

Once the obvious duplicates have been removed for a given 'perfect' model i, we can test the ability of the chosen multivariate climatological metrics to increase skill in the simulation of the out of sample model's future. We do this in two ways: in the first case, we consider the RMSE of the weighted multi-model mean projection of each out of sample model's projection of annual mean gridded temperature and precipitation change at the end of the 21st century under RCP8.5. This is expressed as a fraction of the RMSE one would obtain with a simple mean of the remaining models (again, excluding the obvious duplicates). This process is repeated for each model in the archive, after which the results

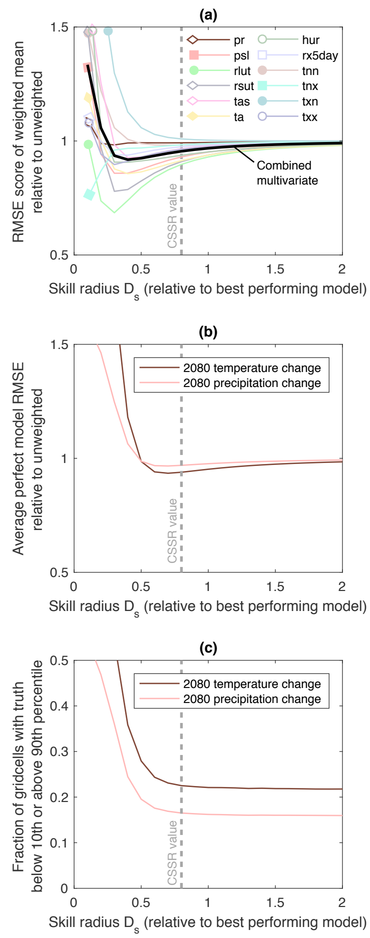

Figure 4: Subplots are functions of D_q, the radius of model quality (all figures take a value of D_u 0.48 times the distance between the best performing model and observations in the CMIP5 archive, as selected in Figure 3). Subplot (a) shows the RMSE of the weighted multi-model mean compared with observations, relative to the non skill-weighted multi-model mean. The vertical dashed grey line indicates the value chosen for the Climate Science Special Report. Colored lines show RMSE values for individual variables, thick black line is the combined multivariate RMSE. Subplot (b) shows the average RMSE of future annual mean gridded temperature change projections in 2080-2100 (relative to 1980-2000) under RCP8.5 for an out-of sample model taken to represent truth (with obvious replicates removed from the ensemble). Subplot (c) shows the average fraction of grid-cells for which the out-of sample 'perfect model' projections lie below the 10th or above the 90th percentile of the inferred weighted distribution.

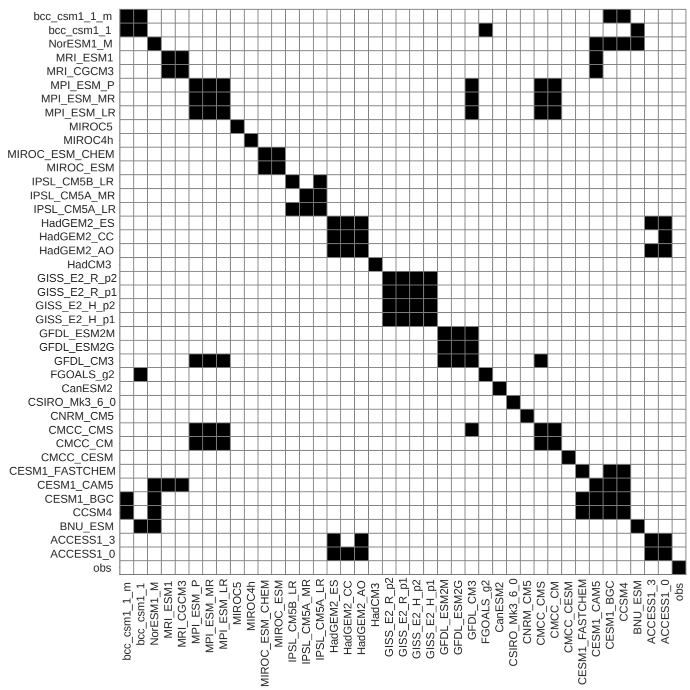

Figure 5: A graphical representation of models which are excluded from the remaining ensemble in the perfect model test when each model in turn is treated as truth. Cells in black represent models which are closer to each other than the best performing model in the archive is to observations.

are averaged and plotted in Figure 4(b), where the optimum value of D_q for the reproduction of future temperature and precipitation change is approximately 70 percent of the distance between the best performing model and observations, for which there is a 9-10 percent reduction in RMSE compared the unweighted case. This suggests that in the perfect model study, some skill weighting based on climatological performance can improve the mean projection of future change.

Finally, we test whether skill-weighting the ensemble increases the chances of the truth lying outside of the distribution of projections suggested by the archive. For Figure 4(c), we consider the ensemble projected values for future temperature and precipitation at each gridcell, where D_q is allowed to vary and D_u is kept at the value determined in Section 3.4. As in Figure 4(b), we consider each model in the CMIP5 archive as truth, each time removing near-neighbors from the remaining set (determined from Figure 5).

We allow the weighted model projected changes in 2080-2100 temperature or precipitation at each grid-cell to define a likelihood distribution for expected future change in the removed model. We then calculate the fraction of grid-cells where the chosen perfect model's actual projected value for temperature or precipitation change lies above the 90th or below the 10th percentile of the inferred likelihood distribution. If the likelihood distribution is representative of expected change for the removed 'perfect' model, one would expect a 20 percent chance that the perfect model lies outside this range. However, if this value increases, it indicates that the weighting is too strong and the weighting is producing an under-dispersive distribution.

Figure 4(c) shows the average fraction of gridcells where the actual missing model projection is above the 90th, or below the 10th percentile of the inferred likelihood distribution, for a given value of D_q, where the average is taken over the entire CMIP5 ensemble. The figure shows that for values of D_q of less than 80 percent of the distance between the best performing model and observations, there is some increased risk of the ensemble being under-dispersive. As such, Figures 4(a-c) together imply that $D_q = 0.8$ is a justifiable, conservative value to use in the further analysis - there is still a demonstrable increase in the out-of-sample skill of the future projection in the perfect model tests, with a minimal risk of an under-dispersive distribution.

Using the values of $D_q = 0.8$ and $D_u = 0.48$ defended in this section, we illustrate skill, independence and combined weights for the CMIP5 archive in Figure 6 and in Table 3.

4 Gridded application

Once derived, the skill and independence weights can be used to produce weighted mean estimates of future change, as well as confidence estimates for those projections. To illustrate this, we modify the significance methodology from the 5th Assessment Report of the IPCC [2], such that:

- Stippling - large changes where the weighted multimodel average change is greater than double the standard deviation of the 20 year mean from con-

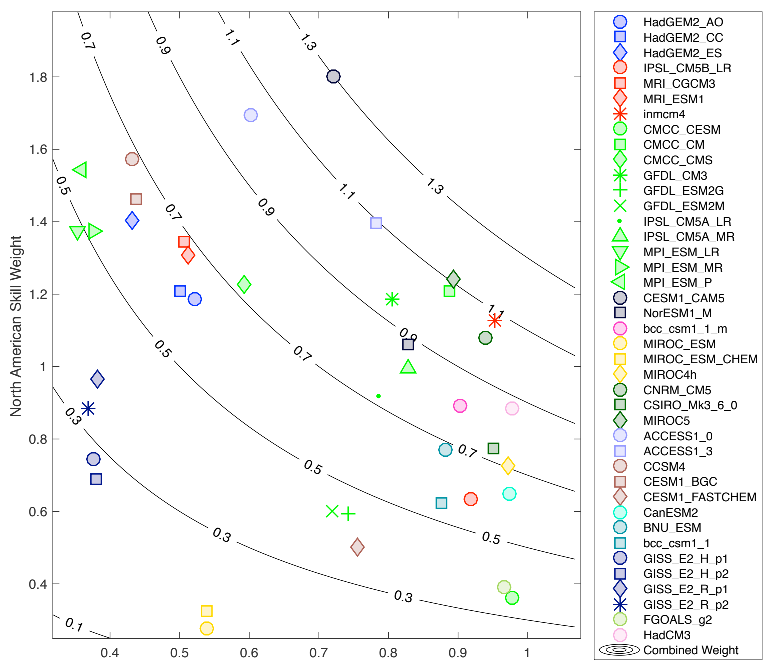

Figure 6: Model skill and independence weights for the CMIP-5 archive evaluated over the CONUS/Canada domain. Contours show the overall weighting, which is the product of the two individual weights.

	Uniqueness weight	Skill Weight	Combined
ACCESS1-0	0.60	1.69	1.02
ACCESS1-3	0.78	1.40	1.09
BNU-ESM	0.88	0.77	0.68
CCSM4	0.43	1.57	0.68
CESM1-BGC	0.44	1.46	0.64
CESM1-CAM5	0.72	1.80	1.30
CESM1-FASTCHEM	0.76	0.50	0.38
CMCC-CESM	0.98	0.36	0.35
CMCC-CM	0.89	1.21	1.07
CMCC-CMS	0.59	1.23	0.73
CNRM-CM5	0.94	1.08	1.01
CSIRO-Mk3-6-0	0.95	0.77	0.74
CanESM2	0.97	0.65	0.63
FGOALS-g2	0.97	0.39	0.38
GFDL-CM3	0.81	1.18	0.95
GFDL-ESM2G	0.74	0.59	0.44
GFDL-ESM2M	0.72	0.60	0.43
GISS-E2-H-p1	0.38	0.74	0.28
GISS-E2-H-p2	0.38	0.69	0.26
GISS-E2-R-p1	0.38	0.97	0.37
GISS-E2-R-p2	0.37	0.89	0.33
HadCM3	0.98	0.89	0.87
HadGEM2-AO	0.52	1.19	0.62
HadGEM2-CC	0.50	1.21	0.60
HadGEM2-ES	0.43	1.40	0.61
IPSL-CM5A-LR	0.79	0.92	0.72
IPSL-CM5A-MR	0.83	0.99	0.82
IPSL-CM5B-LR	0.92	0.63	0.58
MIROC-ESM	0.54	0.28	0.15
MIROC-ESM-CHEM	0.54	0.32	0.17
MIROC4h	0.97	0.73	0.71
MIROC5	0.89	1.24	1.11
MPI-ESM-LR	0.35	1.38	0.49
MPI-ESM-MR	0.38	1.37	0.52
MPI-ESM-P	0.36	1.54	0.56
MRI-CGCM3	0.51	1.35	0.68
MRI-ESM1	0.51	1.31	0.67
NorESM1-M	0.83	1.06	0.88
bcc-csm1-1	0.88	0.62	0.55
bcc-csm1-1-m	0.90	0.89	0.80
inmcm4	0.95	1.13	1.08

Table 3: Uniqueness, Skill and Combined weights for CMIP5 for the CONUS/Canada domain

trol simulations runs and 90 percent of the weight corresponds to changes of the same sign.

- Hatching - No significant change where the weighted multimodel average change is less than the standard deviation of the 20 year means from control simulations runs.

- Blanked out - Inconclusive where the weighted multimodel average change is greater than double the standard deviation of the 20 year mean from control runs and less than 90 percent of the weight corresponds to changes of the same sign.

The standard deviation of the 20 year mean from control simulations is derived using the 'picontrol' simulations in CMIP5. We consider all simulations with a length of 500 years or longer, and discard the first 100 years. The remaining time period is broken into consecutive 20 year periods, and the estimate of control variability for each model is taken as the standard deviation of the 20 year periods. This process is repeated for all models with an appropriate simulation. Finally, the standard deviations are averaged over all models to produce the final estimate for the standard deviation of the 20 year mean from the control simulations (note this differs slightly from [2], where the standard deviation for significance plots is taken as the square root of 2, multiplied by the control standard deviation).

In order to adapt this methodology to a weighted ensemble, we need to apply the weights both to the mean estimate and the significance estimates.

To calculate the weighted average, each model is associated with a weight (e.g. from table 3). The weights must be normalized, and the weighted average p at each gridcell is:

$$p = \sum_{1}^{n} w(i)p(i) \tag{8}$$

where $w(i)$ is the weight of model i and $p(i)$ is the projected value from model i.

Therefore, the significance test is very similar to the IPCC case: if the weighted average exceeds double the control standard deviation, it is a significant change and if it is less than the standard deviation it is not significant.

Sign agreement is slightly modified from the IPCC case - rather than assessing the number of models exhibiting the same sign of change, we consider the fraction of the weight exhibiting the same sign of change, f. This can be expressed as:

$$f = |1/n \sum_{1}^{n} w(i)\text{sign}(p(i))|, \tag{9}$$

for any given set of projections p.

We illustrate the application of this method to future projections of temperature and precipitation change under RCP8.5 in Figures 7 and 8 which show the mean projected quantities as well as the 10th and 90th percentiles of the weighted distribution of change at the gridcell level. In both cases, the weighting has only a subtle effect on the mean projection, but serves to slightly constrain the range of response at a given gridcell. In Section 5, we discuss how more aggressive or targeted weighting can have a greater potential effect.

5 Sensitivity Studies

The parameter choices for D_q and D_u utilized in Section 3, as well as the choice of metrics and the domain were considered appropriate for the specific application of the US National Assessment, where it was desirable to have a single set of weights used for a number of applications. However, in a more general sense, we consider here how different choices may impact the results of weighted analyses, and how the researcher should consider weighting in more targeted (or more global) applications. We briefly consider the sensitivities of the method to different choices.

5.1 Spatial Domain

In the case of NCA4, the strategy was to produce multi-variate metrics which were specific to CONUS/Canada. However, there is an argument that there are aspects of non-local climatology which would ultimately impact the domain of interest (through their influence on global climate sensitivity, for example).

In Figure 9(a-e), we consider the RMSE metrics for both the US and the entire global domain. In this comparison, it is shown that there is a relatively poor correlation between model skill evaluated over CONUS/Canada and globally for any individual metric, however, when individual metrics are combined into a multivariate climate (the approach used in Section 3), there is a correlation of 0.89 between the regional and local metrics. As such, the final weighting for NCA4 would not be highly sensitive to using global rather than CONUS/Canada metrics, but a study using a more restrictive set of variables to assess model quality could potentially be sensitive to domain choice.

5.2 Skill weighting strength

The strength of the skill weighting corresponds to the parameter D_s in Section 3. For the purpose of NCA4, a conservative value was chosen to minimize the potential for overconfidence in future projections from the weighted ensemble. This resulted in only very subtle changes in gridded temperature and precipitation projections for the future (although there are some noticeable differences in the uncertainty range, see Figures 7 and 8).

However, here we consider the impact on temperature projections if a more aggressive weighting strategy were used. In Figure 10(a), we show the sensitivity of global mean temperature change under RCP8.5 as a function of the skill radius. The default value of $D_s = 0.8$ produces a small decrease in projected

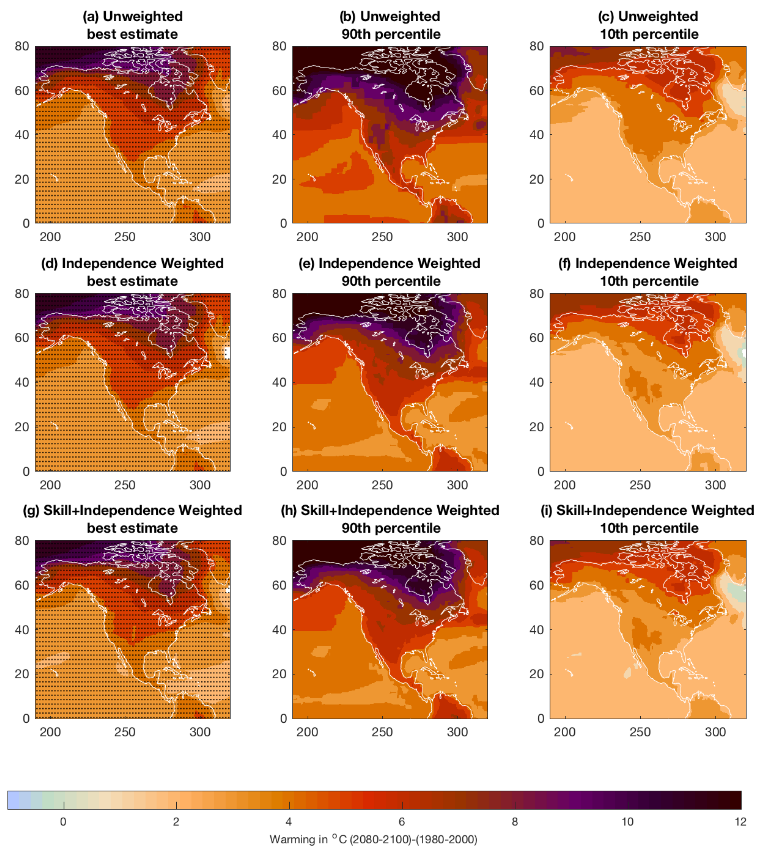

Figure 7: Projections of mean temperature change over CONUS/Canada in 2080-2100, relative to 1980-2000 under RCP8.5. (a-c) show the simple unweighted CMIP5 multi-model average, 90th percentile of warming and 10th percentile of warming using the significance methodology from [2], (d-f) show the weighted results as outlined in section 4 for models weighted by uniqueness only and (g-i) show weighted results for models weighted by both uniqueness and skill.

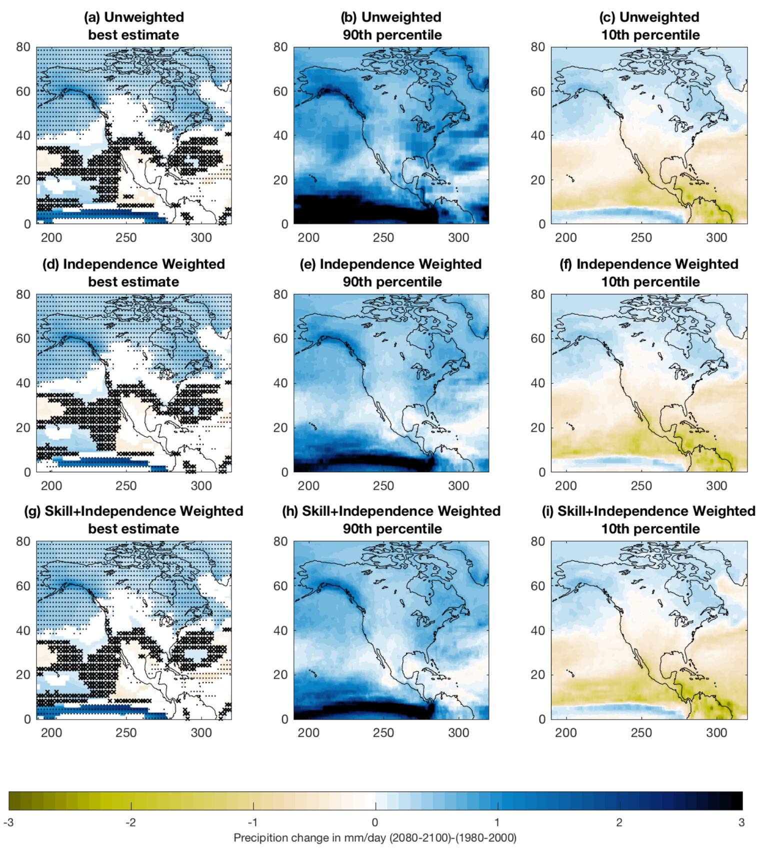

Figure 8: As for Figure 7, but for future mean precipitation change under RCP8.5.

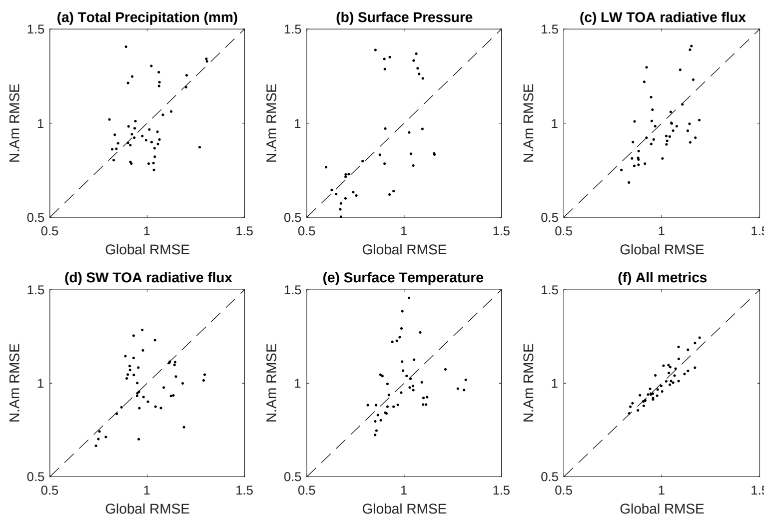

Figure 9: A series of plots showing Root Mean Square Errors evaluated over the CONUS/Canada domain as a function of errors assessed over the global domain. Each point corresponds to a single model in the CMIP5 archive. Plots are shown for some individual fields (a-e) and (f) RMSE averaged over all 12 available fields listed in Figure 2.

2080-2100 global mean temperature increase (a warming of 3.7K above 1980-2000 levels, compared to the non-skill weighted case of 3.9K, Figure 10(d)).

As $D_s \to 0$, the fraction of the percent of the models associated with 90 percent of the weight decreases, and more weight is placed upon the models with higher combined skill scores in Figure 2. If a value of $D_s = 0.4$ is used, 90 percent of the model weight is allocated to just 40 percent of models, and the projected warming is decreased further to 3.45K (Figure 10(c)). However, if D_s is reduced further to 0.1, such that 90 percent of weight is placed on only the top 5 percent of models (which corresponds to only 2 models: CESM1-CAM5 and ACCESS1.0), the weighted warming estimate is higher than the unweighted case at 4.1K (Figure 10(b)).

Hence, we find that although a the skill weighting as used in NCA4 has only a subtle effect on projected temperatures compared to the unweighted case, there is a demonstrable effect when stronger weights are utilized, but there is an increased risk of the weighted ensemble being underdispersive (Figure 4(c)). For very aggressive weighting, projections differ significantly from the unweighted case but the resulting projection is effectively governed by only the best performing few models. Such agressive weighting in the perfect model test was found to result in a less skillful projection (Figure 4(b)).

5.3 Univariate weighting

The requirements for NCA4 were such that a single set of weights should be used for the entire report. However, for some application it might be desirable to tailer a set of weights to optimally represent a particular process or projection. Here, we consider how using weights assessed on precipitation climatology alone could change the result of the projection. The precipitation weighted case is formulated identically to the multivariate case but distances are computed using RMS differences over the mean precipitation field (over the CONUS/Canada domain) only; the selection of D_s is set to 0.8 times the distance of the best performing model, and D_u is taken the 1.5th percentile of the inter-model distance distribution as in the multivariate case.

Figure 11(a) shows the distribution of changes in annual mean grid-level precipitation for the late 21st century under RCP8.5. It is notable that there is negligible difference between the mean precipitation changes in the unweighted case and the multi-variate weighted case, but in the precipitation only case there is an increase in regions exhibiting a large drying trend. This implies that a multivariate metric has little constraint on precipitation change, but a more targeted metric could potentially identify regions which might exhibit extreme drying in the future (just as each individual model exhibits some regions of extreme drying, but the lack of agreement amongst models on where those regions are causes the multi-model mean to lack any such behavior, as noted in Knutti *et al* (2010) [26]).

We can illustrate this behavior by considering the spatial pattern of precipitation change in the three cases, using unweighted(Figure 11(b)), multivariate weighted (Figure 11(c) as in Figure 8) or weighted using only the climatolog-

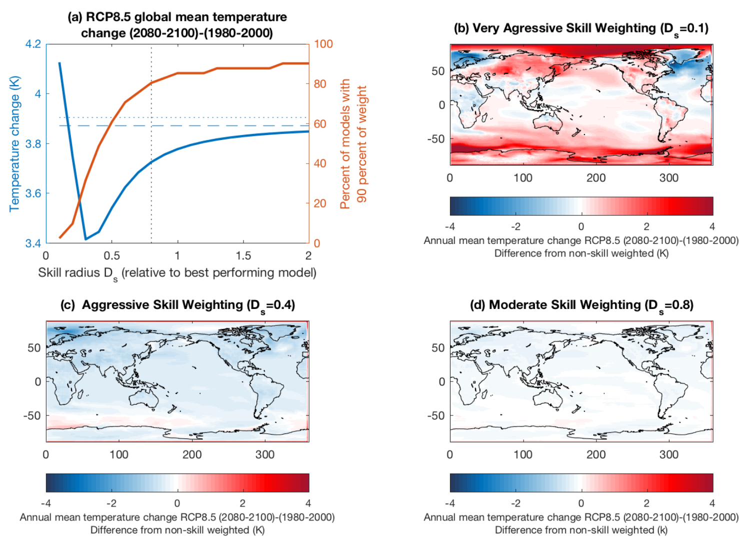

Figure 10: A plot showing the effect of skill weighting strength on global temperature projections. Subplot (a) shows global mean temperature increase for 2080-2100 under RCP8.5 as a function of the skill radius D_s (blue curve), as well as the fraction of models with 90 percent of the allocated weight (red curve). Subplots (b-d) show projected mean temperature maps for 3 cases of D_s=0.1 (b), 0.4 (c) and 0.8 (d).

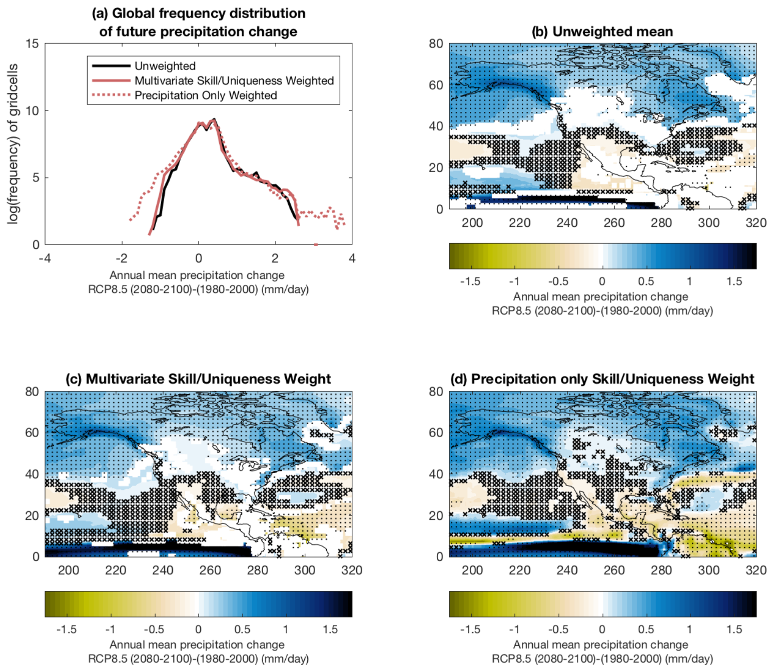

Figure 11: Distribution of changes in annual mean grid-level precipitation precipitation for the late 21st century under RCP8.5. (a) shows the distribution for the mean (black) or weighted by all variables (red solid) and weighted by precipitation only (red dotted) projection of annual precipitation under RCP8.5. (b-d) show maps of precipitation change in the style of Figure 8 for each weighting case.

ical precipitation only (Figure 11(d)). In the unweighted case, large fractions of the continental US show disagreement in the sign of precipitation change. Much of the midwest, northwest and southwest Canada for example are colored white indicating that models disagree on the sign of change, and drying in the southwest is not significant. A multivariate weighting makes little difference to annual mean precipitation projections in North America. However, the seasonal mean precipitation projections presented in the CCSR (not shown here) differ substantially from those presented in the Third US National Climate Assessment during the winter and spring [27]. In those seasons, the stippled regions of decreased precipitation deemed confident to be large in the Southwest US are decreased in area by weighting. Furthermore, the southern edge of the region stippled increases is moved Northward. Summer and fall precipitation changes are largely deemed to be small compared to natural variability in both assessments and are hatched as described above.

A precipitation-based metric, however, seems to make a noticeable difference to the confidence associated with the weighted projection. There is now clear and significant increases in precipitation in the northern part of the US, and significant increases in the northeast. There is also more clearly defined drying along the west coast and significant drying over the northern Amazon which was not evident in the unweighted or multivariate case.

Hence, it seems that there is potential to constrain the spatial patterns of fields which show significant spatial heterogeneity across the multi-model archive by considering targeted metrics which might be more directly informative to relevant processes for that particular projection. One must be cautious as noted in Section 5.1, because individual metrics are more susceptible to domain choices than the multivariate case, and so such a targeted constraint must be thoroughly investigated before application in a general assessment. However, this is a potential line of investigation which would be worthy of future study.

6 Summary and Discussion

This study has discussed a potential framework for weighting models in a structurally diverse ensemble of climate model projections, accounting for both model skill and independence. The parameters of the weighting in this case were optimized for using the CMIP5 ensemble for the Climate Science Special Report (CSSR) to inform the fourth National Climate Assessment for the United States (NCA4); an application which required a weighting strategy targeted towards a particular region (CONUS/Canada), with a single set of weights which could be applied to a diverse range of projections.

The solution proposed in this study adapted the idea first discussed in the context of model sub-selection in Sanderson et al (2015) [7], and applied it to a continuous general weighting scheme (in contrast to the sea-ice specific weighting scheme outlined in [19]). Weights were formulated on the basis of skill and uniqueness, where skill was assessed by considering the climatological bias averaged over a diverse set of variables, and uniqueness was assessed by constructing an inter-model distance matrix from the same set of variables and down-weighting models which lie in each others' immediate vicinity.

It should be noted that although our likelihood weighting function is empirical, the functional form satisfies in a simple way the required parameters of the weighting scheme. Though the structure of this functional form is not fundamental, it can simply be shown to have some useful features. The technique is presented in this paper in a form which maximises clarity and reproducibility, but its effect can be described in Bayesian language. The total model weight is the posterior likelihood of a given model representing truth. Each model's prior probability of representing truth is given by its independence weighting, and the likelihood function is defined for the multivariate dataset using an assumed Gaussian likelihood profile in a space defined by the the sum of the normalized RMSE differences over all variables between each model and the observations. However, the application in this paper is for a simple weighting scheme only and it is left to further study to formally implement such concepts in a Bayesian framework.

The method provides a single set of weights constructed for NCA4, using a multi-variate climatological skill metric and a limited domain size. Two parameters must be determined for the weighting algorithm; a radius of model skill and one of similarity. The former was calibrated by considering a perfect model test where a single model is treated as truth and its historical simulation output is treated as observations, immediate neighbors of the test model are removed from the archive and the remaining models are used to conduct tests which assess skill in reconstructing past and future model performance, as well as assessing the risk of producing an underdispersive ensemble which fails to encompass the perfect future projection at a given grid point. Using these three tests, we take a conservative choice for model weighting which minimizes the risk of under-dispersion (i.e. the risk that the real world might lie outside the entire weighted distribution of projections at a given gridpoint).

The similarity parameter is calculated in a qualitative fashion by considering cases where models are known to be relatively unique, or where there is a known set of closely related models. The parameter is adjusted such that the known unique models are given a weight of near unity, and the models with n near-identical versions are each given a weight of approximately $1/n$.

The requirements of a large assessment places constraints on the choice of parameters for this analysis. Logistical considerations imply that only one set of weights can be constructed, and the broad readership and high stakes of the assessment mean that any risk of under-dispersion of projected future climate is unacceptable for this application. These constraints dictate that only a moderate weighting of model skill is used, where 90 percent of the weight is allocated to 80 percent of models. This, unsurprisingly, creates only a modest change in mean projected results and only a small reduction in uncertainty. A stronger skill weighting is shown to have a more significant effect on projected changes, but with the risk of increased under-dispersion.

In addition, there exists a weak trade-off between model skill and model uniqueness in the CMIP5 ensemble; models which are demonstrably high performing also tend to be the ones with the most near replicates in the archive. As such, there is a compensating effect of the skill and uniqueness components of the weighting algorithm, which tends to mute the effect of the overall weighting when compared to the unweighted case. In other words, the unweighted CMIP5 ensemble is in fact already a skill weighted ensemble to some degree.

However, although this tradeoff is evident in the CMIP5 archive, there is no guarantee that such a tradeoff is a justification for using an unweighted average in future versions of the CMIP archive. A single, highly replicated but climatologically poor model present in a future version of the archive could significantly bias the simple multi-model mean of a climatological projection. As such, it is desirable to have a known and tested weighting algorithm in place to produce robust projections in the case of highly replicated, or very poor models.

Beyond the single set of weights produced for NCA4, the basic structure outlined in this study can be used to produce a more targeted weighting for a particular projection (as was conducted for sea ice projections in [19]). Our provisional results suggest that targeted weights could potentially yield more confidence in projections if only a limited set of relevant projections are included, especially in fields where projections exhibit high degrees of structural diversity within the archive. This tailored weighting approach, however, presents risks which necessitate further study - our sensitivity studies suggest that multivariate metrics are more robust to changes in spatial domain than targeted metrics, and the exact choice of metrics which should be used to best constrain a particular projection is not a trivial matter.

With this in mind, we propose that future studies should further investigate how selection of physically relevant variables and domains should be used to optimally weight projections of future climate change, and that individual projections will need careful consideration of relevant processes in order to formulate such metrics. Confidence in such weighting approaches is highest if there are well understood underlying processes that explain why the chosen metric constrains the projection. Until then, we have presented a provisional and conservative framework which allows for a comprehensive assessment of model skill and uniqueness from the output of a multimodel archive when constructing combined projections from that archive. In so doing, we come to the reassuring conclusion that for this particular application (i.e., domain and variables) the results which would be inferred from treating each member of the CMIP5 as an independent realization of a possible future are not significantly altered by our weighting approach although the localized details of confidence in the magnitude of precipitation changes may be affected. However, by establishing a framework, we make the first tentative steps away from simple model democracy in a climate projection assessment, leaving behind a strategy which is not robust to highly unphysical or highly replicated models of our future climate.

7 Code availability

Complete MATLAB code for the analysis conducted in this manuscript is provided. All CMIP5 data used in this analysis is downloadable from the Earth System Grid (https://pcmdi.llnl.gov/projects/esgf-llnl/).

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