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Climate Model Diversity: Future Climate Predictions from the CMIP5 Multi-Model Ensemble

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1. INTRODUCTION

Efforts to understand how Earth's climate system responds to external radiative or anthropogenic forcing are crucial for informing present and future human behaviour. Climate models are our greatest tool for understanding how and why the climate changes in response to these driving forces. Simulations of the climate under different socioeconomic and emission scenarios yield quantitative predictions of our future.

There are two good reasons why the scientific community has and continues to develop multiple independent climate models. Firstly, it is a critical truth that the mean of a collection of models has smaller error, ie. is more accurate, than any one individual model (Flato 2011; Annan & Hargreaves 2010; Lambert & Boer 2001). All individual models are outperformed by both the mean and the median of the ensemble. The second reason is the fact that no single model outperforms the others in all respects (Flato 2011). One model may perform best for the temperature climate variable, but may not hold the same title with respect to precipitation.

As expected, model diversity yields an equally diverse range of future climate predictions. Even small differences in the predicted value of one climate variable, for example global average temperature, can translate to extreme changes to the way of life for ecosystem inhabitants. It is therefore very important to understand model diversity and isolate the aspects of climate models from which it arises. What is it about different models that lead them to predict different futures?

On the flip side, model diversity can and should be taken advantage of in efforts to quantify the uncertainty of future climate predictions. The ensemble mean benefits from "cancellation of errors" (Flato 2011), enabling more accurate quantification of uncertainty. International collaborations and standardized experiments, such as the Coupled Model Intercomparison Project (CMIP; Taylor et al. 2012; Meehl et al. 2009; Hibbard et al. 2007) are key for making steady progress towards understanding climate variability, climate change, and garnering robust predictions of the future.

In this work, we obtain the future climate predictions of the CMIP Phase 5 (CMIP5) multi-model ensemble under four radiative or anthropogenic forcing scenarios, and analyze the diversity in this collection of models both qualitatively and quantitatively. We focus on two specific large-scale climate variables: global mean temperature and average monthly precipitation. In order to quantify the diversity in the range of future climate predictions, we invoke the concept of the "envelope," which we define as the region within one standard deviation of the ensemble mean. To understand the source of the differences, we discuss the inner workings of overarching model classes and universal concepts in climate modelling.

2. DATA

Our data consist of a subset of the Decadal Predictions Simulations of the CMIP5 multi-model ensemble, as shown in Table 1 (Taylor et al. 2012; Meehl et al. 2009; Hibbard et al. 2007). The Coupled-Model Intercomparison Project Phase 5 (CMIP5) is an extensive experimental framework for studying the output of the global scientific community's atmosphere-ocean general circulation models (GCMs) using a standardized method, and as such is ideal for our purposes.

The downscaled Intergovernmental Panel on Climate Change (IPCC) CMIP5 climate predictions of the future[1] from general circulation models use WorldClim 1.4 as a baseline climate. The outputs predict climate variables distributed over all of Earth's land surface, and are given as monthly averages of 2050 (which themselves are averages of each month for 2041-2060) and 2070 (the same but for 2061-2080). We extracted monthly average maximum and minimum temperatures, as well as average monthly total precipitation, at 10 minute spatial resolution (corresponding roughly to equatorial grid

[1] Available for non-commercial use and free download at: http://worldclim.org/CMIP5v1

cells of 18.5 km sides at the equator). The data exist for four representative concentration pathways (RCP26, RCP45, RCP60 and RCP85).

3. COUPLED MODEL CLASSES

All of the models included in the CMIP5 multi-model ensemble are coupled climate models (CMs), meaning their components (eg. the atmosphere, ocean, sea ice, and land surface) interact via a coupler (Meehl 1990). The coupler works to (1) monitor time for each simulation and (2) input separate information for each climate component, sending it to any other component that requires this information to create the next time step (Rasch 2012).

Within the umbrella of coupled models are roughly four different model classes (though some elude classification and we deem them miscellaneous); however, they share a common limitation. The phenomenon of model drift is especially prevalent in coupled models precisely because they depend on interactions between the atmosphere and ocean. If one component drifts, the other does so as well (Gupta et al. 2013). Refer to Figure 1 for a schematic representation of the climate model components and the sub-classes.

3.1. *Climate System Models (CSMs)*

BC, CC: Climate System Models (CSMs) are comprehensive mathematical representations of the evolving state of four climatic components of the Earth: the atmosphere, land surface, ocean, and sea ice. They formulate mathematical expressions based on physical principles such as thermodynamics, radiative transfer, chemical reactions, and fluid motion. The calculations are carried out in response to naturally occurring external forcings and stable equilibrium, which is reached through millennial intervals with free exchanges of heat, water, and stress on land, as well as water surfaces (Council 2001). CSMs are known for their use of a diverse range of radiative forcings, which include: solar luminosity, atmospheric composition, and land use, making them a valuable contributing subclass to CMIP5 (PCMDI 2018).

The limitations of these models mostly arise from errors in the assumption of natural forcings (including solar luminosity and volcanics) or the misrepresentation of internal variability systems of the climate, through formulated analogues such as El-Niño (Wu et al. 2014).

3.2. *Community Atmosphere Models (CAMs)*

CE: Community Atmosphere Models (CAMs) comprise the atmospheric component of Community Earth System Models (CESMs, distinct from ESMs). CAMs describe the physical parameterization of the dynamics of atmospheric circulation. Though CAMs are capable of running as a standalone model, they can also be coupled to other models. The CMIP5 multi-model ensemble includes one CAM, under the code CE, which is coupled with an active land model, thermodynamic-only sea ice model, and a data ocean model. The main parameterizations include processes relating to precipitation, radiation, clouds, and turbulent mixing (Abiodun et al. 2011). The models represent features of the atmospheric state, thermodynamics characteristics, as well as energy and chemical transportation (Collins et al. 2006).

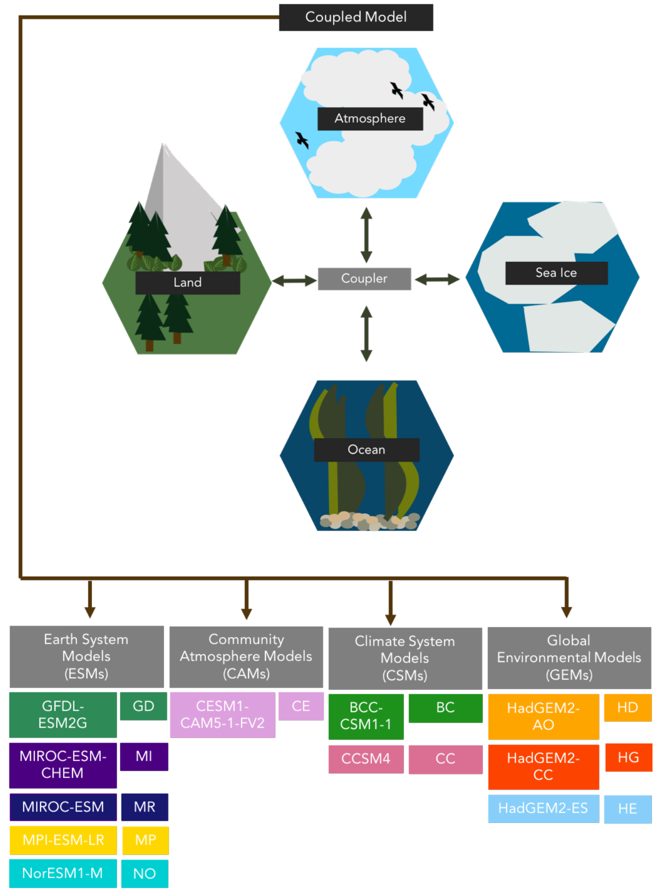

Figure 1. A schematic of the components of coupled models and their subclasses: (1) Earth System Models (ESMs), (2) Community Atmosphere Models (CAMs), (3) Climate System Models (CSMs), (4) Global Environmental Models (GEMs), and (5) miscellaneous (not shown). **Main Point:** We categorize coupled models into major sub-classes.

Table 1. The CMIP5 multi-model ensemble of simulations used in this paper (Taylor et al. 2012; Meehl et al. 2009; Hibbard et al. 2007). All models within the ensemble are Coupled Models (CM), though some may fall into different subclasses: Climate System Models (CSM), Community Atmosphere Models (CAM), Earth System Models (ESM), Global Environmental models (GEM), and Coupled General Circulation Models (CGCM). Models labeled CM do not fall into any of the aforementioned subclasses.

Modeling Center (or Group)	Institute ID	Model Name	Code	Type	Source
Commonwealth Scientific & Industrial Research Org.	CSIRO-BOM	ACCESS1-0 (#)	AC	CM	Ackerley & Dommenget (2016)
Beijing Climate Center	BCC	BCC-CSM1-1	BC	CSM	Wu et al. (2014)
National Center for Atmospheric Research	NCAR	CCSM4	CC	CSM	Gent et al. (2011)
Community Earth System Model Contributors	NSF-DOENCAR	CESM1-CAM5-1-FV2	CE	CAM	Yun et al. (2016)
Centre National de Recherches Météorologiques	CNRMCERFACS	CNRM-CM5 (#)	CN	CM	Voldoire et al. (2013)
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3	GF	CM	Griffies et al. (2011)
NASA Goddard Institute for Space Studies	NASA GISS	GFDL-ESM2G	GD	ESM	Dunne et al. (2013)
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-R	GS	CM	Schmidt et al. (2014)
National Institute of Meteorological Research	NIMR/KMA	HadGEM2-AO	HD	GEM	Martin et al. (2011)
Met Office Hadley Centre	MOHC	HadGEM2-CC	HG	GEM	Collins et al. (2011)
Met Office Hadley Centre	MOHC	HadGEM2-ES	HE	GEM	Martin et al. (2011)
Institute for Numerical Mathematics	INM	INMCM4	IN	CM	Volodin et al. (2010)
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR	IP	CM	Dufresne et al. (2013)
Japan Agency for Marine-Earth Science	MIROC	MIROC-ESM-CHEM	MI	ESM	Watanabe et al. (2011)
Japan Agency for Marine-Earth Science	MIROC	MIROC-ESM (#)	MR	ESM	Watanabe et al. (2011)
Atmosphere and Ocean Research Institute	MIROC	MIRCO5 (#)	MC	CM	Watanabe et al. (2010)
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR	MP	ESM	Giorgetta et al. (2013)
Meteorological Research Institute	MRI	MRI-CGCM3	MG	CGCM	Yukimoto et al. (2012)
Norwegian Climate Centre	NCC	NorESM1-M	NO	ESM	Bentsen et al. (2013)

The magnitude of errors concerning flux divergences and heating rates tend to decrease output values, downplaying the effects of aerosols on the atmosphere. The limitations concerning aerosol effects of shortwave energy flow in the atmosphere tend to cause changes in long wave emissivity and absorptivity, resulting in fluctuations in surface albedo and global temperatures (Abiodun et al. 2011).

3.3. *Earth System Models (ESMs)*

GD, MI, MR, MP, NO: Earth System Models (ESMs) have been developed for the explicit purpose of being able to represent the interaction, or feedback, between the physical climate and biogeochemical processes (Hajima et al. 2014). The carbon cycle is a key example of a biogeochemical process. The atmosphere and ocean components of an ESM can take up carbon dioxide, and the climate can respond appropriately (Flato 2011). ESMs are included in CMIP5 because they incorporate feedback mechanisms between atmospheric carbon and the physical climate, and can therefore be used to isolate the role that each feedback plays in climate sensitivity (Hajima et al. 2014).

The inclusion of biogeochemical processes (as is the trademark of ESMs) is a computationally intensive task, and as such, requires significant simplifications to these models. The atmosphere may be modelled with only one layer or a zonally-averaged cross section (Flato 2011). While ESMs thus cannot give insight into the transport of matter in the atmosphere, they are still useful for understanding long-term climate change, as essential, slow processes are retained.

3.4. *Global Environmental Models (GEMs)*

HD, HG, HE: Global Environmental Multiscale Models (GEMs) including HadGEM2 configurations considered in CMIP5, rely on data assimilation systems to develop forecasts for the future. In addition to troposphere, land surface, ocean, and sea ice processes, GEMs include a well-resolved stratosphere component (Martin et al. 2011). By using a second vertical resolution for the atmosphere, an extension in the same direction is created, encompassing the stratosphere and lower mesosphere (Martin et al. 2011). Inclusion of the mesosphere with computation based in vertical motion improves representation of stratospheric circulation (Senior et al. 2016). Stratospheric circulation is linked to changes in Arctic sea ice extent, stratospheric sudden warming, and strong polar vortices - all of which are vital to understanding climate variability (Smith et al. 2018). As a consequence, in CMIP5, when investigating temperature, GEMs elucidate the purpose of vertically-extended climate configurations on stratospheric circulation in the extratropics (Martin et al. 2011).

Numerical feasibility is not optimal with relation to output calculations, leading to high variability and uncertainty when comparing forecasts in continental-scale regions. These regions exhibit teleconnection patterns, namely, the El-Ñino-Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) (Wu & Lin 2012). The consequence of uncertainty in these areas are cold biases observed in the equatorial Pacific and South America (Martin et al. 2011). Cold biases are not exclusive to these regions for this subclass, as they are also found in the northern hemisphere, where the greatest warming occurs (Baek et al. 2013).

4. METHODS

Our work hinges on the robustness of the ensemble mean and the concept of the "envelope." As such, monthly averages of minimum/maximum temperature and total precipitation from WorldClim are converted into annual and monthly averages, respectively, for each grid cell on the land surface of Earth. We take an average value over all land-surface grid cells in order to obtain the global mean temperature (average of T_{max} and T_{min}) and the global mean total precipitation for 2050 and 2070, as predicted by each general circulation model in the CMIP5 multi-model ensemble. For each of the four RCPs, we find the statistical standard deviation in the value of global mean monthly precipitation and temperature predicted by the suite of models.

5. RESULTS

5.1. *Consistencies in Global Temperature and Precipitation Predictions*

Figure 2 shows, for all four RCPs, each CMIP5 model's prediction of global mean temperature and global monthly mean precipitation, averaged over the periods of 2041-2060 and 2061-2080. We find that, for severer greenhouse gas concentration trajectories, the models generally predict higher values of both global temperature and precipitation. No model predicts a global mean temperature above 12 °C under the RCP26 scenario, and most predict less than 11 °C. Under the RCP85 scenario, the majority of models predict a global mean temperature above 12 °C over the 2061-2080 year period. A similar trend is seen in predictions of global mean precipitation.

Comparing the predictions of individual models to the mean of the collection, we can visually identify particular models that consistently "over-" or "under- predict," in the sense that their predictions lie outside the 1 σ spread about the collection's mean. The concept is particularly clear chromatically in the bottom panel of Figure 2. What's more, we find a consistency between

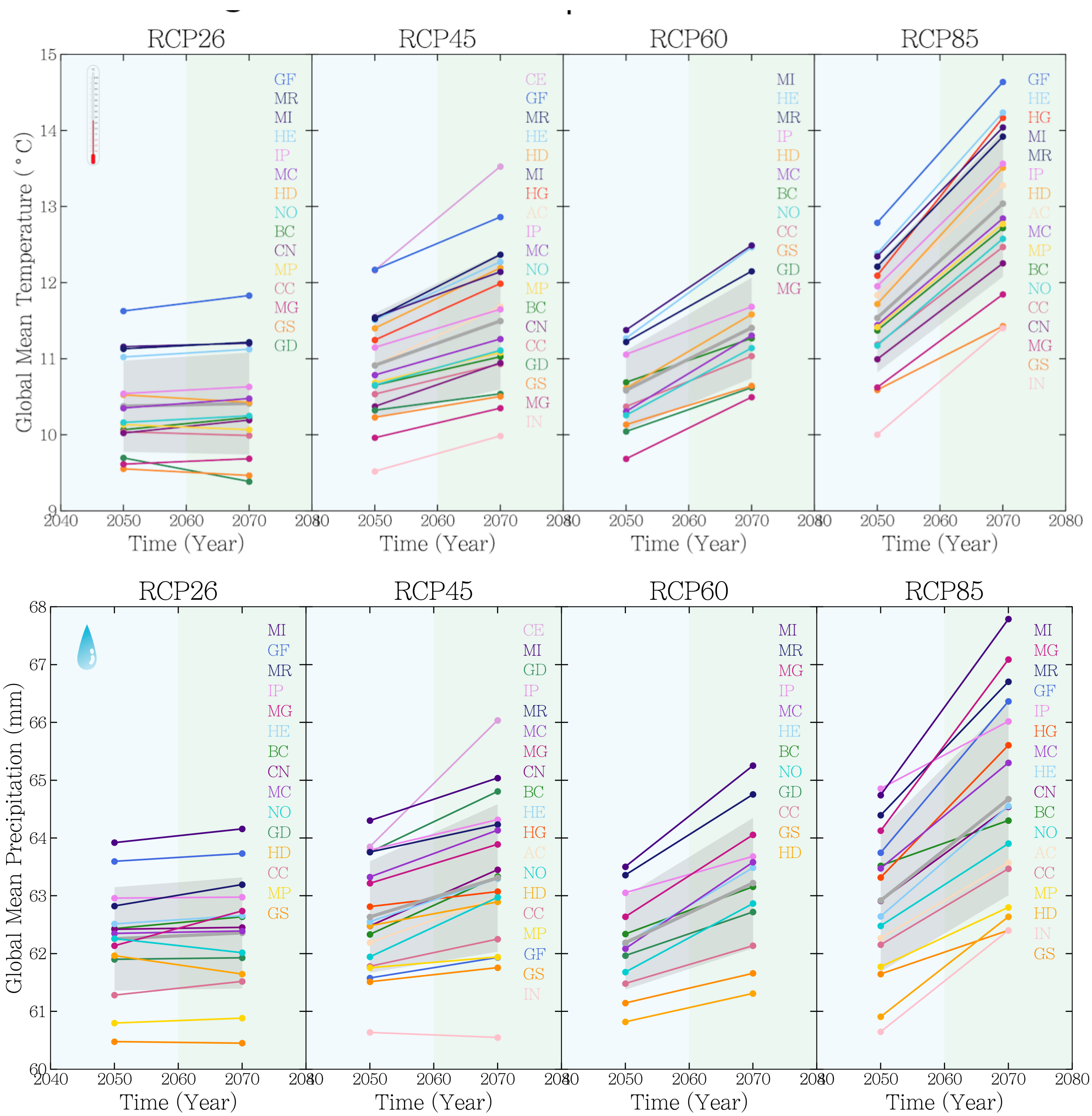

Figure 2. *Top:* The predicted global mean temperature (°C) in each RCP scenario and model for which a prediction was made. *Bottom:* The predicted monthly average precipitation (mm). Points at 2050 represent an average over 2041-2060 (light blue region) and points at 2070 represent the average over 2060-2080 (light green region). Each model is colour-coded and labelled such that the order is preserved. Shown in grey is the mean prediction and one standard deviation spread, or "envelope," used to identify "over/under-predictors." **Main point:** Different climate models predict different values for the future's global mean temperature and mean monthly precipitation.

climate variables: temperature "over-predictors" tend to *also* be precipitation "over-predictors." The models GF, MR, MI, CE tend to "over-predict," and IN, GS, HD tend to "under-predict."

5.2. *Sensitivities to Radiative Forcing*

Under each greenhouse gas concentration trajectory, each model predicts a value of global mean temperature or precipitation for 2070 that is different to their predic-

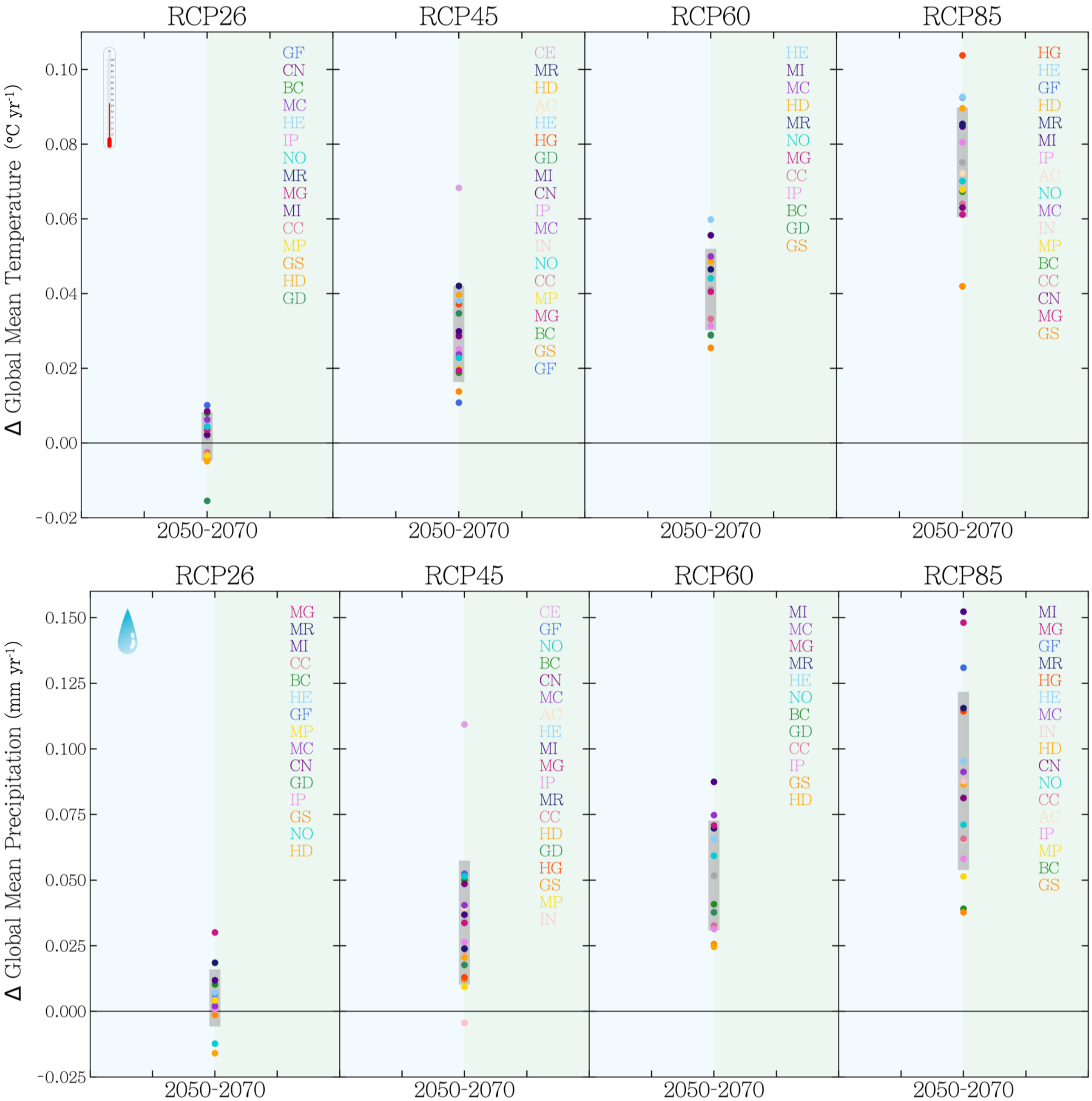

Figure 3. *Top:* The slope in global mean temperature (°C) between the predicted 2041-2060 and 2061-2080 averages (top panel, Figure 2). *Bottom:* The same but for precipitation (mm). Each model is colour-coded and labelled such that the order is preserved. In grey is the mean slope and one standard deviation spread, or "envelope", used to identify "pessimists/optimists." **Main point:** Different climate models are more sensitive or less sensitive to the same forcing.

tion for 2050. To understand how sensitive the different models are in response to the same standard forcing, we plot the slope between 2050 and 2070 predictions in Figure 3. We find that only under RCP26 do any models predict a decrease in global mean temperature or precipitation (with one exception in RCP45: GS). Under all other greenhouse gas concentration scenarios, the CMIP5 multi-model ensemble predicts increasing temperature and precipitation.

Similar to the previous section, we use the mean predicted value $\pm 1\sigma$ to identify which models have significantly different responses to the same input compared to the others in the collection. We term models with slopes higher than those contained in the envelope as "pessimistic" and the models with slopes lower than those in the envelope as "optimistic." The "pessimistic" models consist of MI, MG, GF, MR and the "optimistic" models consist of GS, MP and BC.

We note that our classifications are qualitative, not quantitative, and are meant to inspire investigation rather than suggest strict partitions in the collection. To enhance comprehension, we represent our results schematically in Figure 4 and 5.

6. DISCUSSION

6.1. *Environment*

One of our main findings (Figure 2) is a consistency of the models in the CMIP5 multi-model ensemble: over/under-predictors retain their status relative to the mean in both their temperature and precipitation predictions over the 2050-2070 period. It is not necessarily true, *a priori*, that the models' predictions for different climate variables should be correlated, as the climate is highly complex with numerous interactions between each variable. However, correlations between temperature and precipitation can be attributed to the hydrological cycle.

The rate of the hydrological cycle is highly dependent on evaporation rates, which are closely associated with temperature. As temperature increases, vapour pressure increases accordingly (Peixoto 1995). The intensification is realized within models as an increase in total precipitation and the frequency of precipitation events, though this phenomenon is most pronounced over land (Slaymaker et al. 2009). As there is a predicted overall increase in global temperature, the result is a greater fraction of precipitation falling as rain rather than snow (Peixoto 1995). This result is of significant interest to vital global production industries, namely the agricultural sector, as they are vulnerable to the implications of an intensifying hydrological cycle manifested in the form of heavy rain and extreme precipitation events.

6.2. *Mob "Mean"-tality*

That the mean predicted value of an ensemble of models has a smaller error than that of any individual model can further elucidate our findings. Clearly, there is a range in model performance. As shown in Figure 2 and 3 respectively, we find the model with the code GS to be an "under-predictor" and an "optimist." In a comparison of the CMIP3 multi-model ensemble, Flato (2011) finds GS to have the single largest root-mean-square error for precipitation of all the models carried over to CMIP5. Therefore, it is possible that the predicted values of GS that we find do agree with the ensemble's mean if one considers the model's own uncertainty. Because the WorldClim data to which we had access are already processed, we could not perform the statistical tests and obtain the models' root-mean-square error ourselves.

6.3. *Model Drift*

In climate simulations, models can drift away from the correct solution over time. They show long-term changes that are not caused by the critical factors of radiative or anthropogenic forcing (Gupta et al. 2013). The cause of model drift may be a slowly diverging numerical integration method, or an initial state that is not in dynamical balance. Regardless, since the purpose of climate models is to explore how external forcing determines the state of the climate, model drift is problematic.

It may take thousands of model-years for a model to self-correct and adjust via ocean advection or mixing; however, it is too computationally expensive to allow models to spin-up for thousands of years (Gupta et al. 2013). Instead, models are spun up for only a few hundred years. Therefore, it is possible that the model outputs do not represent climate response to radiative or anthropogenic forcing, but rather the process of equilibration. It is crucial not to conflate climate changes associated with the spin-up adjustment period and changes associated to external forcing.

While most models do not exhibit significant drift, models with ocean and atmosphere components can demonstrate statistically significant drift in large-scale globally averaged quantities, because the direction of drift is systematically consistent (Gupta et al. 2013). Particularly susceptible are models with deep-ocean components. The model with the code GF, which we found to consistently over-predict mean global temperature and precipitation (Figure 2), is one such model (Griffies et al. 2011). Because the simulation does not compute enough ocean observations from the 1860s for the model to reach deep ocean equilibrium, it is still adjusting during the simulated 22nd century decadal years. This explains why GF predicts higher global mean temperatures relative to the envelope.

6.4. *Feedback Mechanisms*

As seen in Figure 2, the models with codes MI and MR yield higher predictions of global mean temperature than the ensemble mean for each of the RCPs in which they appear. Additionally, as seen in Figure 3, MI and MR are among the most sensitive models, exhibiting a steep positive change in response to the forcing scenarios. Biogeochemical feedback mechanisms, the trademark of ESMs, may deserve attribution for this result. For example, in the concentration-carbon feedback, terrestrial ecosystems uptake CO_2 by photosynthesis, increasing the dissolution and diffusion of CO_2

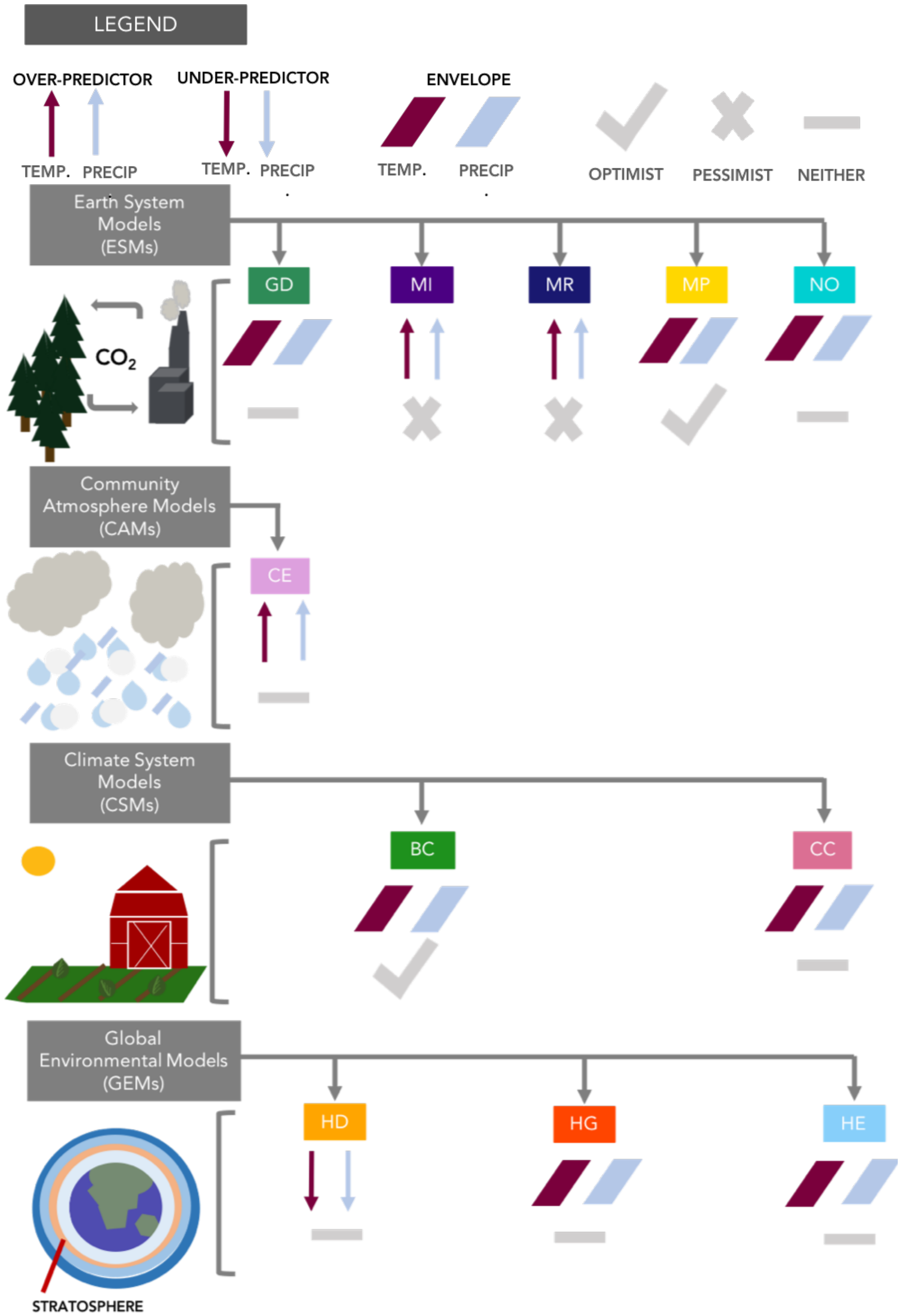

Figure 4. Schematic results: "over/under-predictors" and "optimists/pessimists" with the four coupled model sub-classes. Refer to legend at the top. Pictorial representations of the trademark of each sub-class are included beneath their title. **Main point:** We attempt to understand our results based on coupled model sub-class.

in the oceans (Hajima et al. 2014). The climate-carbon feedback, on the other hand, has global warming induce greater ecosystem respiration, which in turn induces greater global warming (Friedlingstein et al. 2003). As ESMs, the models MI and MR respond to the radiative forcing by reducing the solubility of CO_2 in sea-water, inhibiting vertical mixing, increasing the rate at which carbon exudes from the soil, and generally reducing the ability of the land and ocean components to take up the CO_2 released in the emission scenario (Flato 2011).

All climate feedback mechanisms are crucial to understand because vicious cycles can be difficult or nearly

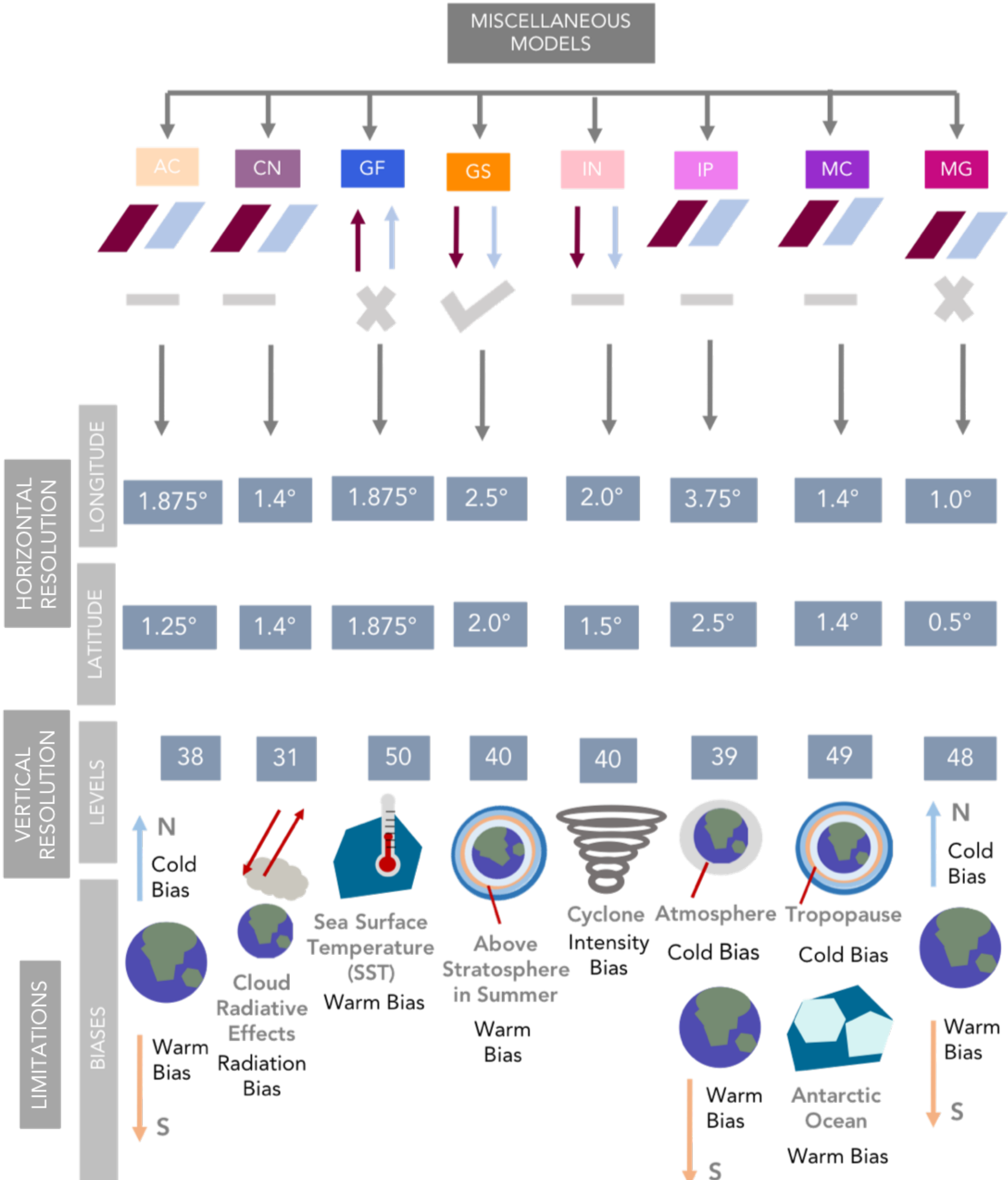

Figure 5. Schematic results: "over/under-predictors" and "optimists/pessimists" with the miscellaneous sub-class. Legend from Figure 4 applies. Horizontal/vertical resolution and limitations take the place of sub-class trademarks. Information sourced from: Davy & Esau (2014); Voldoire et al. (2013); Griffies et al. (2011); Schmidt et al. (2014); Volodin (2013); Volodin et al. (2010); Dufresne et al. (2013); Watanabe et al. (2010); Yukimoto et al. (2012). **Main Point:** Interpreting our results for miscellaneous models cannot be done with broad strokes.

impossible to reverse. Human activity is a powerful component of the biogeochemical cycle. We need to inform ourselves of these cycles in order to make prescient decisions and effective global policies.

6.5. *Intra-Class Variation*

The next question then naturally arises: why aren't all ESMs over-predictors of temperature? Studies examining the behaviour of ESMs in response to a common forcing scenario found that variations in the strength of concentration-carbon feedback between models is likely the cause of intra-class variability (Hajima et al. 2014). Feedback strength is comprised of, for example, the sensitivity of plant productivity to elevated CO_2 levels.

Intra-class variability is demonstrated in our results with the GEMs as well, though this variation stems from differences in the components which have been included. For instance, the model with the code HE incorporates the terrestrial carbon cycle, ocean biogeochemistry, and pure chemical principles; HG includes all of the aforementioned processes with the exclusion of pure chemical principles; HD retains all components of HG with the exception of the terrestrial carbon cycle and ocean biogeochemistry (Martin et al. 2011). Different processes require different levels of complexity, which are achieved with modification to parameters. As shown in Figure 3, there is clear intra-class variability in the sensitivities exhibited by the ESMs (GD, MI, MR, MP, NO) and GEMs (HE, HG, and HD).

Intra-class variation calls into question our approach of understanding our results on the basis of model subclasses. The Coupled-Model Inter-comparison Project makes no effort to distinguish the multi-model ensemble by sub-class, and treats each model as a distinct entity. Without loss of insight, future studies refraining from searching for similarities based on class, and assessing each model independently would avoid confirmation bias and preserve appreciation for model diversity.

7. CONCLUSION

Under simulated scenarios of radiative or anthropogenic forcing, the CMIP5 multi-model ensemble predicts increasing global mean temperature and precipitation over the decadal years of 2041-2080. We have quantified the spread in the ensemble's predictions using the concept of the "envelope" and investigated those models that demonstrated deviant behaviour relative to the mean, either by "over/under-predicting" climate variables (Figure 2) or by responding more/less sensitively to the same forcing (Figure 3). Precise predictions of large-scale climate variables are necessary, as even slight variations have significant impact on biodiversity and quality of life for all species on Earth. This information dictates international policy and our individual behaviour on a day-to-day basis.

Future work should be concerned with additional climate variables; the bio-climatic variables could be extracted from WorldClim and analyzed in order to explore model diversity further. A spatial dimension could be added to the analysis by investigation of the WorldClim outputs using QGIS software. Finally, we could calculate the interquartile range for each model's future temperature and precipitation predictions and observe how they change under different RCPs. Perhaps increasing external forcing would increase the spread, and thus amplify the differences between models, facilitating further insight into the nature and source of model diversity.

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Software: numpy (Oliphant 2006); matplotlib (Hunter et al. 2018); pandas (McKinney et al. 2018)

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APPENDIX

A. TERMINOLOGY

bias correction: a method that removes the effects produced by systematic errors to formulate a set of rescaled data or variables

cold bias: tending toward colder temperatures than are observed

coupler: framework/hub that connects sub system component models to an overarching climate system, where each component model independently shares information with the coupler

drift: spurious changes that occur over long periods of time in climate models, independent of factors such as external or internal forcings and internal low-frequency variability

external forcing: climatic forcing agent that impacts a climate system from an external standpoint, including mechanisms which can either be natural (volcanic, orbital, solar outputs) or anthropogenic (greenhouse gas emissions)

extratropic: mid-latitude region located outside global tropical climate region

long wave absorptivity: infrared energy absorbed by the Earth

long wave emissivity: infrared energy radiating from the Earth

mesoscale analysis: the study of atmospheric phenomena (thunderstorms, tornadoes, etc) spanning spatial scales of 10 to 100km; mesoscale analysis specifically looks at occluded fronts (i.e. warm and cold fronts) found on the mesoscale to describe the phenomena

natural forcing: an imposed influence that directly impacts the energy balance of the Earth, examples include radiative luminosity and volcanic eruptions

shortwave energy flow: consists of emission and absorption of visible light, with relatively more energy than longwave energy flow

spin-up: initial stabilization period for climate models

surface energy flux: measurement of rate of energy transfer in the form of latent heat that occurs due to surface-level condensation or evaporation

teleconnection: climate anomalies connected to each other, while being located thousands of kilometers away from each other

radiative forcing: alteration in energy balance on Earth using the difference between incoming solar radiation and outgoing thermal infrared emission (ie. difference between incoming and outgoing radiation)

warm bias: tending toward warmer temperatures than are observed