Pacific Northwest and Southeast China Climatology: A Comparative Analysis of CMIP5 Global and Regional Climate Model Time of Emergence

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Abstract. The power of climate models are in part derived from their predictive ability. One such prediction is the Time of Emergence (ToE). The ToE is the year in which the year-to-year variability of a given holistic climate variable over a given period, such as 90th percentile maximum temperature, is overtaken by the effects of climate change. The ToE can help society plan for our climate future by dictating deadlines for levy construction completion or other such necessary climate change ready infrastructure. In the Coupled Model Intercomparison Project Phase 5 (CMIP5) models and data sets, there are both Global Circulation Models (GCM) and Regional Climate Models (RCM) models. In these two classes of climate models, there are different resolution scales and different parameters. GCM models are less local, do not consider smaller scale orographic features, and lack the regional resolution of RCM models. This analysis compares these two model classes through the ToE, determining how each model sees the emergence of climate change in the Pacific Northwest and Southeast China at local and global levels. The differences therein elucidate the predictive accuracy of each model class at small scales and further highlights the phenotypical aspects of each model class. **Keywords:** Climatology, Time of Emergence, and CMIP5, GCM, RCM.

I. INTRODUCTION

A watched pot never boils. A frog will jump out of boiling water, but, if you start with tepid water and slowly raise it to a boil, the frog will stay put and be cooked alive. Both idioms/fables attempt to convey perceptions of change and one's ability, or lack thereof, to notice that change. And while these idioms bear no resemblance to reality, they are still important lessons to know and be aware of when comprehending the nature of change. Much to the dismay of climate activists, communicating the severity of climate change, an extremely non-local phenomenon, to the public has been difficult in part due to this incomprehensibility of change. It's no surprise then that one will find the aforementioned fables in the early writings and modern documentaries of climate activism. Al gore used the frog in boiling water in both his 1989 op-ed and in the 2006 motion picture An Inconvenient Truth as a metaphor for humanity's inability to perceive the changes involved in climate change. [1][2] While metaphorical tools of language are certainly important in communicating climate change and should not be replaced [3], a new tool for translating the epistemic frontier of climate research, and specifically the predictions of climate models, into digestible stories that communicate the mystery of change, has arrived.[13] Beginning after the turn of the century, the idea of Time of Emergence (ToE) had entered the climatology literature, with the earliest mention as applied to predictive models being 2007. [4] The ToE is the time at which the signal of climate change emerges from the noise of natural variability. [5] Many works have been put forth in the literature to strengthen both the accuracy and precision of the ToE with respect to different climate signals, predictive models, regions, and greenhouse gas concentration scenarios. [6][7][8] Undoubtedly, these works have helped to strengthen the ToE as a tool for effective climate policy communication. However, ToE has not been explored with respect to different resolution scales found in popular predictive model classes. To that end, in this work, we explore how the ToE of climate signals is affected by the resolution scale and predictive model type within the Coupled Model Intercomparison Project Phase 5 (CMIP5) model ensemble. Specifically, we perform a comparative analysis between climate signals over the Pacific Northwest region in Global Climate Models (GCM) and Regional Climate Models (RCM). This analysis will explore the variable utility of each model class when understanding the ToE. Alternatively, we ask what are the mesoscale differences between the GCM and RCM models that can be gleamed from the Time of Emergence and what do those differences tell us about the viability of each model class in judging our climate future?

II. RESEARCH METHODS

Chosen models and emissions scenario.

The models we have selected for this analysis come from the CMIP5 ensemble. This version of the Coupled Model Intercomparison Project was specifically engineered to help researchers understand the consequences of the current predictive models and to understand climate prediction in the recent past (1970), up to 2035, and finally out to 2100. The subset of this ensemble that we chose has eleven pairs of GCM and RCM simulations submitted to the CMIP5 from academic and governmental organizations around the world. These models were run with the Representative Concentration Pathway (RCP) 4.5 scenario. This greenhouse gas concentration pathway scenario, standardized by the IPCC, describes a radiative forcing parameter of $4.5 W/m^2$. In this scenario, emissions peak in 2040 and decline thereafter. This scenario describes that, by 2100, the mean ocean levels rise 35% more than in RCP 2.6. Comparatively, this scenario is considered an intermediate scenario with many plants and animals being unable to adapt. The models are enumerated in table II-1 below.

Model	Institution
Access1.3	CSIRO (Commonwealth Scientific and Industrial
	Research Organization,
	Australia), and BOM (Bureau of Meteorology,
	Australia)
BCC-CSM1.1	Beijing Climate Center, China Meteorological
	Administration
CANESM2	Canadian Centre for Climate Modelling and Analysis
CCSM4	National Center for Atmospheric Research
CSIRO-MK3.6.0	CSIRO in collaboration with the Queensland Climate
	Change Centre of Excellence
FGOALS-G2	LASG, Inst of Atmos Physics, Chinese Academy of
	Sciences; and CESS, Tsinghua University
GFDL-CM3	Geophysical Fluid Dynamics Laboratory
GISS-E2-H	NASA Goddard Institute for Space Studies
MIROC5	Atmosphere and Ocean Research Inst (The University
	of Tokyo), National Institute for Environmental
	Studies, and Japan Agency for Marine-Earth Science
	and Technology
MRI-CGCM3	Meteorological Research Institute
NORESM1-M	Norwegian Climate Centre

Data structures

Once the models are retrieved from the cloud database hosted by the World Climate Research Program, the data is unpacked and extracted from the multi-dimensional scientific data structure architecture, *Network Common Data Form (NetCDF)*, by python scripts and sent to the python data analysis scripts. After the analysis has been performed the calculated data is then repacked into new NetCDF files for later access.

Climate signals employed

This analysis tracked two predictive climate signals from 1970 to 2099: 95th percentile precipitation and 90th percentile maximum temperature. Each is a standardized climate variable used extensively in the field of Atmospheric Sciences.

Time of emergence calculation

To calculate the ToE over our data set, the following parameters and methods were employed. All models in our ensemble run over the period from 1970 to 2099. The year-to-year variability or noise of the climate signal at each model grid square is calculated over the period of 1970 to 2000. To find this variability, the mean and the standard deviation are found as

$$\bar{\mu} = \frac{1}{T_2 - T_1} \sum_{j=1}^{T_2 - T_1} \mu_j \text{ , } \sigma = \sqrt{\frac{1}{N-1} \sum_{j=1}^{N} \left(\bar{\mu} - \mu_j\right)^2} \text{ where } T_1 \text{ and } T_2 \text{ describe our variability interval.}$$

Then, the trend of the climate signal is found through linear regression over the interval from 2000 to 2099, which results in the following linear equation

$$s = a + bt$$

The ToE is then found to be the year in which the linear regression intersects the mean noise plus/minus one standard deviation. The ToE can then be expressed as

$$ToE = T_2 + \left| \frac{\sigma}{b} \right|$$

Figure II-1 demonstrates two extreme ToE calculations. The ToE calculation methods presented here are in accordance with Maraun et. al.[12]

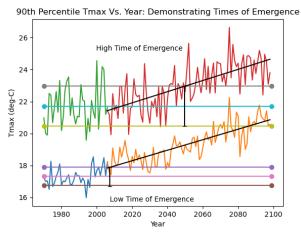


Figure II-1 Example Time of Emergence calculations for 90th percentile maximum temperature

ToE filtering

If any ToE exceeds the year 2300, that datapoint is voided for the rest of the analysis as we consider such late ToEs as spurious and nonconsequential.

Interpolation between GCM and RCM

Once the ToE is calculated over the Pacific-Northwest for each climate signal for each pair of GCM and RCM within each model, we need to interpolate between the GCM and RCM grids. This is done because the RCM and GCM schemes do not share a common spatial resolution. An RCM model has a spatial resolution of 10-50 km while a GCM model has a spatial resolution of 100-250 km. [11] this discrepancy is visualized in figure II-2.

100-300 km

10-50 km

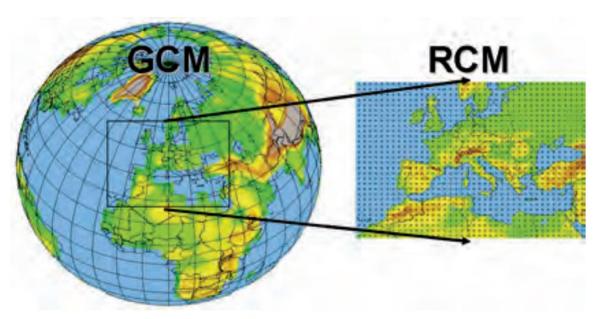


Figure II-2 Visualization of GCM and RCM resolution scales. [15]

To compare these, we need to perform either a dynamical downscaling or an interpolation from the GCM basis to the RCM basis. We chose the latter and employed the use of the Scipy 2d cubic interpolation.

Plotting

For each model in the ensemble and for both of each model's class type (GCM and RCM), a complete ToE story is found for the chosen climate signal. Figure II-3 demonstrates an example of the complete data analysis necessary for each model before they are fed into the mean ToE calculation. Figures II-3d and II-3e demonstrate that RCM models have a greater signal-to-noise ratio, described in terms of the standard deviation, than the GCM counterpart model. The same is true when considering the RCM and GCM slope values from the linear regression (II-3g and II-3h).

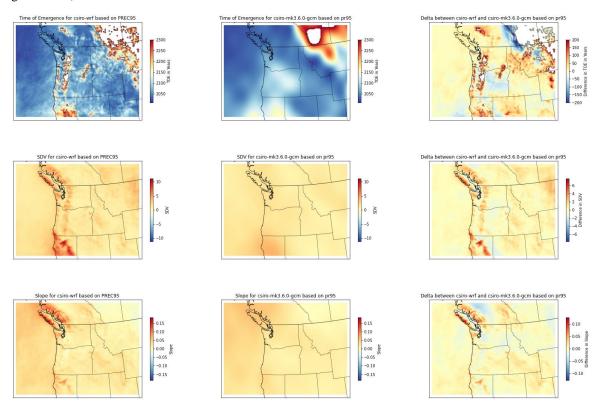


Figure II-3(a-i) complete ToE story for the Commonwealth Scientific and Industrial Research Organization MK3.6.0(CSIRO-mk3.6.0) model. WRF is synonymous with RCM. Note: Missing ToE calculations are ToE calculations greater than 2300, which are considered spurious.

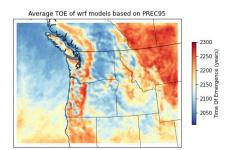
Mean ToE of GCM and RCM models

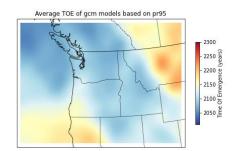
Once interpolation is complete, for each climate signal, we average the ToE over all the models in the ensemble to enable the identification of general trends between the model classes. This process should smooth out the variability in the model ensemble and produce the characteristic features common among each model class.

III. RESULTS

95th Percentile Precipitation

For this climate signal, the following average ToE data is presented in Figure III-1





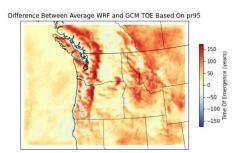
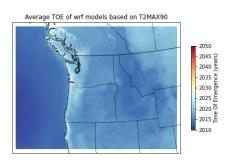


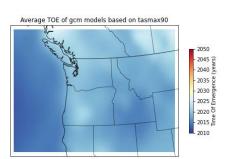
Figure III-1 Ensemble plots of Average ToE between all models for each model type for the precipitation climate signal. The difference is calculated from difference = $\overline{RCM} - \overline{GCM}$.

The difference map (fig III-1c) clearly demonstrates that GCM and RCM models tend to agree on the ToE over the ocean and over the Yakima Valley and the western interior past the Cascade Mountains, as well as south of the Rockies. Where these two classes diverge is over the orographic features contained within the Cascade Mountains and over the Rockies. Here, the RCM's greater spatial resolution is considering smaller topological features than its GCM counterpart, and, most importantly, those topological features are falling out of the ToE calculation as well. These differences demonstrate that, from a predictive and policy standpoint, the RCM model is providing a more detailed account of the ToE, as compared to the GCM, with novel predictions for later ToE over large orographic structures in the region, while maintaining agreement in ToE in floodplains, such as the Puget Sound Basin.

90th Percentile Maximum Temperature

For this climate signal, the following average ToE data is presented in Figure III-2





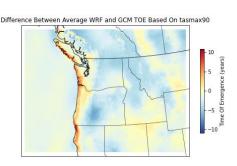


Figure III-2 Ensemble plots of Average ToE between all models for each model type for the temperature climate signal. The difference is calculated from difference = $\overline{RCM} - \overline{GCM}$.

The following analysis comes from figure III-2c. Compared to the precipitation signal, this temperature variable has a consistently earlier ToE among the models and has a lower maximum ToE difference. However, there is still variability between GCM and RCM on the order of 10^1 years. Generally, the predictive models indicate that RCM temperature-based ToE arrives later than its GCM counterpart. But, this trend is only identifiable along the coast. In the interior of the region, between our two dominant mountain regions, the general trend is that RCM models predict an earlier time of emergence than GCM models.

IV. DISCUSSION

Any analysis of ToE is fundamentally an analysis of risk assessment and anticipation of change. And although ToE has already been understood within the literature to be a tool for understanding, at a high level, the urgency of climate policy and the necessity of climate change ready infrastructure, [13] this analysis helps the field further develop an understanding of the variable utility of different resolution scales in ToE analysis. The IPCC currently uses ToE to describe the anthropogenic footprint in climate variables relating to ocean acidity and the cryosphere. [14] They do so with confidence because these variables have early ToE and the anthropogenic effects can be easily tracked. Hopefully, from the work presented in this analysis and those presented in Hawkins and Sutton et al (2012) and others, climate variables with late ToE, such as 95th percentile precipitation, can be used by the IPCC to accurately characterize the timeline of emissions scenarios with respect to climate variables like precipitation. To that end, the sensitivity of ToE from our predictive models with respect to orographic features and resolution scale is of importance.

V. CONCLUSION

RCM models have a greater degree of orographic sensitivity due to their higher resolution scale compared to the GCM scheme. This feature of the model is then borne out in the ToE as RCM models deviate from the GCM models over coastlines and mountains, thereby increasing the localized structure present in the ToE over such orographic regions. Additionally, on average, RCM models predict later ToE over such regions compared to GCM models, which in turn prescribes that climate ready infrastructure and climate policy could become more localized and targeted. In interpreting the results presented here, there are three axes of exploration upon which further analysis is needed to strengthen the applicability of the presented results. First, we must expand the regions and geographical areas over which this analysis is done. The Pacific Northwest is an area of great orographic variability and structure which may affect our predictive models in terms of signal-to-noise ratio and, therefore, ToE. Exploring the same comparative analysis over two more regions, one with similar orographic feature, and one without, will help us make stronger statements about the way resolution scale, topology, and boundary conditions affect localized understandings of ToE through GCM and RCM models. Second, explore different climate signals, such as April 1st snowpack, to understand how GCM and RCM models apply feedback effects at different resolution scales and how that affects the general trends we identified between GCM and RCM generated ToE. Third, explore how different emissions scenarios affect the general trends identified between GCM and RCM ToE. It may be the case that the greater orographic sensitivity in the ToE identified in the RCM models compared to the GCM models may be an artifact of our emissions scenario and may disappear with a greater or lower degree of radiative forcing.

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References

- [1] Gore, Albert. "Opinion | an Ecological Kristallnacht. Listen." The New York Times, 19 Mar. 1989, www.nytimes.com/1989/03/19/opinion/an-ecological-kristallnacht-listen.html. Accessed 10 June 2021.
- [2] Guggenheim, Davis. An Inconvenient Truth. Paramount Vantage, 2006.
- [3] Nerlich, B., Koteyko, N. and Brown, B. (2010), Theory and language of climate change communication. WIREs Clim Change, 1: 97-110. https://doi.org/10.1002/wcc.2
- [4] Solomon, Susan, et al. Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC. Vol. 4. Cambridge university press, 2007
- [5] Hawkins, E., and Sutton, R. (2012), Time of emergence of climate signals, Geophys. Res. Lett., 39, L01702
- [6] Barrow, Elaine M., and David J. Sauchyn. "Uncertainty in climate projections and time of emergence of climate signals in the western Canadian Prairies." International Journal of Climatology 39.11 (2019): 4358-4371.
- [7] Sui, Yue, Xianmei Lang, and Dabang Jiang. "Time of emergence of climate signals over China under the RCP4. 5 scenario." Climatic Change 125.2 (2014): 265-276.
- [8] Lyu, Kewei, et al. "Time of emergence for regional sea-level change." Nature Climate Change 4.11 (2014): 1006-1010.
- [9] National Center for Atmospheric Research Staff (Eds). Last modified 06 Jul 2016. "The Climate Data Guide: CMIP (Climate Model Intercomparison Project) Overview." Retrieved from https://climatedataguide.ucar.edu/climate-model-evaluation/cmip-climate-model-intercomparison-project-overview.
- [10] "Topic 2: Future Changes, Risks and Impacts." IPCC 5th Assessment Synthesis Report, 2016, ar5-syr.ipcc.ch/topic_futurechanges.php.
- [11] "Background Regional and Global Climate." Oregonstate.edu, 2019, regclim.coas.oregonstate.edu/dynamical-downscaling/background/. Accessed 10 June 2021.
- [12] Douglas Maraun 2013 Environ. Res. Lett. 8 014004
- [13] Snover, A.~K. et al. "Time of Emergence: A Tool for Exploring When and Where Climate Change Could Matter." AGU Fall Meeting Abstracts.
- [14] Abram, N., J.-P. Gattuso, A. Prakash, L. Cheng, M.P. Chidichimo, S. Crate, H. Enomoto, M. Garschagen, N. Gruber, S. Harper, E. Holland, R.M. Kudela, J. Rice, K. Steffen, and K. von Schuckmann, 2019: Framing and Context of the Report. In: IPCC Special Report on the Ocean and Cryosphere in a Changing Climate [H.-O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.)]. In press.
- [15] F. Giorgi, WMO Bulletin 52(2), April 2008