A Mathematical Modelling of A Multi-Physics Ensemble Approach for Exploring the Sensitivity of Climate

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Abstract. The amount of global surface warming that will effectively respond to twice of atmospheric CO2 concentrations compared with pre-industrial levels is referred to as climate sensitivity. The aim to explore the sensitivity of climate by using the mathematical model of the multi-physics ensemble approach. It’s considered as a multi-physics MM5 ensemble of 30 years hindcast simulations run through a complicated and climatically varied area. In this study, eight multi-physics ensembles (MPEs) models were used, MIROC5 physics systems were replaced with MIROC3 physics systems. The analysis is based on a seasonal time scale with an emphasis on average temperature and precipitation values as well as interannual variability. Multi-parameter MPE was made a set ensemble of perturbed-physics in which the parameter value for individual MPE model is swept. The previously evaluated MPE approach can be better understand and improve in the simulation of the multi-physics climate by using Bayesian inference. Bayesian inference allows actions often associated with a post-model flexible project to be incorporated into the model development process. As a result, an ensemble of model configurations has been created, which allows for a more thorough assessment of the remaining uncertainties. The value of model physics is shown by demonstrating that the dispersion between experiments is comparable.

Keywords: multi-physics ensemble; sensitivity of climate; Bayesian inference etc.

1. Introduction

Climate sensitivity (CSs) varies between general circulation models (GCMs) and are represents the global average surface atmospheric pressure responses to the doubling of CO2 levels in the atmosphere. Previous research analyzed the outputs of multi-model ensembles (MMEs) and concluded that the spread of CSs was mostly influenced by radiative forcing (RF) and feedback (FB) uncertainties due to cloud movements (Shiogama et al. 2014). The MME is significant in comprehension of the uncertainty sources in the CS has its limitations. Moreover, each GCM is fine-tuned through changing the unpredictable cost function in physics systems, analysing only the MME makes it difficult to separate between the structural and functional issues. To examine the structural uncertainty of CS, researchers used the ‘multi-physics ensembles’ (MPE) technique. These researchers swapped one or more physics structures across two GCM variants developed simultaneously modelling facility in the MPEs (Webb, Lambert, and Gregory 2013).

W12 combined the MIROC5 GCM and the MIROC3 GCM to create the seven hybrid models. The CS of the 8 MPE models includes the one as MIROC5 then, the other 7 hybrid version ranges from 2.3 to 5.9 C. such an MPE technique can help us comprehend the structural constraints in CS better (Jerez et
al. 2013). The goal of all climate research, whether observational, simulation or theoretical is to better understand the nature is controlled by physical ways or balance ways. The concepts, methodologies and a case study of using a Bayesian inference technique to synthesize data constraints on climate model improvement is offered here. It comes with a number of challenges, but it could eventually give a more reliable way of data should be used to inform analysis process (Jackson 2009).

The MPE has two clear limitations: the results are dependent also on regular models as well as the MPE versions have a specific value of a parameter set. A perturbed-physics ensemble (PPE) can help characterize the single GCM parametric sensitivities by providing useful information (Murphy et al. 2007). The attributes of a climate system originate in PPE, however, were not always communicated to another MME types or PPEs of various model’s correlations between cloud changes in climate and related in present climate (Nomani et al. 2020). W12 produced MPE models. Despite the reality that the PPEs of various MPE models suggested a variety of parameter assumption for FB, the eight MPE models shared a common characteristic. In climate model development, a Bayesian inference methodology is used to synthesize data constraints on options. It comes with its set of difficulties, but it could eventually deliver a more powerful path for data-driven decision-making evolution of model development (Semenov and Stratonovitch 2010). It should be highlighted that the goal of this research was to establish a new ensemble approach rather than to deduce any credible, observationally restricted CS range.

The remaining part of this paper explains the mathematical model of multi-physics ensemble approach and Bayesian inference; part 2 defines highlights the previous effort that can be done by the scholars in this domain with the various experimental tasks; part 3 offers the proposed methodology and its mechanism, part 4 represents the result and discussion of this study and part 5 represents the conclusion.

2. Literature Review
(Ji et al. 2014) analyzed the weather research and forecasting (WRF) ability multi-physics ensemble to simulating the storm scheme is called east coast lows (ECLs). This scheme may cause problem on the area. On the other side, these schemes are advantageous because they produce the vast high on flow to coastal reservoirs. To recreate the observed rainfall pattern in space. Individual physics scheme combination’s performance, as well as ensembles of numerous combinations of physics system, are assessed independently. The outcome suggests that employing the ensemble mean yields higher talent than utilizing ensemble’s median executor. Choosing a compound mean of the improved execution pbl and cu systems can significantly develop the quantitative and spatial view of high rainfall.

(Yang et al. 2013) analyzed the maritime glacier mass balance and its sensitivity climate on the Tibetan plateau. The model’s core physical parameters were calibrated locally using appropriate glacial-meteorological data sets. The finding results indicate, over the period 2005-2010 the yearly parameter was roughly 0.9m water equivalent. The climate regime of parlung No.94 glacier was anything but ideal, resulting in zero wave equation. Seasonality of local rainfall, which is influenced by numerous atmospheric compositions at the same time is also found to be intimately linked to climatic sensitivity of the glacier mass balance.

(Berner et al. 2011) combined the multi-physics and kinetic energy backscatter scheme utilizing a meteorological study and forecasting method to describe measurement error in the context of a mesoscale ensembles forecasting model. Both play an important improvement on the ensemble system. However, there is a minor difference in some details. Except at the surface, the backscatter of stochastic potential energy techniques outperforms the Multiphysics techniques. Both methods are employed at the same time, the best results are obtained, demonstrating that a combination of various scheme is the best way to capture model error.

(Stegehuis et al. 2015) analyzed the difficulties in climate reproducing extremes on conditions of a heatwave. We employ the weather research and forecasting (WRF) regional climate model in conjunction include the NOAA land surface system to find the most sensitive physics and identify those that are most suitable for replicating the heat waves of 2003 in western Europe and 2010 in Russia. We create a condensed ensemble of five effective and diversified scheme combinations based
on these comparisons, which might be utilized with in approach of extreme heat studies and the effect of climate change in Europe will be conducted across the year (Nomani 2019).

3. Methodology

This section provides a brief note on the Bayesian inference and the multi-physics ensembles (MPE).

a) Bayesian inference use in model development

Bayesian inference can assist in the development of models by merging data from different sources, modelling results, and relevant error information to guide complex development of model decisions includes the values allocated to many, parameters that are not linearly connected. Bayesian inference entails a stochastic sources sampling of error, with individual sample requiring a separate calculation (Antonov et al. 2016). Model integration may be used to assess the sensitivity to input parameters, however, this is not the case model development is unrealistic. These sensitivity studies are specifically designed to extract out features of model predictions that are most robust. The issues have been that these actions are primarily concerned with error propagation forward. Typically, they only calculate the univariate mean statistic. If we want to execute this research in model development, we’ll need a better path to quantify the relationships.

The amount of solution space or since there is probably a good match to experimental data percentage of the whole number of potentialities, which is another problem for model creators. As a result, Bayesian inference resembles difficulties in geophysical inversion considerably more closely. Instead of entire probability densities, gradient-based solutions or maximum a posteriori (MAP) for solving inverse issues focus on point estimates among the most likely parameter models. This single goal may be extremely susceptible to assumptions about the usefulness of gathered data or a specific modelled occurrence. Model development should bear this in mind because climate phenomena constitute a spectrum of interactions (Von Toussaint 2011). A Bayesian technique, which provides a mechanism to gather additional information about the full statistical picture, may be more beneficial to the technical goals for constructing a multi-physics model is an explanation of the data and modelling choice’s inherent uncertainties.

Assume we want to evaluate the shared possibility of choosing a vector n of model constraint values that is consistent with the observation vobs in the climate of model p(n). the explanation of posterior probability of density (PPD) as it is known in Bayesian nomenclature, that assumes Gaussian errors is given below;

\[
PPD(n \mid v_{obs}, p(n)) \propto \exp \left[ -\frac{1}{2} (p(n) - v_{obs})^T H_{noise}^{-1} (p(n) - v_{obs}) \right]. prior (n)
\]

Where prior(n) represents the prior chance for parameter model n independent of vobs, with H-1noise expressing the problems in associating the output model to information. The number included in the cost function is commonly referred to this as square brackets or model metric mistakes about what is seen. The PPD is often not gaussian due to the non-linearities reflected in the climatic model p, although using the gaussian condition for the experimental data and that the modelling errors (n). while equation (1) does not have a closed-form solution, it must be estimated.

b) Multi-physics ensemble approach (MPE)

We employed the MIROC5 (hereinafter MIROC5A) atmospheric general circulation model (AGCM) and the 7 hybrid AGCMs (W12), in which multiple or single physics cloud system, turbulence and MIROC5 cumulus convection was observed and substituted by the appropriate method of the previous version, MIROC3. Using the Latin-hypercube sampling method, we picked 20 pairs of 6 physics variables as two for each system swept inside the minimum-to-maximum ranges for each of the eight MPE models (Shiogama et al. 2012). Because of the significant structural distinctions between the MIROC5 and MIROC3 systems, we were unable to select parameters both base models have something in common. Instead, the altered parameters and their ranges were chosen from those. Excluding the am10 in turbulence method of MIROC3, utilized in prior of MIROC5 (S12) PPEs and the MIROC3. The specifics of the parameters chosen may be found in S12 (Watanabe et al. 2010). We ran the mean values from 2 to 6 years were examined for the 3 kinds of AGCM runs shown below using these 20 x 8 MPE models: AGCMs compelled by pre-industrial meteorology of sea surface
temperature (SST) and the sea ice limited period of the couple’s air. Ocean general circulation model (CGCM) version of MIROC5 with conventional different classifiers and the pre-industrial CO2 absorptions of the attached atmosphere (Yuan and Wood 2012). Observing changes in radiation at the apex of the mountain M is for the atmosphere, and G is for the average global surface air; Temperature (I) from the 3 kinds of AGCMs mentioned above. Calculate the RF, the FB and the active climate using runs model’s sensitivity (ECS) is given below:

\[
RF = \frac{M(\text{CO2}) - M(\text{CTL})}{2} \quad \ldots(1)
\]

\[
FB = \frac{M(\text{SST}) - M(\text{CTL})}{I(\text{SST}) - I(\text{CTL})} \quad \ldots(2)
\]

\[
ECS = -\frac{RF}{FB} \quad \ldots(3)
\]

Equation (1) uses a factor of $\frac{1}{2}$ to translate the RF of 4 CO2 to that of 2 CO2. We can achieve diagnoses that are statistically significant of Fb, ECS, and RF using very short length simulations because that employ AGCM instead of CGCM. We used the conventional MIROC% AGCM to run 20-years simulations of CTL, SST and CO2 and found that the 6-years of replications are sufficient for statistically strong outcomes. Then AGCM runs were also allowed of climate drifts that can happen in MMR, MPR and PPE experiments (Murakami, Mizuta, and Shindo 2012). Our AGCM method on other hand has some limitations. The atmosphere and the ocean have no interaction. While the atmosphere reacts quickly to increased CO2 levels, the ocean changes over decadal to several hundred-year time frames. Our method does not allow us to investigate these delayed replies. As a result, it’s important to note that the ECS standards determined by our system should only be used as a guideline.

The use of Bayesian inference in the mathematical simulations construction of multi-physics situations like as climatic models has the advantage of formalizing the process of the prediction model and withstand the effects for evaluating model development options (Potrzebowski, Trehella, and Andre 2018). Some models can imitate accurate behaviors for the right intensions because they have so many freedom degrees (Nomani 2020). The researcher can utilize Bayesian inference to create relevant measures and employ unique sampling tactics to select coherent model configurations. As a result, an ensemble of configuration has been created, which allows for a more thorough assessment of the remaining uncertainties.

4. Result and Discussion

The purpose of this work is to evaluate the model’s role multi-physics ensembles on the sensitivity of climate. Figure 1 illustrates the total feedback and radiative force. MPE covers a wide range value of ECS. Except for single group model, ECS was in the variety of 2.1-6°C, in a one extremely increases participant at 10.4°C. Though the PPEs of 5 MPE models are MIROC5A, CLD, VDF, CNV and CNV+VDF show ECSs of less than 4C, the ECSs of the remaining three MPE models are higher in figure 3. ECS increases as we get closer to MIROC3. This is in line owing to the fact that ECS of the normal MIROC3 model as 3.6C is greater than the ECS of the MIROC5C model as 2.85C.
Fig.1. The total feedback and radiative force

The alterations in the entire FB and ECS were highly correlated with the average global shortwave cloud feedback values (SWcld) SWcld changes in cloud shortwave forcing as SST minus CTL is reduced by the surface temperatures in figure 2 and figure 3. SWcld values in ECS lower runs were negative, while SWcld values in ECS higher runs were positive.
The importance of low-altitude clouds in connection to the uncertainty of SW cloud feedback has been emphasized in most MME and some PPE research. Mid-level clouds, according to S12, also contribute to the SW cloud feedback spread in the MIROCCSPPE. Discovered first inconsistencies in the clouds contribution and for the SWcld spread all around the MPE models when we should have focused on strong winds or mid-level clouds, i.e., a cloud after a certain level could boost the intra-PPE SWcld distribution in certain MPEs but restrict it in others. We hypothesized that, additionally to the independent contribute the coupling of mid and low-level clouds, as well as the coupling cloud shelters might distress the transmission of SW cloud feedback. PPE evaluations had previously been confined to two ensembles. The development of PPEs from a variety of models allowed us to investigate common traits among the various PPEs. The challenge that would most establish Bayesian inference’s relevance for model development would be that it assists in the discovery of biological mechanism or the balance of systems that govern environment (Nomani 2000).

5. Conclusion
To evaluate ECS’s structural issues and parametric. This MPE is a hybrid of the PPE, a form of MME for investigating parametric uncertainty then the MPE a kind of MME investigating organizational issues. Our MPE was made up of PPEs that used 8 MPE representations produced by the W12 is created on MIROC5 and MIROC3 representations. The MPE results can be affected by the common models, the substituted physics methods, the perturbed variables and their parameter ranges, and the parameter value sampling mechanism. Despite these drawbacks, MPE offers a novel and practical method. To gain a deeper understanding of the functional and physical issues of ECs, we believe that our discovery of the basic trait numerous PPEs will stimulate the intercomparison of the PPEs from other models, mentioned to as ‘super-ensembles’. The road to this is to initially recognize models that reflect the experimental climate crisis for the appropriate details and then it incorporates the important parts into an optimal solution then we already can’t lost capacity to keep this amount of talent in upcoming system growth attempts.

6. References
[1] Antonov, Lubomir D, Simon Olsson, Wouter Boomsma, and Thomas Hamelryck. 2016. “Bayesian Inference of Protein Ensembles from SAXS Data.” Physical Chemistry Chemical Physics 18 (8): 5832–38.
[2] Berner, J., S.-Y. Ha, J. P. Hacker, A. Fournier, and C. Snyder. 2011. “Model Uncertainty in a Mesoscale Ensemble Prediction System: Stochastic versus Multiphysics Representations.” Monthly Weather Review 139 (6): 1972–95. https://doi.org/10.1175/2010MWR3595.1.

[3] Jackson, Charles S. 2009. “Use of Bayesian Inference and Data to Improve Simulations of Multi-Physics Climate Phenomena.” Journal of Physics: Conference Series 180 (July): 012029. https://doi.org/10.1088/1742-6596/180/1/012029.

[4] Jerez, Sonia, Juan Pedro Montavez, Pedro Jimenez-Guerrero, Juan Jose Gomez-Navarro, Raquel Lorente-Plazas, and Eduardo Zorita. 2013. “A Multi-Physics Ensemble of Present-Day Climate Regional Simulations over the Iberian Peninsula.” Climate Dynamics 40 (11–12): 3023–46. https://doi.org/10.1007/s00382-012-1539-1.

[5] Ji, Fei, Marie Ekström, Jason P. Evans, and Jin Teng. 2014. “Evaluating Rainfall Patterns Using Physics Scheme Ensembles from a Regional Atmospheric Model.” Theoretical and Applied Climatology 115 (1–2): 297–304. https://doi.org/10.1007/s00704-013-0904-2.

[6] Jerez, Sonia, Juan Pedro Montavez, Pedro Jimenez-Guerrero, Juan Jose Gomez-Navarro, Raquel Lorente-Plazas, and Eduardo Zorita. 2013. “A Multi-Physics Ensemble of Present-Day Climate Regional Simulations over the Iberian Peninsula.” Climate Dynamics 40 (11–12): 3023–46. https://doi.org/10.1007/s00382-012-1539-1.

[7] Ji, Fei, Marie Ekström, Jason P. Evans, and Jin Teng. 2014. “Evaluating Rainfall Patterns Using Physics Scheme Ensembles from a Regional Atmospheric Model.” Theoretical and Applied Climatology 115 (1–2): 297–304. https://doi.org/10.1007/s00704-013-0904-2.

[8] Jerez, Sonia, Juan Pedro Montavez, Pedro Jimenez-Guerrero, Juan Jose Gomez-Navarro, Raquel Lorente-Plazas, and Eduardo Zorita. 2013. “A Multi-Physics Ensemble of Present-Day Climate Regional Simulations over the Iberian Peninsula.” Climate Dynamics 40 (11–12): 3023–46. https://doi.org/10.1007/s00382-012-1539-1.

[9] Nomani, M.Z.M. 2000. “The Human Right To Environment In India: Legal Precepts And Judicial Doctrines In Critical Perspective.” Asia Pacific Journal of Environmental Law 5(2):113-34.

[10] Nomani, M.Z.M. 2019. “The Access And Benefit-Sharing Regime: A Environmental Justice Perspective.” Environmental Policy and Law 49(4-5): 259-263; https://doi.org/10.3233/EPL-190172.

[11] Nomani, Z.M. 2020. “Case Comment: Divya Pharmacy v. Union of India.” Biotechnology Law Report 39(2):122-128; https://doi.org/10.1089/blr.2020.29161.zmn

[12] Potrzebowski, Wojciech, Jill Trewhella, and Ingemar Andre. 2018. “Bayesian Inference of Protein Conformational Ensembles from Limited Structural Data.” PLoS Computational Biology 14 (12): e1006641.

[13] Semenov, Ma, and P Stratonovitch. 2010. “Use of Multi-Model Ensembles from Global Climate Models for Assessment of Climate Change Impacts.” Climate Research 41 (January): 1–14. https://doi.org/10.3354/cr00836.

[14] Shiogama, Hideo, Masahiro Watanabe, Tomoo Ogura, Tokuta Yohkohata, and Masahide Kimoto. 2014. “Multi-parameter Multi-physics Ensemble (MPMPE): A New Approach Exploring the Uncertainties of Climate Sensitivity.” Atmospheric Science Letters 15 (2): 97–102. https://doi.org/10.1002/asl2.472.

[15] Shiogama, Hideo, Masahiro Watanabe, Masakazu Yoshimori, Tokuta Yohkohata, Tomoo Ogura, James D Annan, Julia C Hargreaves, et al. 2012. “Perturbed Physics Ensemble Using the MIROC5 Coupled Atmosphere–Ocean GCM without Flux Corrections: Experimental Design and Results.” Climate Dynamics 39 (12): 3041–56.

[16] Stegehuis, Annemiek I, Robert Vautard, Philippe Ciais, Adriaan J Teuling, D Gonzalez Miralles, and Martin Wild. 2015. “An Observation-Constrained Multi-Physics WRF Ensemble for Simulating European Mega Heat Waves.” Geoscientific Model Development 8 (7): 2285–98.

[17] Von Toussaint, Udo. 2011. “Bayesian Inference in Physics.” Reviews of Modern Physics 83 (3): 943.
[18] Watanabe, Masahiro, Tatsuo Suzuki, Ryouta O’ishi, Yoshihiko Komuro, Shingo Watanabe, Seita Emori, Toshihiko Takemura, et al. 2010. “Improved Climate Simulation by MIROC5: Mean States, Variability, and Climate Sensitivity.” Journal of Climate 23 (23): 6312–35.

[19] Webb, Mark J., F. Hugo Lambert, and Jonathan M. Gregory. 2013. “Origins of Differences in Climate Sensitivity, Forcing and Feedback in Climate Models.” Climate Dynamics 40 (3–4): 677–707. https://doi.org/10.1007/s00382-012-1336-x.

[20] Yang, Wei, Tandong Yao, Xiaofeng Guo, Meilin Zhu, Shenghai Li, and Dambaru B. Kattel. 2013. “Mass Balance of a Maritime Glacier on the Southeast Tibetan Plateau and Its Climatic Sensitivity: MASS BALANCE OF A TIBETAN GLACIER.” Journal of Geophysical Research: Atmospheres 118 (17): 9579–94. https://doi.org/10.1002/jgrd.50760.

[21] Yuan, Xing, and Eric F Wood. 2012. “Downscaling Precipitation or Bias-Correcting Streamflow? Some Implications for Coupled General Circulation Model (CGCM)-Based Ensemble Seasonal Hydrologic Forecast.” Water Resources Research 48 (12).

[22] Natarajan, B., Obaidat, M.S., Sadoun, B., Manoharan, R., Ramachandran, S. and Velusamy, N., 2020. New Clustering-Based Semantic Service Selection and User Preferential Model. IEEE Systems Journal. DOI: 10.1109/JSYST.2020.3025407.

[23] Nataraj, S.K., Al-Turjman, F., Adom, A.H., Sitharthan, R., Rajesh, M. and Kumar, R., 2020. Intelligent Robotic Chair with Thought Control and Communication Aid Using Higher Order Spectra Band Features. IEEE Sensors Journal, DOI: 10.1109/JSEN.2020.3020971.

[24] Babu, R.G., Obaidat, M.S., Amudha, V., Manoharan, R. and Sitharthan, R., 2020. Comparative analysis of distributive linear and non-linear optimised spectrum sensing clustering techniques in cognitive radio network systems. IET Networks, DOI: 10.1049/iet-net.2020.0122.

[25] Sitharthan, R., Yuvaraj, S., Padmanabhan, S., Holm-Nielsen, J.B., Sujith, M., Rajesh, M., Prabaharan, N. and Vengatesan, K., 2021. Piezoelectric energy harvester converting wind aerodynamic energy into electrical energy for microelectronic application. IET Renewable Power Generation, DOI: 10.1049/rg2.12119.

[26] Sitharthan, R., Sujatha Krishnamoorthy, Padmanahan Sanjeevikumar, Jens Bo Holm-Nielsen, R. Raja Singh, and M. Rajesh. "Torque ripple minimization of PMSM using an adaptive Elman neural network-controlled feedback linearization-based direct torque control strategy." International Transactions on Electrical Energy Systems 31, no. 1 (2021): e12685. DOI: 10.1002/2050-7038.12685.