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Improving the representation of anthropogenic CO_2 emissions in climate models: a new parameterization for the Community Earth System Model (CESM)

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Abstract. ESMs (Earth System Models) are important tools that help scientists understand the complexities of the Earth's climate. Advances in computing power have permitted the development of increasingly complex ESMs and the introduction of better, more accurate parameterizations of processes that are too complex to be described in detail. One of the least well-controlled parameterizations involves human activities and their direct impact at local and regional scales. In order to improve the direct representation of human activities and climate, we have developed a simple, scalable approach that we have named the POPEM module (POpulation Parameterization for Earth Models). This module computes monthly fossil fuel emissions at grid point scale using the modeled population projections. This paper shows how integrating POPEM parameterization into the CESM (Community Earth System Model) enhances the realism of global climate modeling, improving this beyond simpler approaches. The results show that it is indeed advantageous to model CO_2 emissions and pollutants directly at model grid points rather than using the forcing approach. A major bonus of this approach is the increased capacity to understand the potential effects of localized pollutant emissions on long-term global climate statistics, thus assisting adaptation and mitigation policies.

1 Introduction

The Earth system is a complex interplay of physical, chemical and biological processes that interact in non-linear ways (Ladyman et al., 2013; Lorenz, 1963; Rind, 1999; Williams, 2005). Much effort has been devoted to understanding these complex interactions, and several improvements have been made since the end of the last century.

One of the most important advances in this field has been the use of coupled numerical climate models, dubbed Earth System Models, or ESMs (Edwards, 2011; Flato, 2011; Schellnhuber, 1999). These models aim to simulate the complex interactions of the atmosphere, ocean, land surface, and cryosphere, together with the carbon and nitrogen cycles (Giorgetta et al., 2013; Hurrell et al., 2013; Martin et al., 2011; Schmidt et al., 2014).

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However powerful, climate models are far from being perfect (Hargreaves, 2010; Hargreaves and Annan, 2014). Unresolved processes (Williams, 2005), limited computational resources (Shukla et al., 2010; Washington et al., 2009), and model uncertainties (Baumberger et al., 2017; Lahsen, 2005; Steven and Bony, 2013) are ongoing issues that still require attention and further improvement.

One of the fields most in need of development, is the inclusion of co-evolutionary dynamical interactions of the socioeconomic dimension in global models with other Earth system components (Robinson et al., 2017; Sarofim and Reilly, 2011). To date, most global models have used basic socioeconomic assumptions about the behavior of societies and are only unidirectionally linked to the biogeophysical part of the Earth system (Müller-Hansen et al., 2017; Smith et al., 2014). The standard way of introducing anthropogenic climate change into ESMs is through Representative Concentration Pathways (RCPs). These are consistent sets of projections involving only radiative forcing components (van Vuuren et al., 2011) that represent a step forward from the scenario approach of the last decade (Moss et al., 2010; van Vuuren et al., 2014; van Vuuren and Carter, 2014). However, RCPs are not fully-integrated socioeconomic parameterizations, but rather estimates for describing plausible trajectories of human climate change drivers (Moss et al., 2010; Vuuren et al., 2012). They provide simplified accounts of human activities and processes, including population density and economic development, from non-coupled Integrated Assessment Models (IAMs; (Müller-Hansen et al., 2017)).

This general approach is used in climate models because it has a low computational cost. However, advances in computational resources allow us to parameterize human-Earth processes in a more detailed way. This is the main aim of the POPEM (POpulation Parameterization for Earth Models) module (Navarro et al., 2017). Nevertheless, the enormity of this issue means that we have initially restricted the module's integration into ESMs to an exploration of anthropogenic perturbation of the carbon cycle.

One important, but sometimes overlooked process is the direct, regional effect of anthropogenic greenhouse gas (GHG) emissions. Although some GHGs quickly mix in the atmosphere (IPCC, 2014a), their mixing times and lifetimes vary (Archer et al., 2009; Prather, 2007), and localized emissions may produce a transient response in the atmosphere. Given the highly non-linear character of the processes involved, it is not unreasonable to assume that location is significant, and the spatial and time distribution of these emissions may affect global climate (Alter et al., 2017; Grandey et al., 2016; Guo et al., 2013). This hypothesis has seldom been investigated, as most current models treat certain GHG emissions as a homogeneously distributed forcing. Thus, for instance, the most typical CESM (Community Earth System Model) simulations prescribe a CO_2 concentration on the assumption that it is well-mixed in the atmosphere (Neale et al., 2012).

This paper describes the results of a 50-year simulation with a simple parameterization of fossil fuel CO_2 emissions at model grid point scale, integrating the POPEM module into the CESM. The aim of this paper is to show that this grid point scale modeling of anthropogenic CO_2 emissions (and other pollutants) represents an improvement, and that two important variables, namely global precipitation distribution and surface temperature, are not negatively affected by this more-detailed approach.

The purpose of the new modeling is not only to improve precipitation and temperature estimates, but also help understand the carbon cycle feedback, and evaluate the climate sensitivity of the Earth under alternative GHG emission scenarios. While our focus here is anthropogenic CO_2 emissions, the POPEM parameterization can accommodate other GHGs and human-dependent processes in order to advance CESMs towards a comprehensive, fully-coupled modeling of anthropogenic dynamics in the global climate.

2. Material and methods

2.1 The CESM model

The Community Earth System Model (CESM) is a state-of-the-art ESM and probably the most widely used climate model. It was developed and is maintained by the National Center for Atmospheric Research (NCAR), with contributions from external researchers funded by the U.S. Department of Energy (DOE), the National Aeronautics and Space Administration (NASA), and the National Science Foundation (NSF) (Hurrell et al., 2013). CESM is an ESM comprising a system of multi-geophysical components, which periodically exchange two-dimensional boundary data in the coupler (Craig et al., 2012). It consists of five component models and one central coupler component: the atmosphere model CAM (Community Atmosphere Model; (Tilmes et al., 2015), the ocean model POP (Parallel Ocean Program; (Kerbyson and Jones, 2005); the land model CLM (Community Land Model; (Lawrence et al., 2011); the sea ice model CICE (Community Ice Code; (Hunke and Lipscomb, 2008); and the ice sheet model CISM (Community Ice Sheet Model; (Lipscomb et al., 2013).

A major advantage of CESM over other ESMs is its availability. Some climate models are developed by scientific groups and access to the source code is limited. The CESM source code is free and available to download from the NCAR website. This approach helps improve the model by setting up a framework for collaborative research and makes the model fully auditable. CESM is a good example of a 'full confidence level' model, after Tapiador et al. (2017), where many 'avatars' of the code are routinely run in several independent research centers, and there is an entire community improving the model and reporting on issues and results.

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The CESM has been used in many hundreds of peer-reviewed studies to better understand climate variability and climate change (Hurrell et al., 2013; Kay et al., 2015; Sanderson et al., 2017). Simulations performed with CESM have made a significant contribution to international assessments of climate, including those of the Intergovernmental Panel on Climate Change (IPCC) and the CMIP5/6 project (Coupled Model Intercomparison Project Phase 5/6) (Eyring et al., 2016; IPCC, 2014b; Taylor et al., 2012).

2.2 The POPEM parameterization module

The POPEM module is a set of FORTRAN routines that are intended to estimate monthly fossil fuel CO_2 emissions at model grid point scale using population as the input. Due to a lack of actual GHG measurements at appropriate spatial and temporal scales, it is necessary to use some sort of proxy. For this, POPEM uses a population, whose evolution is modeled. The idea of using population as proxy is not new, and population density has previously been used to downscale national CO_2 emissions (Andres et al., 1996, 2016). However, these inventories were not dynamical, but instead tied to historical data so it is not possible to use them either to estimate future changes in emissions, or coupled with other components of the model.

Detailed information on POPEM and its validation in the demographic realm can be found in (Navarro et al., 2017). In short, from an initial condition, the routine computes the population for each model grid point in a 2D matrix and then calculates fossil fuel CO_2 emissions using per capita emission rates by nations. The process is repeated for each time step (e.g. annually) throughout the simulation period.

Figure 1 about here

As seen in Figure 1, POPEM stores gridded emission data in a 3D array (time, latitude and longitude) to be used by the modified version of the *co2_cycle* module. This module reads emissions data and passes this to the *atm_comp_mct,* which calculates the total amount of CO_2 emissions from different sources (land, ocean and fossil fuel).

2.2.1 Population trend verification

Prior to coupling POPEM with CESM we performed several tests to evaluate its ability to reproduce historical population trends and CO_2 emissions. To do this, we ran the module in standalone mode. In a first test, we ran a short simulation (1950-2013) and compared the emissions data with a standard emissions inventory (CDIAC). In a second test, POPEM was run for 70 years (1950-2020) and population estimates were validated against the UN (United Nations) population statistics database for those years when data was available.

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Figure 2 about here

As shown in Figure 2, POPEM is capable of satisfactorily simulating the dynamics of the population. Comparison with UN data shows good agreement. However, POPEM presents slight differences from the reference data in some regions. Several of these discrepancies can be explained by the initial model conditions; POPEM uses the same age distribution inside each grid cell to initiate the model (only for the first time-step). This distribution is based on the global average age structure. Consequently, the model overestimates the population in those regions with a more elderly age structure, i.e., Europe and North America, and underestimates areas with younger populations, i.e., Latin America and Asia.

These disparities in population counts have a diverse effect on the outputs in terms of GHG emissions. Thus, for example, the bias in Europe seems to be more important than the bias in Latin America and Oceania. Two principal reasons could explain this: population size, as Europe has a larger population than Oceania, so there is greater bias in the CO_2 emissions estimation; and the per capita emissions rate, as Latin American countries have lower per capita emissions rates than European nations.

It is worth noting here that the POPEM outputs in Figure 2 are clearly non-linear and thus not trivially derived from simply extrapolating population. The North American estimate of CO_2 emissions (second row from the bottom) clearly shows the added value introduced by the model.

Figure 3 shows how POPEM distributes CO_2 emissions for different years in the recent past. In 1950, the majority of emissions tended to be concentrated in the USA and Europe, while in 2000, China, the USA and India were the most polluting countries. This is consistent with the literature: POPEM's estimates generally agree with the emissions maps for the recent past (Andres et al., 1996; Boden et al., 2017; Oda et al., 2018; Rayner et al., 2010), as well as with regional studies on CO_2 emissions (Gately et al., 2013; Gurney et al., 2009).

Figure 3 about here

The regionalized distribution of emissions depicted in Figure 3 represents a vast improvement over the standard procedure of using globally-averaged emissions. Even accounting for rapid mixing of GHGs gases, transient effects are likely to appear given the hemispheric contrast and regional differences in the emissions. The differences in Asia are illustrative of the economic changes in the recent past and the exponential pace of industrialization in that region.

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2.3 CESM experimental setup

The CESM used in this work is based on version 1.2.2 (http://www.cesm.ucar.edu/models/). This set includes active components for the atmosphere, land, ocean, and sea ice, all coupled by a flux coupler. The latest atmospheric module CAM5 (Neale et al., 2012) is used to introduce more accurate modeling of atmospheric physics. Additionally, the carbon cycle module is included in CESM's atmosphere, land, and ocean components (Lindsay et al., 2014).

We ran an experiment at 1.9^{o} degrees of spatial resolution for the period 1950-2000. Two simulations were performed to analyze the effects of the regionalized emissions (Figure 3) on the CESM. Our control case used global CO_2 concentration parameters (standard procedure in ESMs), while the POPEM case used geographically-distributed CO_2 emissions data. In the latter, the POPEM module was coupled with the atmospheric CO_2 flux routine to provide monthly gridded CO_2 emissions. The gridded data was used at each time step by the atmospheric routine. Apart from this change, both simulations were identical in order to identify the effects (if any) of the POPEM parameterization.

2.4 Validation data

2.4.1 GPCP data set

Precipitation is one of the key elements for balancing the energy budget, and one of the most challenging aspects of climate modeling. Hence, high quality estimates of precipitation distribution, amount and intensity are essential (Hou et al., 2014; Kidd et al., 2017; Xie and Arkin, 1997). While there are many sources of precipitation data to be used as a reference (see (Tapiador et al., 2012) for a review), only a few qualify as 'full confidence level validation data' (Tapiador et al., 2017).

The Global Precipitation Climatology Project GPCP (Adler et al., 2016) has several products suitable for validating climate models. GPCP-Monthly is one of the most popular precipitation data sets for climate variability studies. It combines data from rain gauge stations and satellite observations to estimate monthly rainfall on a 2.5-degree global grid from 1979 to the present. The careful combination of satellite-based rainfall estimates results in the most complete analysis of rainfall available to date over the global oceans, and adds necessary spatial detail to rainfall analyses over land. Due to its relevance and global coverage, it has been widely used for validating precipitation in climate models (Li and Xie, 2014; Pincus et al., 2008; Stanfield et al., 2016; Tapiador, 2010).

2.4.2 CRU data set

Global surface temperature data sets are an essential resource for monitoring and understanding climate variability and climate change. One of the most commonly used data sets is produced by The Climate Research Unit at the University of

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East Anglia (CRU). This group produces a high-resolution gridded climate dataset for land-only areas, the Climate Research Unit Timeseries (CRUTS) (Harris et al., 2014). CRUTS contains monthly time series of ten climate variables, including surface temperature. The data set is derived from monthly observations at meteorological stations. Station anomalies are interpolated into 0.5º latitude/longitude grid cells covering the global land surface and combined with existing climatology data to obtain absolute monthly values (New et al., 1999, 2000). It is commonly used in the validation of climate models because of its confidence levels, together with temporal and spatial coverage, and the fact it compiles station data from multiple variables from numerous data sources into a consistent format (Christensen and Boberg, 2012; Hao et al., 2013; Liu et al., 2014; Nasrollahi et al., 2015).

3. Results and discussion

3.1 Comparisons between the CONTROL and POPEM runs

It is worth stressing that a parameterization which performs well when tested for the variable it models does not necessarily translate into an overall improvement of the other variables in the model. An accepted practice in climate modeling is to tune ESMs by adjusting some parameters to achieve a better agreement with observations (Hourdin et al., 2017; Mauritsen et al., 2012). These adjustments to specific targets may, however, decrease the model's overall performance (Hourdin et al., 2017), and give poor scores for variables other than those tuned. Thus, for example, if a model is biased with respect to aerosol concentrations or humidity, then improved parameterization of cloud formation may worsen the performance of the model with regard to precipitation (Baumberger et al., 2017). This mismatch can be caused by model over-specification, or over-tuning.

The first step in evaluating the new parameterization is to compare the outputs with a control simulation to make sure the new addition does not negatively interact with the dynamical core or spoil the contributions of rest of the parameterizations. Figures 6C-6D and 8C-8D show that this is not case with the POPEM parameterization, which does not negatively affect the outputs of precipitation and temperature. Rather, both variables are now closer to the observed data than they were in the control run, especially in terms of reducing the double ITCZ, which artificially features in global models.

Direct comparison of aggregated data is a standard procedure for gauging model abilities. Figure 4 compares two latitude-time graphs for precipitation (A) and surface temperature (B), both for the CONTROL case and for the new POPEM parameterization.

Figure 4 about here

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It is clear from the figure that POPEM does alter the spatial pattern of precipitation and exerts a definite effect on the climate pattern, as the module reduces the otherwise exaggerated ITCZ precipitation in the Southern Hemisphere (South East Asia and Australia). Disparities in temperature between the CONTROL and POPEM runs are apparent at high latitudes. In this case, POPEM produces lower temperatures at both poles, a result which deserves further attention.

Figure 5 about here

There are also important differences in precipitation in the 30N-30S band. Here POPEM reduces model bias, especially in the Southern Hemisphere and on the Tibetan Plateau. On the other hand, POPEM departs from the control simulation in the Asia-Pacific region between 10N-10S.

These results show that the POPEM parameterization generally agrees with historical data for population, and also compares well with the control simulation in the sense of addressing some of the known biases in precipitation and temperature, offering a more detailed version of CO_2 emissions at a relatively cheap computational cost. As discussed above, the CONTROL run uses global concentration values to include CO_2 on the assumption that it is well-mixed in the atmosphere (Neale et al., 2012). This assumption reduces the computational burden of the simulation but does not allow for precise emissions modeling in the future. This is an important aspect for regionalized emissions scenarios, since even if the new parameterization is not significantly better than the old approach (but no worse), it is desirable as it allows sensitivity analyses, such as evaluating the effects of the U.S. leaving the Paris agreement.

3.2 Validation against observational data sets

Once it has been verified that the new parameterization does not worsen the modeling, the next step in evaluating the performances is comparing the simulation outputs for both the CONTROL run and the POPEM module using actual observational data. Direct comparisons with historical data can help show whether or not a climate model correctly represents the climate of the past. However, although observational measurements are often considered the ground truth to validate models against, it is important to be aware that measurements have their own uncertainties (Tapiador et al. 2017).

Figure 6 shows a comparison of CESM precipitation simulations for the period 1980-2000 using the GPCP. It is apparent that there is an overall consensus, even though there are differences. Despite these known biases, the model agrees with the observations on the major features of global precipitation. In Figure 6C, there is just a slight discrepancy in the absolute difference in rainfall between the GPCP and CESM simulations (Q1 and Q3 remain between ± 0.4 mm/day). Grid point to grid point comparison between the model and GPCP (a stringent comparison; Figure 6D) indicates the ability of CESM to

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reproduce the spatial distribution of precipitation. In both simulations, the CESM exhibits a good correlation coefficient (0.72 R^2) compared with the reference data.

Figure 6 about here

The improvements in parameterizing emissions become clearer if we focus on specific regions. For the El Niño-4 area, there are statistically-significant differences (at the 0.05 significance level) between both the CONTROL run and the POPEM modeling when compared with the reference data. This observation illustrates the limitations of the modeling and the need of advances in the parameterizations. However, for this area the correlation (R^2) between POPEM and GPCP is slightly better than CONTROL and GPCP (0.706 R^2 versus 0.692 R^2).

The real added value, however, is not in a better estimation of the totals but in the ability of POPEM to better capture the structure of the precipitation. Figure 7 shows the histograms of mean precipitation in the El Niño-4 area using the POPEM parameterization (top), the standard forcing approach (CONTROL, middle), and the reference GPCP estimates (bottom). While the CONTROL simulation severely overestimates the low end of the distribution, POPEM gives a more realistic value. This result is not apparent in the otherwise improved correlation of POPEM, and is also buried in the box plots.

El Niño-4 is important because it presents a lower variance in the SST than any other of the El Niño areas, playing a key role in identifying El Niño Modoki events (Ashok et al., 2007; Ashok and Yamagata, 2009; Yeh et al., 2009). The consequences of such events are severe disruptions in human activities due to the increased risk of droughts, heat waves, poor air quality and wildfires (McPhaden et al., 2006). Thus, precise modeling of the processes in this sector of the Pacific is extremely important.
The improvements of POPEM for the El Niño-4 area show that detailed, dynamical modeling of GHG emissions is important for more precisely quantifying precipitation in dry areas, which validates the main hypothesis of the paper. Also, this example shows that the transient effects of regionalized GHG emissions may even translate into (long) 50-yr climatologies, meaning there is room for improvement in the 'rapidly mixing, well-mixed gases' forcing approach.

Figure 7 about here

Figure 8 compares the annual mean temperatures for the period 1950-2000. CESM simulations show a significant bias in high latitudes of the Northern Hemisphere (cfr. Figures 8A and 8B). In these areas, the model produces colder temperatures than those registered in the CRUTS reference data but this is also an issue in the CONTROL run. This deviation is apparent in Figure 8D, where negative values lie away from the idealized regression line, and indicate further improvement of the CESM.

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Figure 8 about here

4. Conclusions and future work

Like all models, climate models are simplified versions of the real world and therefore do not include the full complexity of the Earth system. Due to certain limitations, e.g. computational resources, or spatial and temporal resolution, climate models have to make assumptions and resort to parameterizations.

One important simplification is to use prescribed forcings instead of dynamically modeling GHG emissions. However, precise modeling of anthropogenic CO_2 emissions is important for climate change research as it allows sensitivity analyses to be performed.

Here we present a new module of gridded CO_2 emissions that is coupled with CESM. The module, denominated POPEM, computes anthropogenic CO_2 emissions by using population estimates as a proxy for disaggregating emissions beyond the national level. POPEM makes CESM use dynamical emissions data instead of fixed concentration parameters.

In terms of population and emissions, the module compares well when validated with data. Thus, POPEM's estimates for the 1950-2000 period are in general agreement with population and emission inventories from the recent past. In spite of the more realistic depiction of the actual emissions (Figure 3), issues persist. The performance of the model can be further improved in places where population projections are difficult to model. For instance, POPEM tends to underestimate emissions on the West Coast of the United States and the Anatolian Plateau, and overestimates emissions in China and Japan.

When the POPEM module is coupled with CESM to generate climatologies, the ability to successfully model precipitation and surface temperature is preserved. Moreover, the results of 50-year simulations show that the dynamical modeling of emissions produced by POPEM results in slight but noticeable differences in the resultant precipitation regime and surface temperature. Thus, dynamically modeling the emissions alters the ITCZ by reducing precipitation in the Southern Hemisphere and increasing it in the Northern Hemisphere. For particularly interesting areas, such as the El Niño-4 region, the POPEM outperforms the traditional approach.

Further work will be devoted to improving the modeling of those areas and hopefully minimizing some of the original biases of the CESM model. These include the emergence of a double ITCZ (Intertropical Convergence Zone) in CESM

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simulations, which is a common bias for most climate models (Oueslati and Bellon, 2015), as well as sea surface temperatures (SST) simulated by climate models, which are generally too low in the Northern Hemisphere and too high in the Southern Hemisphere (Wang et al., 2014).

Although the version of POPEM presented here is already functional, this work is intended to be just the first step in fully coupling socioeconomic dynamics with ESMs. Current applications of the parameterization include evaluating the effects of changes in regional policies, and a better understanding of the carbon cycle (Friedlingstein et al., 2006). Future work will be devoted to evaluating climate response to alternative anthropogenic CO_2 emissions; to increasing the spatial resolution of the simulations; and to refining the spatial and temporal distribution of emission estimates. It is envisioned that CESM simulations employing an enhanced representation of societal processes will provide a more realistic depiction of the Earth System, improving the modeling of temperature, precipitation and other variables of interest.

Author Contribution

ANM, RMG and FJT contributed to experiment design, coding, analysis, and manuscript writing.

Competing interests

The authors declare that they have no conflict of interest.

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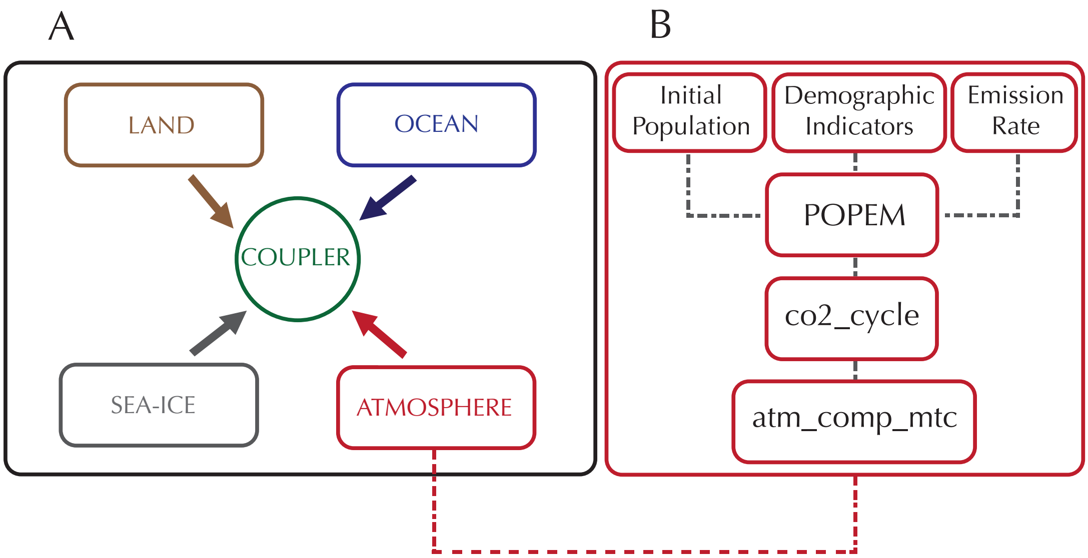

Figure 1: (A) Basic structure of an ESM and (B) conceptual schema of the POPEM module coupled with the CESM atmosphere module. POPEM requires three input data sets to compute emissions: initial population distribution; demographic parameters (age structure, death and birth rates); and per capita emission rates by countries. POPEM provides a 3D array (time, latitude, longitude) with emissions that are read by the *CO2_cycle* module and passed to the *atm_comp_mct* module which compute the total amount of CO_2 in the atmosphere.

Earth Syst. Dynam. Discuss., https://doi.org/10.5194/esd-2018-12
Manuscript under review for journal Earth Syst. Dynam.
Discussion started: 19 March 2018
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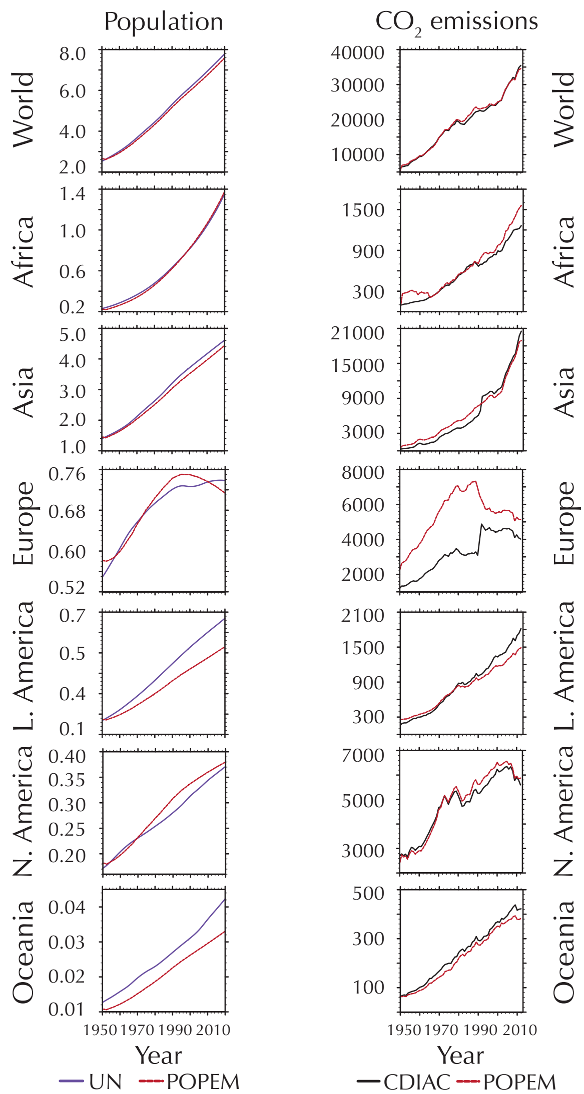

Figure 2: Comparison of the population estimates for the years 1950-2020 (left column) and the historical CO_2 emissions estimates for the years 1950-2012 (right column). The first row compares global data, the second to seventh compare regional data (Africa, Europe, Latin America, North America and Oceania). In the left-hand column, the red line shows the estimates given using POPEM and blue indicates UN estimates. Values are given in thousand millions of people. On the right, the red line shows the estimates given using POPEM and the black indicates CDIAC estimates. Units are given in million metric tons.

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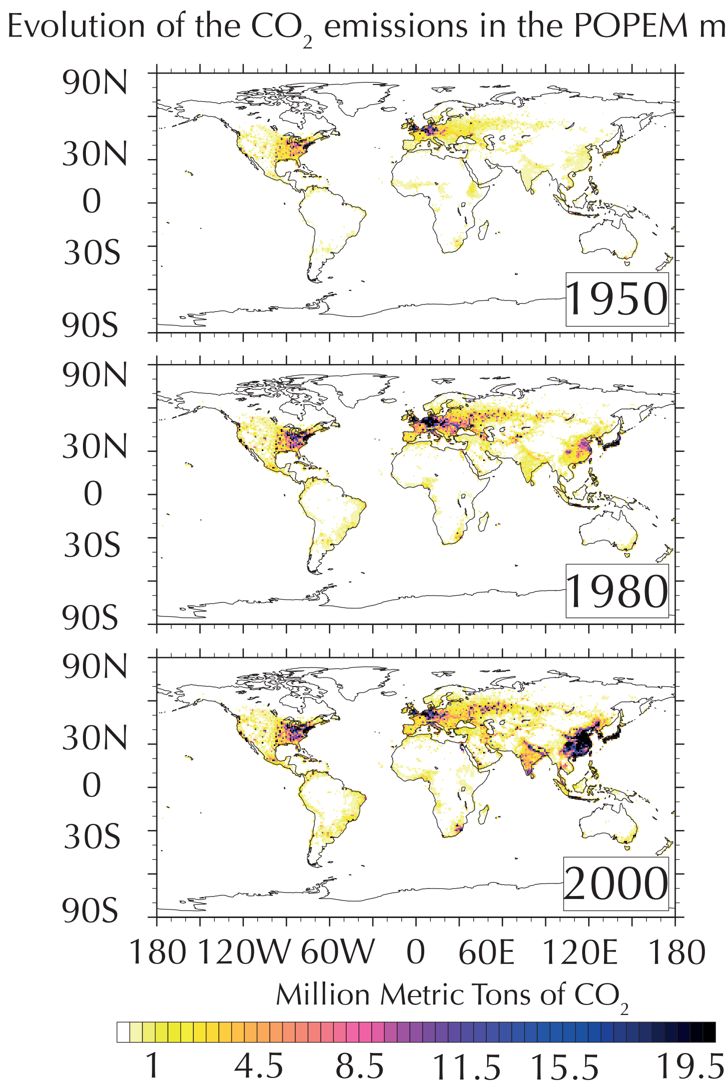

Figure 3: POPEM CO_2 emissions estimates for 1950, 1980 and 2000. POPEM produces a gridded representation of anthropogenic CO_2 emissions using population dynamics and country per capita emissions derived from the CDIAC database. Values are given in millions of metric tons per year.

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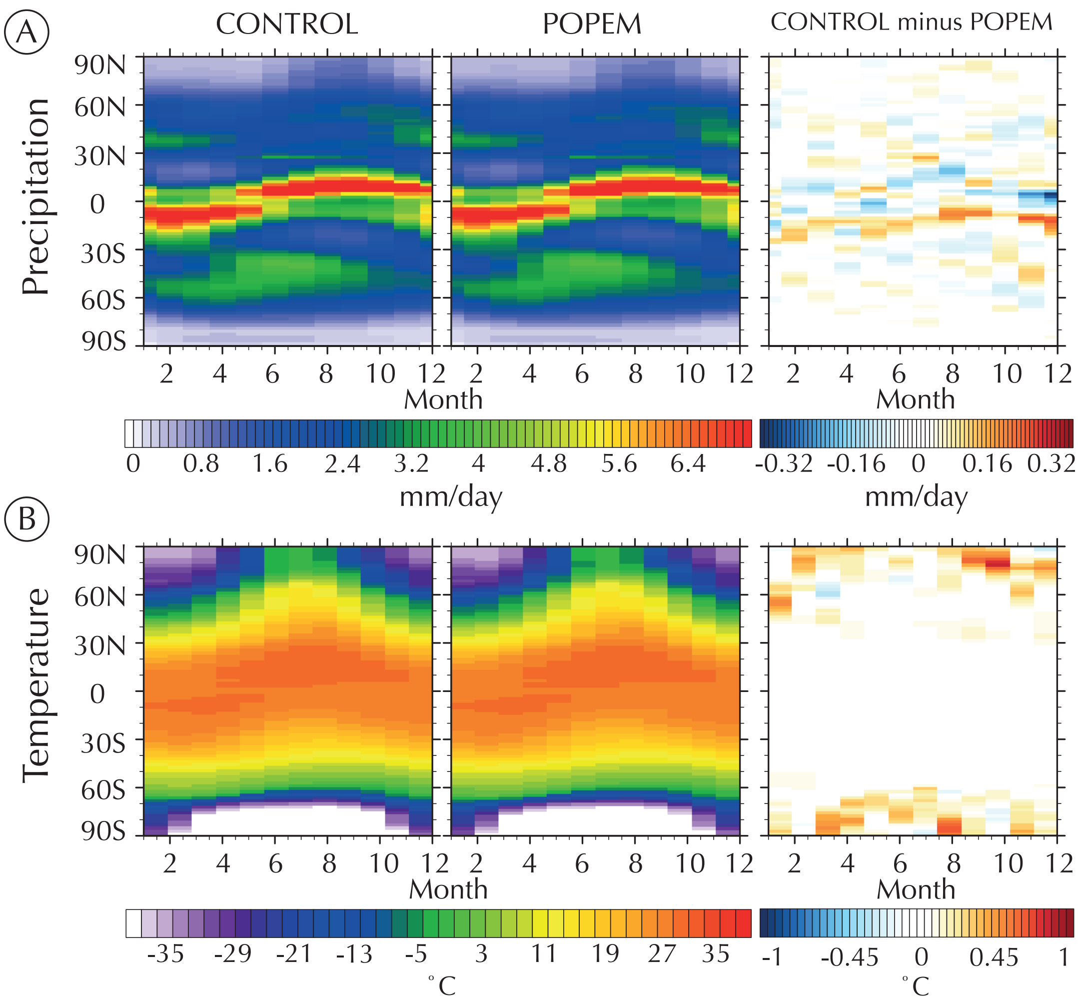

Figure 4: Latitude vs time plots for precipitation (A) and surface temperature (B). For absolute difference graphs, blue represents higher values in POPEM and red represents higher values in the CONTROL. Units are in mm/day for precipitation and in Celsius for temperature.

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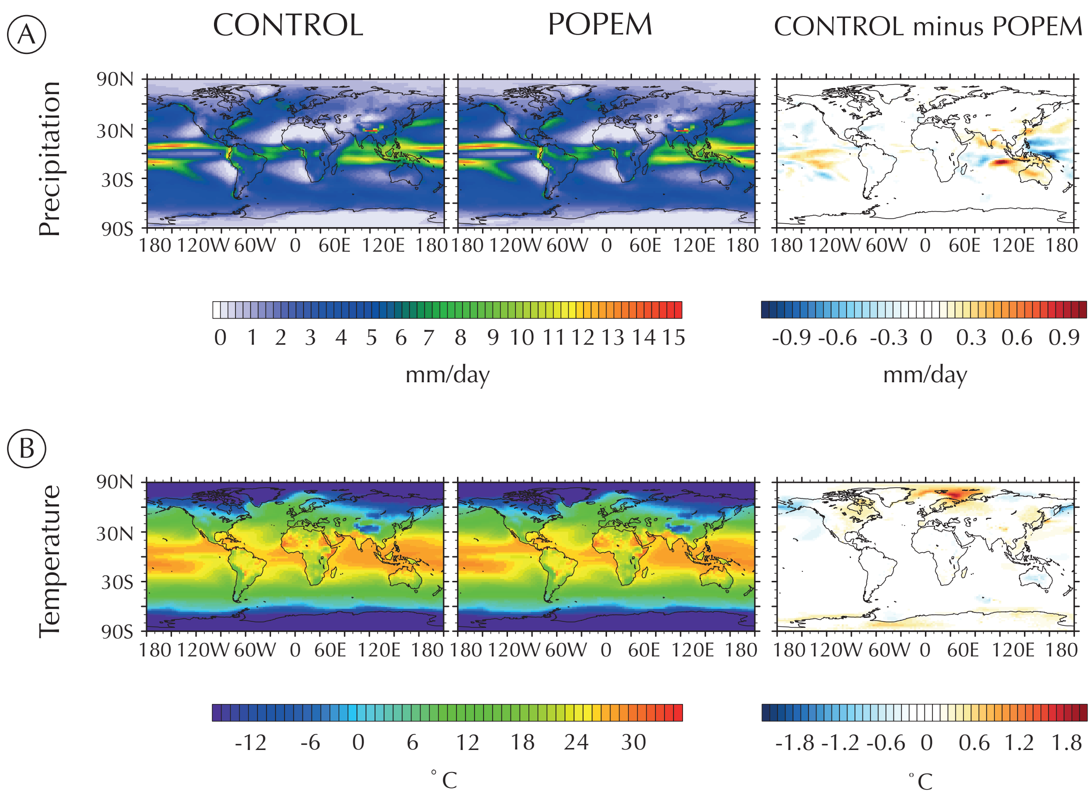

Figure 5: A comparison of global annual mean precipitation (1950-2000) for the CONTROL and POPEM (A). (B) is a comparison of annual mean surface temperatures. The maps in the right-hand column show the absolute differences between the simulations (CONTROL minus POPEM). In these, blues represent higher values in POPEM and reds represent higher values in the CONTROL.

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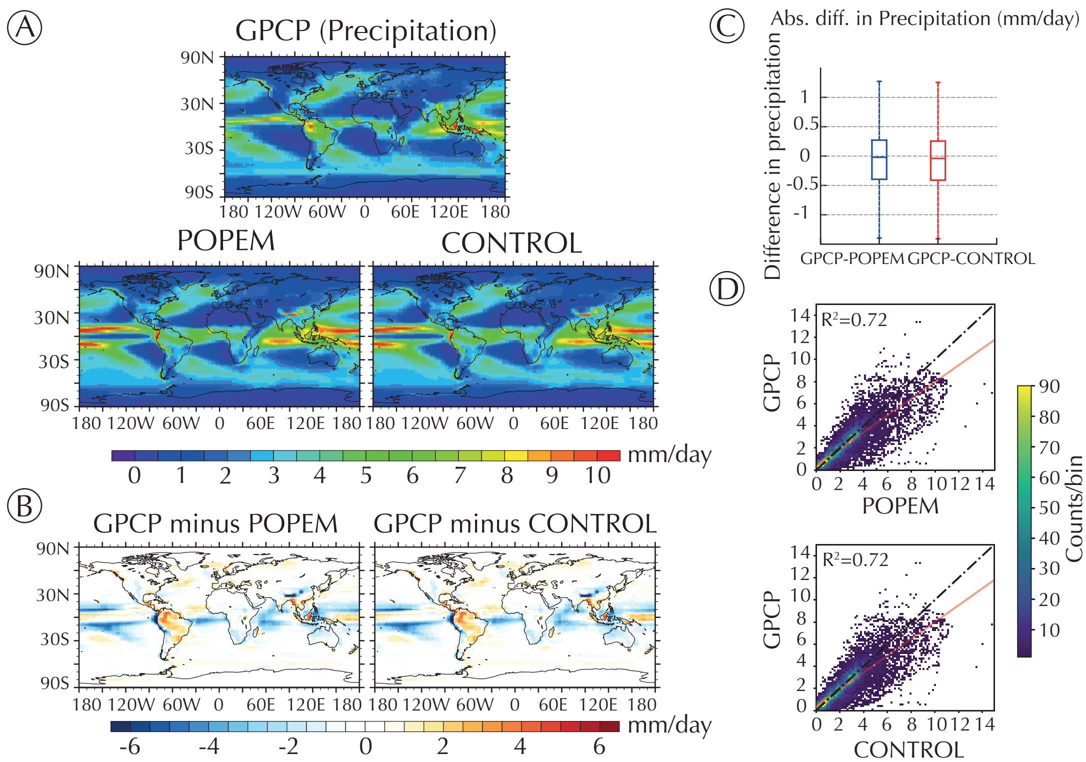

Figure 6: A comparison of the global annual mean precipitation (1980-2000) as simulated by the CESM (POPEM and CONTROL) model and GPCP observational database. (A) Global annual mean precipitation maps for GPCP, POPEM and Control. (B) Absolute difference maps. (C) Boxplots of CESM simulation biases. (D) Scatter plots comparing the annual mean (1980-2000) at every grid point for GPCP and CESM simulations (POPEM and control). Units are in mm/day.

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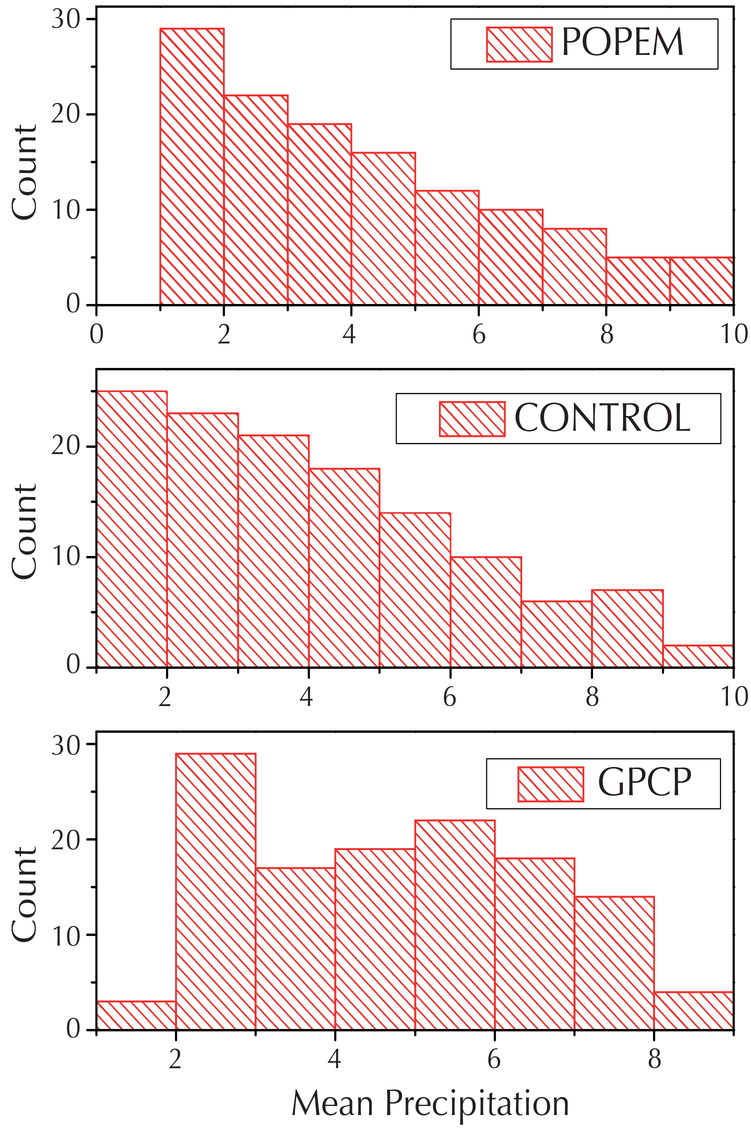

Figure 7: Histograms of the mean precipitation in the El Niño-4 area (5N-5S, 160E-150W) using the POPEM parameterization (top), the standard forcing approach (CONTROL, middle), and the reference GPCP estimates (bottom).

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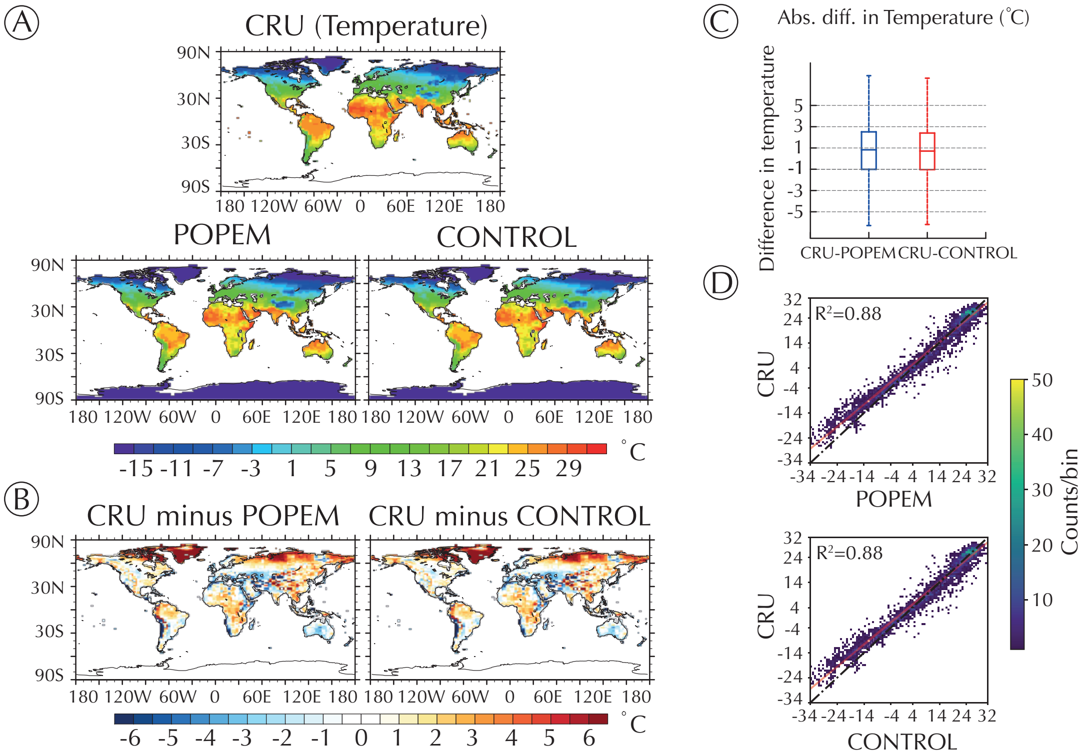

Figure 8: A comparison of the annual mean temperature (1950-2000) as simulated by the CESM model (POPEM and CONTROL) and CRU observational database. (A) Global annual mean temperature maps for CRU, POPEM and CONTROL. (B) Absolute difference maps. (C) Boxplots of CESM simulation bias. (D) Scatter plots comparing the annual mean temperature at every grid point for CRU and CESM simulations (POPEM and CONTROL). Units are in degrees Celsius.