

# Enhanced response of global wetland methane emissions to the 2015-2016 El Niño-Southern Oscillation event

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**Abstract:** Wetlands are thought to be the major contributor to interannual variability in the growth rate of atmospheric methane (CH<sub>4</sub>) with anomalies driven by the influence of the El Niño-Southern Oscillation (ENSO). Yet it remains unclear whether (i) the increase in total global CH<sub>4</sub> emissions during El Niño versus La Niña events is from wetlands and (ii) how large the contribution of wetland CH<sub>4</sub> emissions is to the interannual variability of atmospheric CH<sub>4</sub>. We used a terrestrial ecosystem model that includes permafrost and wetland dynamics to estimate CH<sub>4</sub> emissions, forced by three separate meteorological reanalyses and one gridded observational climate dataset, to simulate the spatio-temporal dynamics of wetland CH<sub>4</sub> emissions from 1980-2016. The simulations show that while wetland CH<sub>4</sub> responds with negative annual anomalies during the El Niño events, the instantaneous growth rate of wetland CH<sub>4</sub> emissions exhibits complex phase dynamics. We find that wetland CH<sub>4</sub> instantaneous growth rates were declined at the onset of the 2015-2016 El Niño event but then increased to a record-high at later stages of the El Niño event (January through May 2016). We also find evidence for a step increase of CH<sub>4</sub> emissions by  $7.8 \pm 1.6$  Tg CH<sub>4</sub> yr<sup>-1</sup> during 2007-2014 compared to the average of 2000-2006 from simulations using meteorological reanalyses, which is equivalent to a  $\sim 3.5$  ppb yr<sup>-1</sup> rise in CH<sub>4</sub> concentrations. The step increase is mainly caused by the expansion of wetland area in the tropics (30°S-30°N) due to an enhancement of tropical precipitation as indicated by the suite of the meteorological reanalyses. Our study highlights the role of wetlands, and the complex temporal phasing with ENSO, in driving the variability and trends of atmospheric CH<sub>4</sub> concentrations. In addition, the need to account for uncertainty in meteorological forcings is highlighted in addressing the interannual variability and decadal-scale trends of wetland CH<sub>4</sub> fluxes.



## 44 Introduction

45

46 Methane (CH<sub>4</sub>) is a potent greenhouse gas and has contributed to ~20% of observed  
47 warming since pre-industrial times (IPCC, 2013). Atmospheric CH<sub>4</sub> concentrations  
48 have risen from preindustrial levels of 715 parts per billion (ppb) since the 1800s  
49 (Etheridge *et al.*, 1998; MacFarling Meure *et al.*, 2006) to current global  
50 concentration of ~1847 ppb, a 2.5-fold increase, primarily driven by anthropogenic  
51 activities (Kirschke *et al.*, 2013), e.g. fossil fuel activities, agriculture, and also by the  
52 biogeochemical feedbacks of natural processes to climate change (Arneth *et al.*,  
53 2010; Tian *et al.*, 2016; Saunio *et al.*, 2016). However, the variability in the annual  
54 growth rate of atmospheric CH<sub>4</sub> is strongly related to the climatic sensitivity of  
55 biogenic CH<sub>4</sub> sources, of which global wetland CH<sub>4</sub> comprises 60-80% of natural  
56 emissions (Quiquet *et al.*, 2015; Hopcroft *et al.*, 2017) and this large role is likely to  
57 persist into the future (Zhang *et al.*, 2017b). Thus, interannual variability in the  
58 growth rate of atmospheric CH<sub>4</sub> is largely affected by the response of global wetland  
59 CH<sub>4</sub> emissions to the year-to-year mode of global climate variability such as the El  
60 Niño-Southern Oscillation (ENSO). ENSO is one of the largest climate phenomena  
61 that drives carbon dynamics and their anomalies across large portions of the globe  
62 (Chatterjee *et al.*, 2017).

63

64 El Niño, the positive phase of ENSO, influences water- and carbon- fluxes of tropical  
65 terrestrial ecosystems through a change in patterns of atmospheric pressure and  
66 sea surface temperature (Philander 1990). These changes induce strong warming  
67 and reduced precipitation patterns by shifting the Intertropical Convergence Zone  
68 southward, causing amplified wildfires (Worden *et al.*, 2013) and reduced wetland  
69 areal extent and CH<sub>4</sub> emissions (Hodson *et al.*, 2011). Tropical wetlands, which  
70 comprise 50-70% of global wetland CH<sub>4</sub> emissions (Bousquet *et al.*, 2006), are  
71 similarly influenced by the periodic variations of air temperature and precipitation  
72 related to ENSO phases (Pison *et al.*, 2013). Atmospheric measurements of CH<sub>4</sub>  
73 provide evidence that the growth rate of global CH<sub>4</sub> concentrations can rise during  
74 strong El Niño years (Nisbet *et al.*, 2016; Bousquet *et al.*, 2006), but terrestrial  
75 biogeochemical models suggest that tropical and global wetland CH<sub>4</sub> emissions are  
76 usually found to decrease during El Niño (Hodson *et al.*, 2011; Zhu *et al.*, 2017;  
77 Ringeval *et al.*, 2014).

78

79 At decadal time scales, the relationship between the annual CH<sub>4</sub> growth rate and  
80 variability in global wetland CH<sub>4</sub> emissions is not fully agreed upon, and the  
81 observed pause in the growth rate during 2000-2006 and subsequent return of the  
82 growth rate since 2007 (Nisbet *et al.*, 2014) is not fully understood. A recent study  
83 suggests that global wetlands have played a limited role during the renewed rise of  
84 the growth rate through 2012 (Poulter *et al.*, 2017). However, isotopic  
85 measurements indicate that the resumed increase in the growth rate could originate  
86 either from biogenic sources (Schwietzke *et al.*, 2016) like tropical wetlands (Nisbet  
87 *et al.*, 2016), from agricultural sources (Schaefer *et al.*, 2016), or from the combined  
88 effect of decreased biomass burning (Worden *et al.*, 2017) and increased fossil-fuel  
89 emissions (Helmig *et al.*, 2016). In addition, simple-box models and more complex

90 atmospheric inversion models can attribute the recent CH<sub>4</sub> change to varying  
91 hydroxyl radical (OH) concentration, the major CH<sub>4</sub> sink in the atmosphere (Turner  
92 *et al.*, 2017; Rigby *et al.*, 2017). Our poor understanding of wetland CH<sub>4</sub> responses at  
93 annual to decadal time scales calls for revisiting the role of relationships between  
94 climate forcings and wetland CH<sub>4</sub> fluxes to help reconcile top-down and bottom-up  
95 methodologies.

96  
97 Previous El Niño anomalies, in years 1982-1983, 1997-1998, and 2015-2016, had  
98 significant impacts on terrestrial ecosystems and these events were considered key  
99 drivers of the atmospheric CO<sub>2</sub> growth rate variability (Liu *et al.*, 2017). The most  
100 recent El Niño event (2015-2016) caused unprecedented warming and extreme  
101 drought over most of the Amazonia regions (Jiménez-Muñoz *et al.*, 2016; L'Heureux  
102 *et al.*, 2016; Lim *et al.*, 2017; Chatterjee *et al.*, 2017). The occurrence of this extreme  
103 El Niño event disrupted regional ecosystems, causing sharp increases in  
104 atmospheric CO<sub>2</sub> concentrations (Betts *et al.*, 2016) and a doubling of fire-induced  
105 emissions in Southeast Asia (Whitburn *et al.*, 2016). The more recent El Niño event  
106 may have also contributed to record warming during 2015 and the first third of  
107 2016, with global air temperature at 0.94°C above the 20th century mean annual  
108 average (<http://www.ncdc.noaa.gov/sotc/global/201613>, last access in August  
109 2017). Exactly how much the 2015-2016 ENSO phenomenon has impacted global  
110 wetland CH<sub>4</sub> emissions and to what extent it has affected the annual growth rate of  
111 atmospheric CH<sub>4</sub> concentration remains unknown due to challenges in monitoring  
112 and modeling.

113  
114 Here, we analyze the relationship between ENSO phase and wetland CH<sub>4</sub> emissions  
115 by addressing two main questions: First, how does ENSO, with particular attention  
116 to the ENSO event in 2015-2016, affect the interannual variability of CH<sub>4</sub> emissions  
117 from global wetlands? Second, what are the major mechanisms that link wetland  
118 CH<sub>4</sub> emissions to the atmospheric increases observed since 2007?

## 121 **Methods**

122  
123 We use a process-based ecosystem model LPJ-wsl (Lund-Potsdam-Jena model, *WSL*  
124 version) forced with four different meteorological forcings to simulate wetland CH<sub>4</sub>  
125 emissions from 1980 to 2016. These drivers include one station-based monthly geo-  
126 interpolation dataset (CRU) and three meteorological reanalyses products (Table 1).  
127 We use multiple climate datasets to investigate uncertainty from meteorological  
128 forcing driving simulated atmospheric CH<sub>4</sub> concentrations, and hence, to better  
129 characterize CH<sub>4</sub> variation in response to climate variations.

130  
131 LPJ-wsl (Poulter *et al.*, 2011) is a process-based dynamic global vegetation model  
132 (DGVM) developed for studying terrestrial ecosystems, based on an earlier LPJ core  
133 model (Sitch *et al.*, 2003). The version of the model applied in this study includes a  
134 new hydrology model, TOPMODEL, to determine wetland area and its inter- and

135 intra-annual dynamics (Zhang et al., 2016), a permafrost and dynamic snow model  
136 (Wania et al., 2009), and a prognostic wetland CH<sub>4</sub> emission model (Hodson et al.,  
137 2011), each of which is incorporated into the LPJ-wsl framework with explicit  
138 representation of the effects of snow and freeze/thaw cycles on soil temperature  
139 and moisture and thus CH<sub>4</sub> emissions (Zhang *et al.*, 2016). We apply an empirical  
140 model to estimate CH<sub>4</sub> emissions in the model which is based on soil respiration,  
141 inundated area, and a temperature-based ecosystem emission efficiency  
142 (Christensen *et al.*, 1996). Soil respiration is modelled empirically in response to  
143 temperature and soil moisture based on an Arrhenius type equation where varying  
144 effective activation energies for respiration and a dampening of the temperature  
145 sensitivity ( $Q_{10}$ ) due to acclimation were considered (Sitch *et al.*, 2003). The  
146 simulated dynamics of wetland area and CH<sub>4</sub> emissions have been evaluated against  
147 large-scale observations in previous studies (Hodson *et al.*, 2011; Zhang *et al.*, 2016;  
148 Zhang *et al.*, 2017b). Here, we calibrated temperature-modified CH<sub>4</sub> emitting factors  
149 by scaling simulated global estimates to match 172 Tg CH<sub>4</sub> yr<sup>-1</sup> in 2004, which was  
150 estimated from an independent atmospheric inversion study (Spahni et al., 2011),  
151 and is in agreement with independent satellite-based methods from Bloom *et al.*  
152 (2010). We improved inundation estimates by calibrating the TOPMODEL  
153 parameter ‘maximum inundation potential’ ( $F_{max}$ ) (Zhang et al., 2016) using an  
154 independent inundation dataset (Poulter *et al.*, 2017) that was derived from a  
155 satellite-based Surface Water Microwave Product Series (SWAMPS) (Schroeder *et al.*,  
156 2015), an inventory-based dataset Global Lakes and Wetlands Database (GLWD)  
157 (Lehner and Döll, 2004), and a regional wetland map derived from satellite  
158 retrievals for Amazonia (Hess et al., 2015). To avoid confusion regarding double  
159 counting (Thornton *et al.*, 2016), we clarify that our simulated wetland area includes  
160 seasonally inundated wetlands, e.g. floodplains, and permanently inundated  
161 vegetated wetlands, but excludes rice agriculture, non-vegetated reservoirs,  
162 medium to large sized lakes, rivers, and coastal wetlands that are not accounted for  
163 by the GLWD.

164

165 The climate datasets included the monthly meteorology from the Climate Research  
166 Unit (CRU) TS 3.25 (Harris *et al.*, 2014) and three state-of-the-art metrological  
167 reanalysis products. The reanalysis products were comprised of 1-hourly reanalysis  
168 Modern-Era Retrospective analysis for Research and Applications Version 2  
169 (MERRA2) (Gelaro *et al.*, 2017) from the NASA Global Modeling and Assimilation  
170 Office (GMAO), 6-hourly ERA-Interim (ERA-I) (Dee *et al.*, 2011) from the European  
171 Centre for Medium-Range Weather Forecasts (ECMWF) data assimilation system  
172 and, and lastly, a 6-hourly Japanese 55-year Reanalysis (JRA-55) (Kobayashi *et al.*,  
173 2015) from the Japan Meteorological Agency (JMA). The reanalysis data (total  
174 precipitation, 2m air temperature, downward shortwave radiation, and downward  
175 longwave radiation) were aggregated to a common daily time-step and downscaled  
176 to 0.5° spatial resolution grid using first order conservative interpolation. The soils  
177 dataset we used was the Harmonized World Soil Database v1.2 (Nachtergaele *et al.*,  
178 2008) and using pedotransfer functions of the surface soil texture (Cosby *et al.*,  
179 1984) to estimate volumetric water holding capacity. For the monthly CRU data,  
180 LPJ-wsl was set up to use a wet-day frequency dataset, a weather generator (Geng *et*

181 *al.*, 1986) to generate daily precipitations, and a set of simplified equations with  
182 monthly cloud cover as input to calculate daily photosynthetically active radiation  
183 flux and potential evapotranspiration (Prentice *et al.*, 1993). Additional details of  
184 the climate datasets and model experiments are in the Supplementary Material  
185 (Table S1). The LPJ-wsl state variables (i.e., carbon in vegetation, litter, and soils)  
186 were simulated to reach equilibrium by using a 1000-year spinup, with fire  
187 dynamics, and a 398-year spinup for land use change using Land-Use  
188 Harmonization dataset (LUHv2) (Hurtt *et al.* 2011). Spin-up was done using  
189 randomly selected climate inputs from 1901-1930 for CRU and 1980-2000 for  
190 reanalysis with fixed atmospheric CO<sub>2</sub> to the 1860 value. After equilibrium, a  
191 transient simulation with fire effects and varying land cover was performed for the  
192 years 1901-2016 (for CRU) and 1980-2016 (for reanalysis), forced with changing  
193 climate conditions and varying atmospheric CO<sub>2</sub> concentration  
194 (<https://www.esrl.noaa.gov/ccgg/trends>, last access at August 2017). The  
195 simulations consider gross land-use transitions (with no wood harvest) with  
196 primary and secondary lands treated separately (for details, see Arneeth *et al.*, 2017),  
197 where the soil moisture and soil respiration were calculated by fraction-weighting  
198 individual land stands within a grid cell.

199

200 We used the Multivariate ENSO index (MEI) for representing the ENSO strength  
201 (Wolter and Timlin, 1998). The MEI index represents the first unrotated principal  
202 component of the combined, normalized fields of the primary climate variables  
203 observed over the tropical Pacific, reflecting a global signal of climate-land-  
204 atmosphere interaction for both El Niño and La Niña events. Given that previous  
205 studies (Fang *et al.*, 2017; Liu *et al.*, 2017) have shown a hysteresis in the Earth  
206 systems response to changes in temperature and precipitation patterns, we carried  
207 out a cross-correlation analysis to examine possible time-lag effects of wetland CH<sub>4</sub>  
208 response to El Niño events.

209

210 To test whether annual wetland CH<sub>4</sub> anomalies contributed to the growth rate of  
211 atmospheric CH<sub>4</sub>, we compared our results against the annual mean global CH<sub>4</sub>  
212 growth rate and monthly CH<sub>4</sub> trend derived from NOAA/ESRL  
213 (<https://www.esrl.noaa.gov/gmd/ccgg/flask.php>, last access at August 2017). We  
214 then used the first derivative of spline-smoothed monthly wetland CH<sub>4</sub> anomalies to  
215 calculate the wetland CH<sub>4</sub> instantaneous growth rate. The time series of CH<sub>4</sub>  
216 concentration measurements, derived from NOAA cooperative air sampling  
217 network, were processed with a curve fitting method (Thoning *et al.*, 1989) that  
218 decomposes the full signal into a long-term growth rate fit by a polynomial function,  
219 seasonal oscillations by a harmonic function, and a low pass digital filter to retain  
220 interannual and short-term variations. From the decomposed signal, we derived  
221 component signals such as trend, growth rate, and annual amplitude. The CH<sub>4</sub>  
222 amplitude of the seasonal cycle from Mauna Loa surface site (MLO: 19.53°N,  
223 155.58°W) in NOAA/ESRL was applied to the analysis as an indicator of the strength  
224 of CH<sub>4</sub> seasonality in the Northern Tropics, where CH<sub>4</sub> amplitude is mainly  
225 controlled by OH and fluxes from the land biosphere. Given that wetlands contribute  
226 the largest fraction of natural CH<sub>4</sub> sources and that the interannual variability of OH

227 is relatively small (Montzka *et al.*, 2011), the changing trends in the CH<sub>4</sub> amplitude  
228 consequently imply that the variation in the trend is largely affected by changing  
229 CH<sub>4</sub> dynamics in wetland ecosystems. To test whether the shifting spatio-temporal  
230 patterns of simulated wetland CH<sub>4</sub> dynamics are consistent with observations, we  
231 compared the observed MLO CH<sub>4</sub> amplitude with simulated wetland CH<sub>4</sub> amplitude,  
232 which was calculated as the difference between annual maxima and minima in  
233 spline-smoothed monthly wetland CH<sub>4</sub> anomalies.

234

235 For evaluation of wetland areal changes we used terrestrial water storage (TWS)  
236 anomalies, observed by the Gravity Recovery and Climate Experiment (GRACE)  
237 satellite measurement, as a proxy for groundwater storage and surface inundation  
238 (Bloom *et al.*, 2012; Boening *et al.*, 2012). We used the Level-3 monthly 'solutions',  
239 version RL05, from Geo Forschung Zentrum (GFZ), the University of Texas Center  
240 for Space Research (CSR), and the Jet Propulsion Laboratory (JPL) from April 2002  
241 to December 2016 to analyze the temporal variations of water mass in the tropics.  
242 The monthly TWS was multiplied by a spatial grid of scaling coefficients derived  
243 from post-processing of GRACE observations (Landerer and Swenson, 2012) to  
244 restore the signals attenuated in the processing at small spatial scales. We used the  
245 ensemble mean of monthly TWS from three different products in the analysis  
246 because the ensemble mean was the most effective in reducing the noise in gravity  
247 fields solutions from GRACE data (Sakumura *et al.*, 2014).

248

## 249 **Results and Discussion**

250

### 251 **Long-term response of wetland CH<sub>4</sub> to ENSO**

252

253 The ensemble climate simulations indicate a strong link between ENSO and wetland  
254 CH<sub>4</sub> emissions, with higher emissions during La Niña and lower emissions during El  
255 Niño (Figure 1a). We find significant negative correlations ( $r_{\text{MERRA2}}=-0.51$ ,  $r_{\text{ERA-I}}=-$   
256  $0.36$ ,  $r_{\text{CRU}}=-0.45$ ,  $r_{\text{JRA-55}}=-0.35$ , d.f.=443,  $p < 0.01$ ) between the ENSO MEI index and  
257 monthly wetland CH<sub>4</sub> anomalies, regardless of the climate data used in the  
258 simulations. This is consistent with findings from bottom-up modeling estimates  
259 (Hodson *et al.*, 2011; McNorton *et al.*, 2016; Zhu *et al.*, 2017), atmospheric modeling  
260 (Pison *et al.*, 2013; Chen and Prinn, 2006) and satellite observations. For instance,  
261 the atmospheric CH<sub>4</sub> variations of the mid-troposphere measured by the Infrared  
262 Atmospheric Sounding Interferometer (IASI) aboard METOP satellite, and by the  
263 Atmospheric Infrared Sounder (AIRS) aboard NASA's Aqua satellite, also show  
264 higher increases in 2007-2008 and 2010-2011 when strong La Niña events occurred  
265 (Xiong *et al.*, 2016). Airborne-based estimates of the interannual variability of CH<sub>4</sub>  
266 fluxes for eastern Amazon Basin also provide ancillary evidence that the CH<sub>4</sub>  
267 emissions are greatest in 2008, a year of La Niña phase (Basso *et al.*, 2016). Recent  
268 satellite observations from the Greenhouse gases Observing SATellite (GOSAT) also  
269 suggest large-scale fluctuations in atmospheric CH<sub>4</sub> during ENSO events, indicating  
270 that wetland CH<sub>4</sub> emissions are ~5% higher during La Niña events (Pandey *et al.*,  
271 2017). The increase in CH<sub>4</sub> emissions from wetlands during La Niña can be

272 attributed to a large increase in flood extent, primarily over tropical areas (including  
273 SE Australia, northern South America, and Southeast Asia) (Boening *et al.*, 2012),  
274 whereas the decreases during El Niño are possibly due to drought-induced  
275 decreases in flooded area. All of the evidence above suggests a robust negative  
276 relationship between annual anomalies of wetland CH<sub>4</sub> emissions and ENSO events,  
277 i.e., positive anomalies during La Niña and vice versa.

278

279 However, negative anomalies of annual wetland CH<sub>4</sub> emissions do not necessarily  
280 lead to a decrease in the instantaneous growth rate of wetland CH<sub>4</sub> emissions during  
281 El Niño. We find that the growth rate of wetland CH<sub>4</sub> emissions is initially decreased  
282 but then is in a rising phase during the later stages of strong El Niño events.  
283 Although, the amplitude of the rising varied depending on which meteorological  
284 forcing was used in the simulations (Figure 1b). This is mainly because strong El  
285 Niño events drive negative wetland CH<sub>4</sub> growth rates at the beginning of the ENSO  
286 anomaly, but then the growth rate rapidly recovers to positive values. Despite  
287 positive atmospheric methane growth rate correlations with El Niño events, the  
288 general decline in wetland area causes declines in wetland CH<sub>4</sub> emissions at the  
289 beginning of strong El Niño phases. The high temperatures over the tropics strongly  
290 increase the CH<sub>4</sub> growth rate due to higher soil decomposition rates during the later  
291 stages of the 2015-2016 El Niño event. Cross-correlation analyses between the  
292 monthly growth rate of wetland CH<sub>4</sub> emissions and the MEI index suggest that the  
293 peak correlation occurs at a 3-month lag (when ENSO leads  $\Delta\text{CH}_4/\Delta t$ ) for the globe.  
294 As expected, the timing of wetland response to ENSO varies regionally, where  
295 Tropical Asia and Tropical South America exhibit a ~4 month lag and no lag,  
296 respectively (Figure S1). The Interannual Variability (IAV) of wetland CH<sub>4</sub> emissions  
297 is dominated by the Tropics (30°S-30°N) with relatively small contributions from  
298 the Northern Hemisphere (Figures 1c, 1d). MERRA2 showed the highest IAV among  
299 all four simulations, whereas the CRU-based simulation had the lowest IAV. The rise  
300 of wetland CH<sub>4</sub> emission growth rate is consistent with the observed spikes of  
301 atmospheric CH<sub>4</sub> growth rates during strong El Niño events (Nisbet *et al.*, 2016).

302

### 303 **Impact of 2015-2016 El Niño on wetland CH<sub>4</sub>**

304

305 The amplitude of instantaneous growth in wetland CH<sub>4</sub> emissions during the 2015-  
306 2016 El Niño was higher than that in the previous periods 1982-1983 and 1997-  
307 1998, suggesting an increased sensitivity of wetland CH<sub>4</sub> in response to the recent El  
308 Niño (Figure 1b). Our results captured the magnitude of this large increase in  
309 wetland CH<sub>4</sub> emissions with an instantaneous growth rate of  $\sim 7.6 \pm 1.6 \text{ Tg CH}_4 \text{ yr}^{-1}$   
310 during 2015-2016 El Niño. The meteorological datasets drove instantaneous growth  
311 rates that ranged between  $9.2 \text{ Tg CH}_4 \text{ month}^{-1}$ ,  $8.6 \text{ Tg CH}_4 \text{ yr}^{-1}$ ,  $7.2 \text{ Tg CH}_4 \text{ yr}^{-1}$ , and  
312  $5.5 \text{ Tg CH}_4 \text{ yr}^{-1}$  using MERRA2, JRA-55, CRU, and ERA-I, respectively. Although the  
313 2015-2016 El Niño was not as strong as the 1997-1998 El Niño according to the MEI  
314 index ( $\sim 3$  in 1997-1998 and  $\sim 2.5$  in 2015-2016), the combined effect of rising CO<sub>2</sub>  
315 concentrations and high temperatures most likely amplified the impact, causing 1.8  
316 times the maximum growth rate of CH<sub>4</sub> of the 1997-1998 El Niño event (mean  
317 growth rate of  $\sim 4.2 \pm 1.4 \text{ Tg CH}_4 \text{ yr}^{-1}$  for the respective time period).



318

319 The spatial distribution of wetland CH<sub>4</sub> anomalies demonstrated that the large  
320 increases in soil respiration drove the strong growth rate and occurred during the  
321 March-April-May (MAM) season in 2016 as a consequence of warming and droughts  
322 in the wet seasons (October 2015 - May 2016) (Figure 2). There was a widespread  
323 increase in CH<sub>4</sub> emissions over western Amazonia, mainly attributed to increased  
324 soil respiration. Despite a large decline in wetland extent due to severe drought,  
325 significant positive anomalies in CH<sub>4</sub> emission peaked across the western  
326 Amazonian basin, likely due to high temperatures. Temperature is the primary  
327 climatic variable driving the increasing long-term trend in CH<sub>4</sub> emissions (Zhang *et*  
328 *al.*, 2017b). However, precipitation is the dominant climatic variable regulating  
329 interannual variability in CH<sub>4</sub> emissions by altering the inundation extent and  
330 creating anaerobic conditions suitable for methanogenesis in the tropics (Zhang *et*  
331 *al.*, 2017b).

332

### 333 **Wetland CH<sub>4</sub> trends between 2000-2006 and post-2007**

334

335 Using the meteorological reanalysis data, we find evidence for a step increase in  
336 global annual wetland emissions between the periods of 2007-2014 relative to that  
337 of 2000-2006 (Figure 3a). These simulations suggest that the average annual CH<sub>4</sub>  
338 emissions from 2007-2014 increased by  $\sim 7.8 \pm 1.6$  Tg CH<sub>4</sub> yr<sup>-1</sup> compared to the  
339 average of 2000-2006, which is equivalent to an increase in the growth rate of up to  
340  $\sim 3.5$  ppb CH<sub>4</sub> yr<sup>-1</sup> for the post-2007 period, or about half of the observed increase in  
341 concentrations. The CRU-based simulation in this study did not show a strong step-  
342 increase between these two periods, suggesting only a marginal contribution from  
343 wetlands with a 1.5 Tg CH<sub>4</sub> yr<sup>-1</sup> increase in the post-2007 growth rate. This is  
344 consistent with findings from an ensemble modeling experiment using CRU as a  
345 forcing dataset, which found no significant increase of global wetland CH<sub>4</sub> emissions  
346 during the period of renewed atmospheric CH<sub>4</sub> growth (Poulter *et al.*, 2017).  
347 Another recent atmospheric modeling study, also using CRU as forcing for their  
348 prior inputs, likewise suggested that wetlands made only a small contribution to the  
349 post-2007 growth at  $\sim 1$  ppb/yr (McNorton *et al.*, 2016). In contrast to the CRU  
350 simulations just listed, all our simulations using meteorological reanalysis data  
351 suggest that more than 90% of the increase in the growth rate of wetland CH<sub>4</sub> is  
352 from the Tropics (Table 2), and mainly due to increases in precipitation across  
353 South America, Tropical Africa, and Southeast Asia since 2007. MERRA2-based  
354 simulations suggest that the post-2007 rise in global CH<sub>4</sub> concentrations primarily  
355 comes from South America and Tropical Africa, whereas ERA-I and JRA-55 identify  
356 South America as the largest contributor to the CH<sub>4</sub> growth rate (Figure S2).

357

358 The different IAV patterns of CH<sub>4</sub> emissions among these simulations suggest  
359 considerable uncertainties in CH<sub>4</sub> emissions due to climate drivers (Figure 3a). The  
360 model experiments demonstrated that the discrepancy originates mainly from  
361 different model behavior when using products like CRU and meteorological  
362 reanalyses like MERRA2, ERA-I, and JRA-55, regardless of the temporal resolution of  
363 climate inputs used (Figure S3). We found only minor differences using a daily or

364 monthly temporal resolution, which likely reduced uncertainties from applying the  
365 simulated weather generator and thus show that the weather generator covered the  
366 internal climatic variability at monthly scale. The importance of considering  
367 uncertainty of climate forcing was also reflected in the representation of the  
368 seasonal cycle of CH<sub>4</sub> emissions. The comparison of simulated CH<sub>4</sub> emissions with  
369 independent estimates using an atmospheric model STILT based on CARVE airborne  
370 experiments (Zona *et al.*, 2016) suggested a dominant role of climate forcings in  
371 capturing CH<sub>4</sub> seasonality in arctic regions (Figure 3b). MERRA2, ERA-I, and JRA-55  
372 underestimated the peak CH<sub>4</sub> emission in growing season but were able to capture  
373 the general seasonal cycle in CH<sub>4</sub> emissions for the North Slope of Alaska, while  
374 CRU-based estimates failed to reproduce a similar pattern. The seasonal cycle of CH<sub>4</sub>  
375 emissions was also generally underestimated by most bottom-up models that used  
376 CRU climate data in a synthesis modeling experiment (Melton *et al.*, 2013),  
377 highlighting the need to better constrain the CH<sub>4</sub> emissions by taking into account  
378 several datasets that represent climate forcing uncertainty.

379

### 380 **Sensitivity of wetland CH<sub>4</sub> emissions to ENSO**

381

382 To further investigate whether the influence of ENSO on global wetland CH<sub>4</sub>  
383 fluctuation was strengthening, we evaluated the average sensitivity of simulated  
384 wetland CH<sub>4</sub> emissions and wetland areas in the tropics to ENSO events. To this  
385 means we calculated the ratio of the annual anomaly of CH<sub>4</sub> emission/wetland area  
386 to the annual MEI index for three different time periods, 1980-1999, 2000-2006,  
387 and 2007-2016 (Figure 4). We observed a minor change in the sensitivity of CH<sub>4</sub>  
388 emissions and wetland areas between 1980-1999 and 2000-2006, which suggests a  
389 subtle change in the response of global wetland CH<sub>4</sub> emissions to increasing global  
390 temperatures. However, the sensitivity of the modeled results strongly increased for  
391 the period of 2007-2016 relative to the two previous time periods. The sensitivity in  
392 CH<sub>4</sub> emissions increased by ~200% in MERRA2, ERA-I, and JRA-55, whereas the  
393 CRU run resulted in a lower percent increase (42%) compared to the other model  
394 experiments. The concurrent increase in the sensitivity of CH<sub>4</sub> emissions and  
395 wetland areas indicates that the increase of CH<sub>4</sub> emissions since 2007 can mainly be  
396 attributed to an increased sensitivity of wetland areas, which was driven by the  
397 changing precipitation patterns found in meteorological reanalysis products. The  
398 GRACE measurement for relative equivalent water storage confirms the large  
399 increase for the period of 2007-2014 compared to earlier periods (Figure 5),  
400 suggesting that our simulated increases in tropical wetland areas are robust. All of  
401 the modeled wetland areas have significant correlations ( $r_{\text{MERRA2}}=0.59$ ,  $r_{\text{ERA-I}}=0.59$ ,  
402  $r_{\text{CRU}}=0.56$ ,  $r_{\text{JRA-55}}=0.5$ , d.f.=176,  $p < 0.01$ ) with GRACE TWS, and suggest a ~150 10<sup>3</sup>  
403 km<sup>2</sup> increase in inundation over time period of 2007-2014. This also implies that,  
404 despite an observed decline in open waters in the tropics (due to the anthropogenic  
405 effect from denser populations and impacts from human activities for the period of  
406 1990s and early 2000s (Prigent *et al.*, 2012)), the enhanced precipitation since 2007  
407 (Sun *et al.*, 2017; Rodell *et al.*, 2018) was primarily related to the ENSO phase over  
408 Tropical land, which has affected wetland patterns and CH<sub>4</sub> emissions globally.

409

## 410 **Relationship between wetland CH<sub>4</sub> and atmospheric growth rate**

411

412 There was a statistically significant ( $p < 0.10$ ) positive trend in the simulated annual  
413 amplitude of wetland CH<sub>4</sub> emissions, suggesting an increasingly enhanced  
414 sensitivity of wetland CH<sub>4</sub> emissions to climate change in recent decades (Figure 6).  
415 All model simulations indicated positive trends of the annual amplitude of wetland  
416 CH<sub>4</sub> emissions with small differences depending on climate forcings. These  
417 simulated positive trends are consistent with observed trends in CH<sub>4</sub> amplitude at  
418 the MLO site, for which MERRA2, ERA-I, and JRA-55 runs were correlated with MLO  
419 observations ( $r_{\text{MERRA2}}=0.36$ ,  $r_{\text{ERA-I}}=0.42$ ,  $r_{\text{CRU}}=0.29$ ,  $r_{\text{JRA-55}}=0.37$ , d.f. = 30,  $p < 0.05$ ) and  
420 only CRU-based simulations showed a weak correlation between wetland CH<sub>4</sub>  
421 emissions and enhanced global CH<sub>4</sub> seasonality. These significant correlations  
422 suggest relationships between atmospheric CH<sub>4</sub> seasonality and natural wetland  
423 emissions, despite the major role of OH in determining CH<sub>4</sub> seasonality. The  
424 increasing trends in CH<sub>4</sub> amplitude also imply a high likelihood that there is an  
425 underlying shift of CH<sub>4</sub> seasonality in wetland ecosystems and this shift in  
426 seasonality is likely greatest in tropical regions.

427

428 We found a small, but significant, positive correlation between annual wetland CH<sub>4</sub>  
429 emissions and the annual atmospheric CH<sub>4</sub> growth rate in simulations forced by the  
430 daily meteorological datasets MERRA2 ( $r= 0.31$ , d.f.= 33,  $p < 0.1$ ), ERA-I ( $r= 0.36$ ,  
431 d.f.=33,  $p < 0.1$ ), and JRA-55 ( $r=0.38$ , d.f.=33,  $p < 0.05$ ) for the period of 2000-2015,  
432 whereas no significant correlation was found in CRU-based runs ( $r=0.07$ , d.f.= 33,  
433  $p>0.75$ ). For the period of 1980-1999, none of the simulations showed a significant  
434 correlation with the annual atmospheric CH<sub>4</sub> growth rate. The atmospheric CH<sub>4</sub>  
435 growth rate is not exclusively a result of changes in wetland emissions, but rather  
436 due to a combined influence of anthropogenic and natural sources, and also due to a  
437 hydroxyl radical sink (Turner *et al.*, 2017; Rigby *et al.*, 2017). Recent studies have  
438 reported an increase in annual CH<sub>4</sub> emissions from global livestock (Wolf *et al.*,  
439 2017) and an expansion of agricultural areas for rice paddies in Southern Asia  
440 (Zhang *et al.*, 2017a), a region where precipitation has largely increased since 2007.  
441 Thus, we hypothesize that a combination of tropical wetlands and agricultural  
442 sources are likely responsible for the resumed growth rate of atmospheric CH<sub>4</sub>  
443 concentrations, which is consistent with the depletion in the global isotopic  
444 signature in <sup>13</sup>CH<sub>4</sub> (Schaefer *et al.*, 2016) and with regional measurements of <sup>13</sup>CH<sub>4</sub>  
445 in the Tropics (Nisbet *et al.*, 2016).

446

447

## 448 **Conclusions**

449

450 We demonstrate that global wetland CH<sub>4</sub> emission anomalies are strongly related to  
451 ENSO variability using an extended, multi-meteorological ensemble. At sub-annual  
452 time-scales, we also found that the instantaneous growth rate of wetland CH<sub>4</sub>  
453 anomalies was positively correlated with ENSO strengths, which provides an  
454 explanation for the observed rise of atmospheric CH<sub>4</sub> growth rate during strong El  
455 Niño events. The ongoing warming trend, as well as the shifting patterns of global

456 precipitation, has likely had a significant impact on increasing global CH<sub>4</sub>  
457 interannual variability. The strong El Niño event in 2015-2016, associated with  
458 extreme heat and drought over the Amazonian regions, caused record-high growth  
459 rates of wetland CH<sub>4</sub> emissions compared to the previous three decades. We also  
460 found an increasing sensitivity of wetland CH<sub>4</sub> emissions to ENSO oscillation since  
461 2007, which we attribute to increases in the areal extent of tropical wetlands from  
462 increased precipitation. Our study also highlights the need to account for  
463 uncertainty in the climate forcing for estimating wetland CH<sub>4</sub> emissions.

464

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466

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480

## 481 **Data availability**

482

483 The data that support the findings of this study are available upon request, for  
484 access please contact Z. Zhang (yuisheng@gmail.com). Atmospheric CH<sub>4</sub>  
485 concentration datasets were obtained from the NOAA ESRL GMD Carbon Cycle  
486 Cooperative Global Air Sampling Network  
487 (<https://www.esrl.noaa.gov/gmd/ccgg/flask.php>, last access at August 2017). The  
488 annual mean global CH<sub>4</sub> growth rate and monthly trend were derived from  
489 NOAA/ESRL (([www.esrl.noaa.gov/gmd/ccgg/trends\\_ch4/](http://www.esrl.noaa.gov/gmd/ccgg/trends_ch4/)). Terrestrial Water  
490 Storage products were derived from the GRACE website  
491 (<https://grace.jpl.nasa.gov/data/get-data/>, last accessed on October 2017). We used  
492 the multivariate ENSO index (MEI) (<https://www.esrl.noaa.gov/psd/enso/mei/>,  
493 last access at October 2017) as indices for representing ENSO strength.

494

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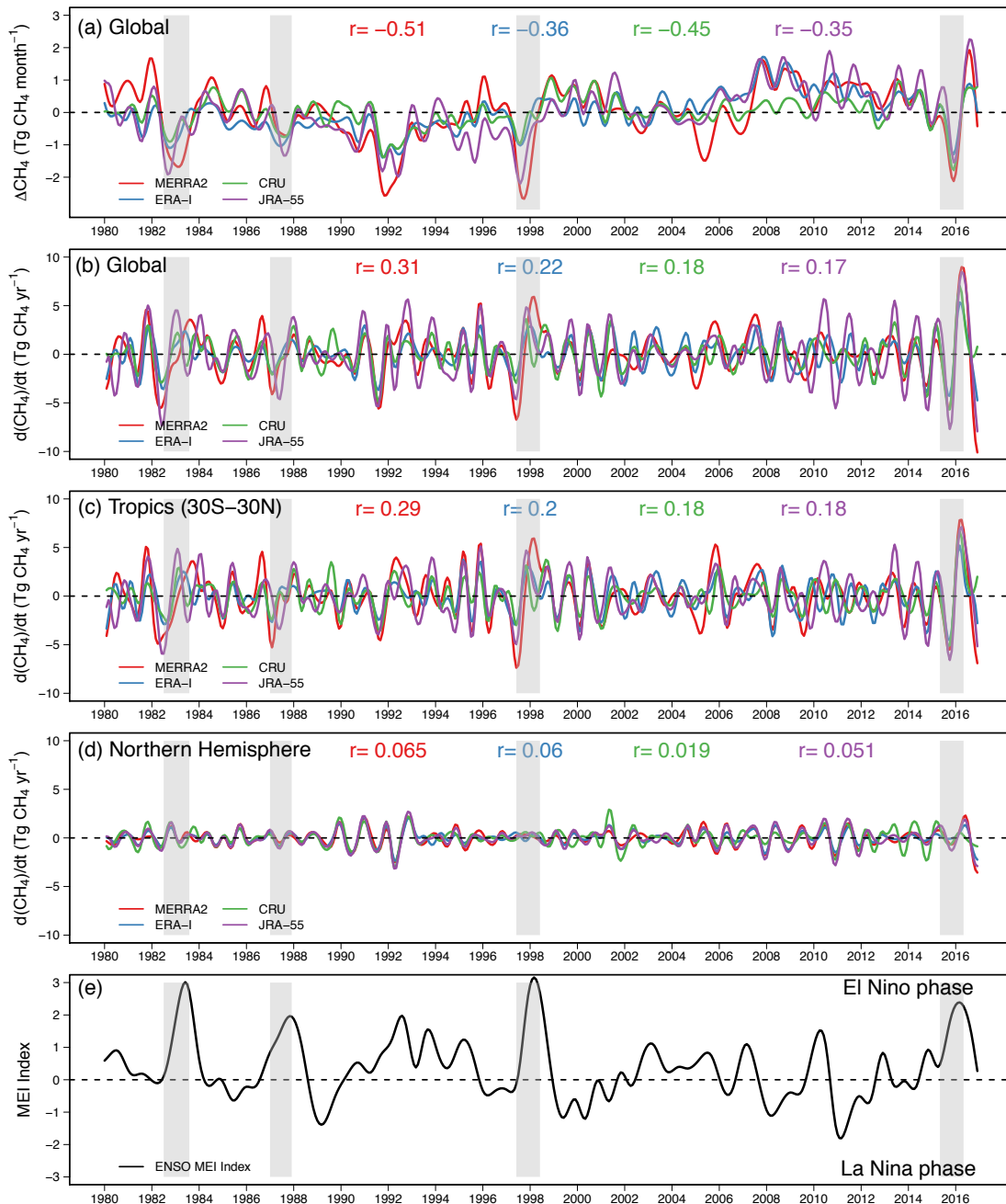
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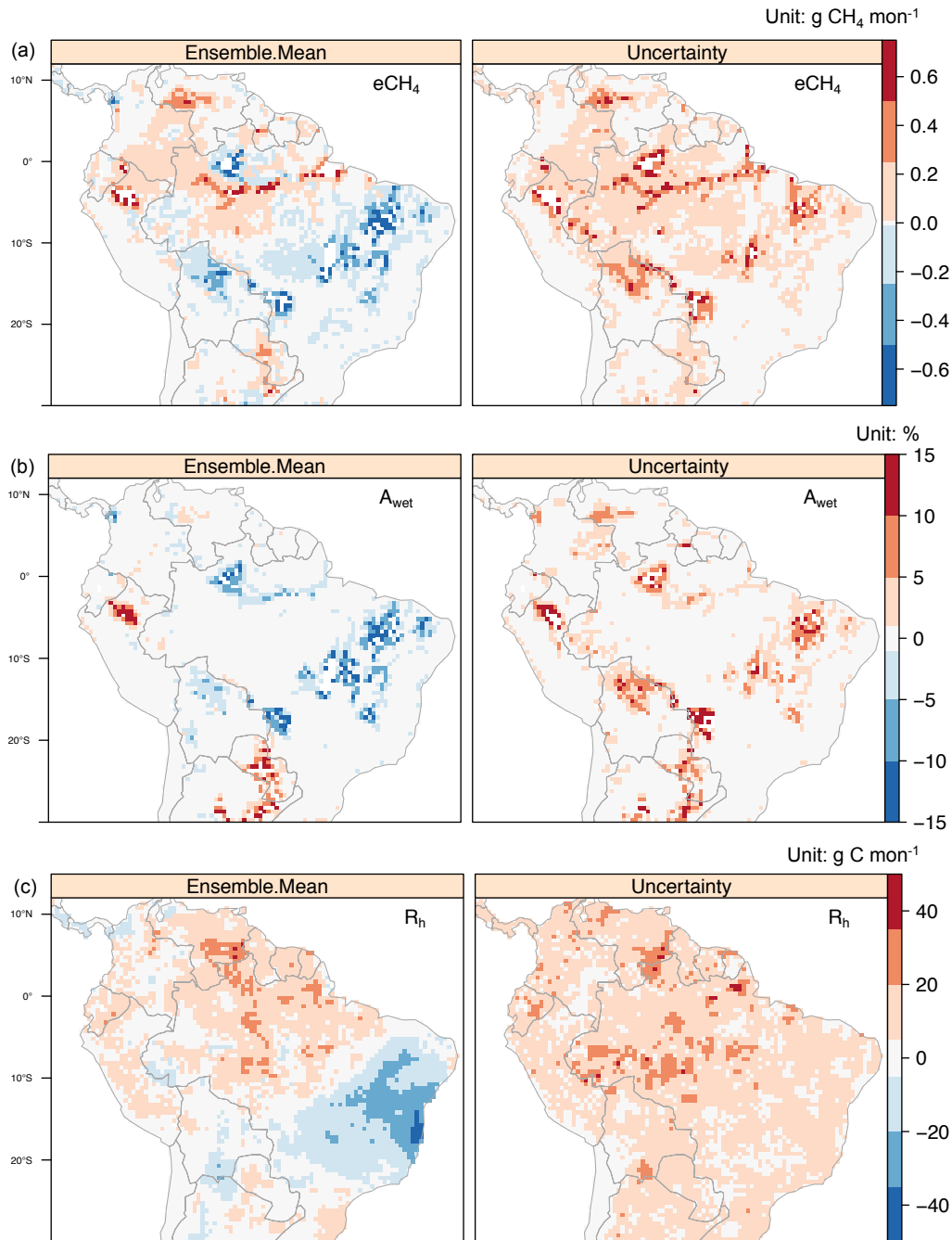
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Figure 1. Global anomalies of monthly wetland CH<sub>4</sub> emissions (a) and instantaneous growth rates of wetland CH<sub>4</sub> emission anomalies from 1980 to 2016 for the Global (b), Tropics (middle, 30°S-30°N) (c), and Northern Hemisphere (bottom, >30°N) (d). The global anomalies of wetland CH<sub>4</sub> emissions were calculated relative to monthly average from 1980-2016. The instantaneous growth rate for each simulation is a time derivative of the smoothed monthly CH<sub>4</sub> anomalies using spline functions. The Spearman rank correlation coefficients between the multivariate ENSO index (MEI) and monthly wetland anomalies were derived from cross correlation analyses

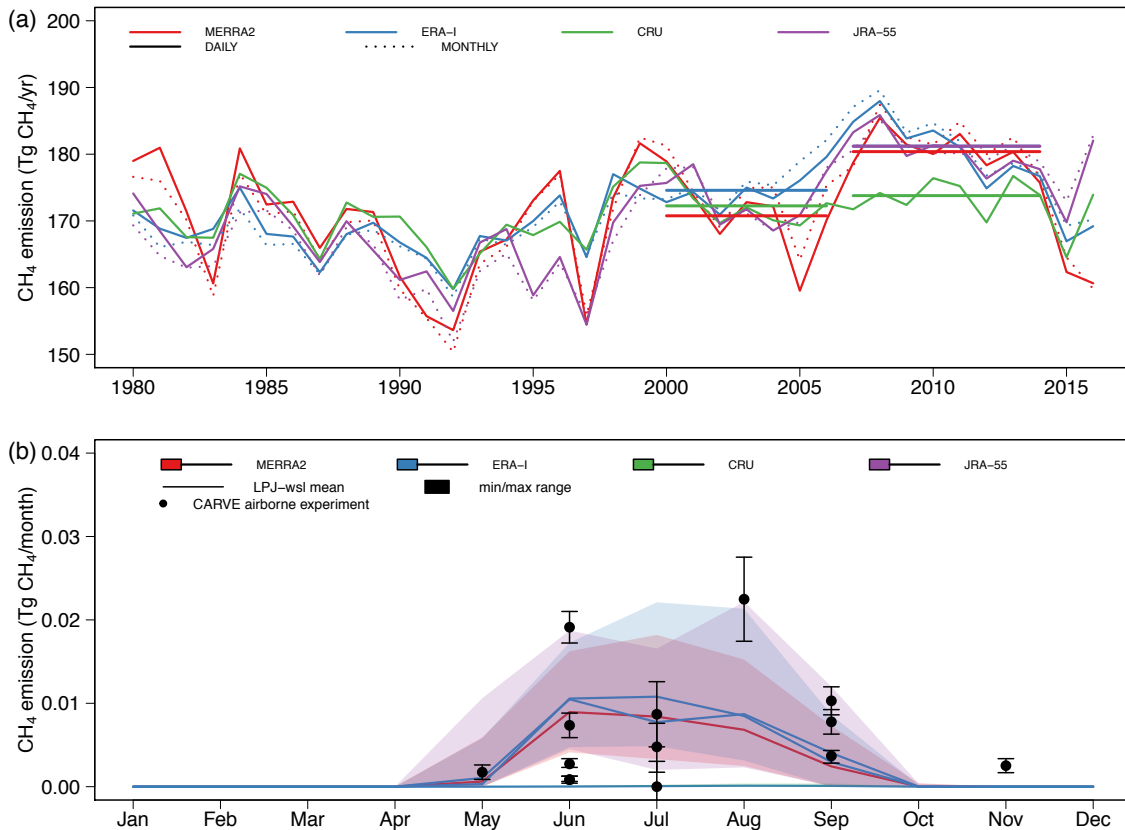
768 (Figure S1) at 3 month lags (Lag= -3), with different colors corresponding to specific  
769 runs. Shaded grey areas represent the strong El Niño phases with MEI strength > 60  
770 according to MEI ranks (<https://www.esrl.noaa.gov/psd/enso/mei/rank.html>, last  
771 access at January 2018).  
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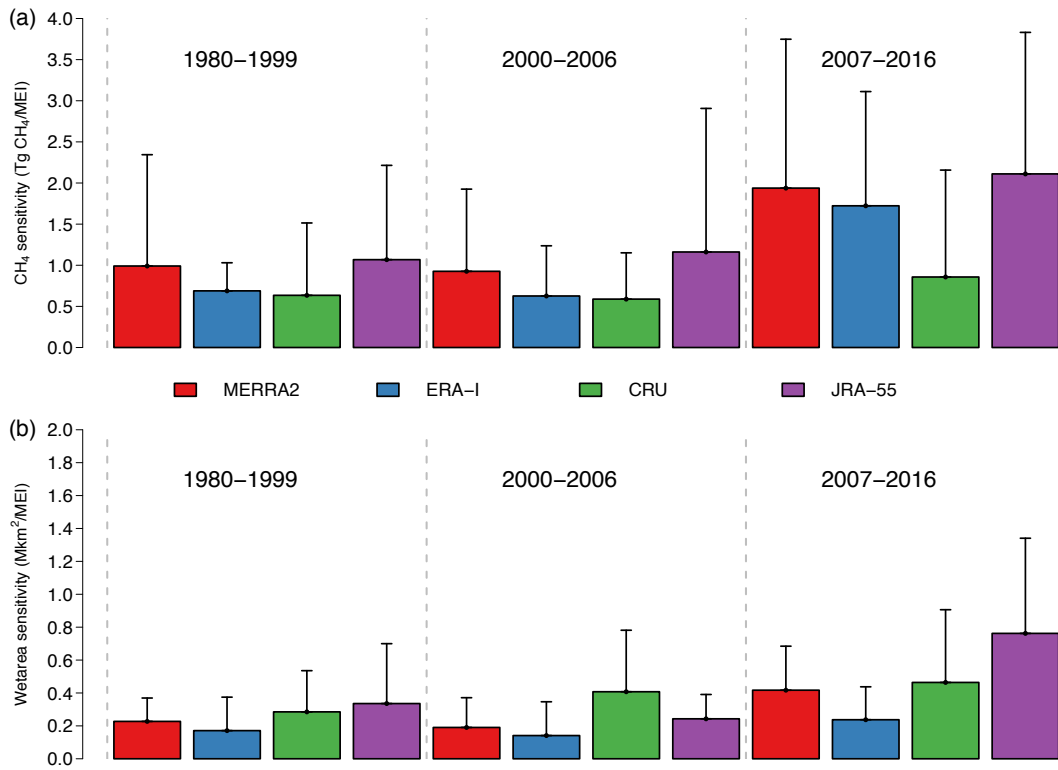
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775 Figure 2. Spatial distributions of seasonal ensemble mean anomalies in wetland  $\text{CH}_4$   
 776 emissions (a:  $e\text{CH}_4$ , Unit:  $\text{g CH}_4 \text{ m}^{-2} \text{ mon}^{-1}$ ), inundated areas (b:  $A_{\text{wet}}$ , Unit: %), and  
 777 heterotrophic respiration (c:  $R_h$ , Unit:  $\text{g C m}^{-2} \text{ mon}^{-1}$ ) of the greater Amazonia region  
 778 for the March-April-May season, 2016, where  $e\text{CH}_4$  shows the highest growth rate  
 779 during the 2015-2016 ENSO event. The anomalies are calculated as seasonal means  
 780 during the MAM season of 2016 relative to average over the period of 1980-2016  
 781 level, with the uncertainty calculated as one-standard deviation from the four  
 782 simulations forced by each meteorological dataset.



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Figure 3. Simulated temporal patterns of CH<sub>4</sub> from all model experiments (see details in Table 1). (a) Time series of annual CH<sub>4</sub> emissions using climate forcings with daily and monthly temporal resolution. The daily forcings were aggregated to monthly values to evaluate the influence of daily variations of climate variables on CH<sub>4</sub> estimations. Solid and dotted lines represent daily and monthly inputs, respectively. The horizontal lines represent averaged annual CH<sub>4</sub> emissions for two time periods, 2000-2006 and 2007-2014, with the different colors representing different climate forcings. (b) Comparison between the seasonal cycle of LPJ-wsl simulated monthly CH<sub>4</sub> fluxes (solid line) using different climate forcings, with min/maximum range (areal shaded) over the Northern Slope of Alaska for 2012-2014 in comparison to the observed regional CH<sub>4</sub> fluxes (dots) estimated from analysis of 15 aircraft flights by the National Aeronautics and Space Administration's Carbon in Arctic Vulnerability Experiment (CARVE).



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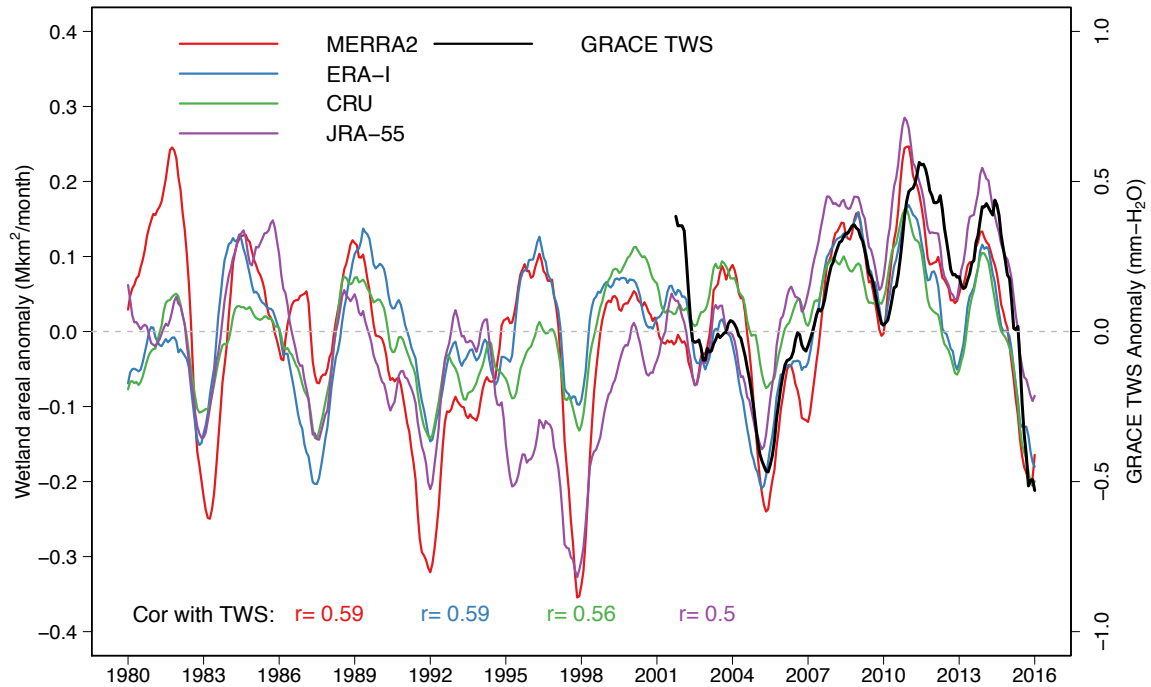
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Figure 4. Sensitivity of (a) wetland CH<sub>4</sub> anomalies (Unit: Tg CH<sub>4</sub> /yr/MEI) and (b) wetland area anomalies for the tropics (Unit: Mkm<sup>2</sup>/yr/MEI; Mkm<sup>2</sup> = 10<sup>6</sup> km<sup>2</sup>) to global ENSO strength for the period of 1980-1999, 2000-2006, and 2007-2016. The sensitivity metric is calculated as the ratio of averaged annual cumulative anomalies of wetland CH<sub>4</sub> emissions and wetland areas to the MEI index. Bars represent the modeled sensitivity from experiments with different forcing datasets, and the error bars represent one standard deviation.



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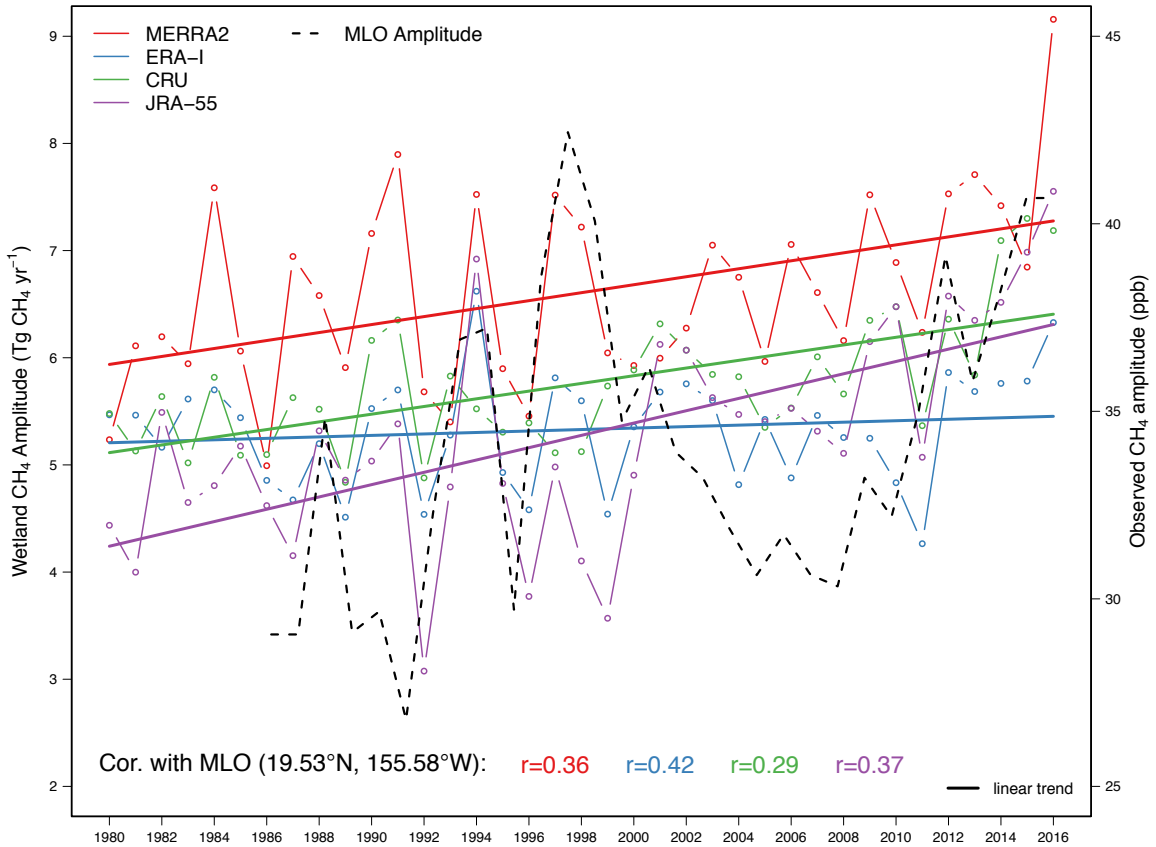
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Figure 5. Trends of simulated wetland areal anomalies (Unit: Mkm<sup>2</sup>/month; Mkm<sup>2</sup>=10<sup>6</sup> km<sup>2</sup>) for the tropics (30°S-30°N) compared to area-weighted average terrestrial water storage (TWS; Unit: mm-H<sub>2</sub>O) from the ensemble mean of GRACE satellite measurement. The wetland anomalies were calculated relative to the monthly mean of 1980-2016, while TWS anomalies were relative to means of the 2004-2009 period. The fitted trends were calculated by smoothing the monthly anomalies with a 12-month moving average. The Spearman rank correlation coefficients between model and TWS are given for each simulation with different climate forcings in corresponding colors.





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Figure 6. Time series of the seasonal amplitudes of global CH<sub>4</sub> fluxes. The seasonal amplitude of CH<sub>4</sub> fluxes (dashed dotted line) is calculated as the difference between maxima and minima of simulated monthly CH<sub>4</sub> emissions. The dashed black line represents observed peak-to-through seasonal amplitude of atmospheric CH<sub>4</sub> concentration at Mauna Loa observational station. The solid lines represent linear fitted long-term trends of the seasonal CH<sub>4</sub> cycle with Spearman rank correlation coefficients between models and observed amplitudes listed for each model runs in corresponding colors.

824 Tables:

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826 Table 1. Model experiment descriptions. Climatic variables T, P, SW, LW, CLD, and  
827 WETD represent temperature, precipitation, shortwave radiation, longwave  
828 radiation, cloud cover, and wet days respectively.

Run ID number	Forcing	Temporal Resolution	Climatic Variables	Time periods
i	MERRA2	Daily	T, P, SW, LW	1980-2016
ii	MERRA2	Monthly	T, P, SW, LW*	1980-2016
iii	ERA-I	Daily	T, P, SW, LW	1980-2016
iv	ERA-I	Monthly	T, P, SW, LW	1980-2016
v	JRA-55	Daily	T, P, SW, LW	1980-2016
vi	JRA-55	Monthly	T, P, SW, LW*	1980-2016
vii	CRU	Monthly	T, P, CLD, WETD	1901-2016

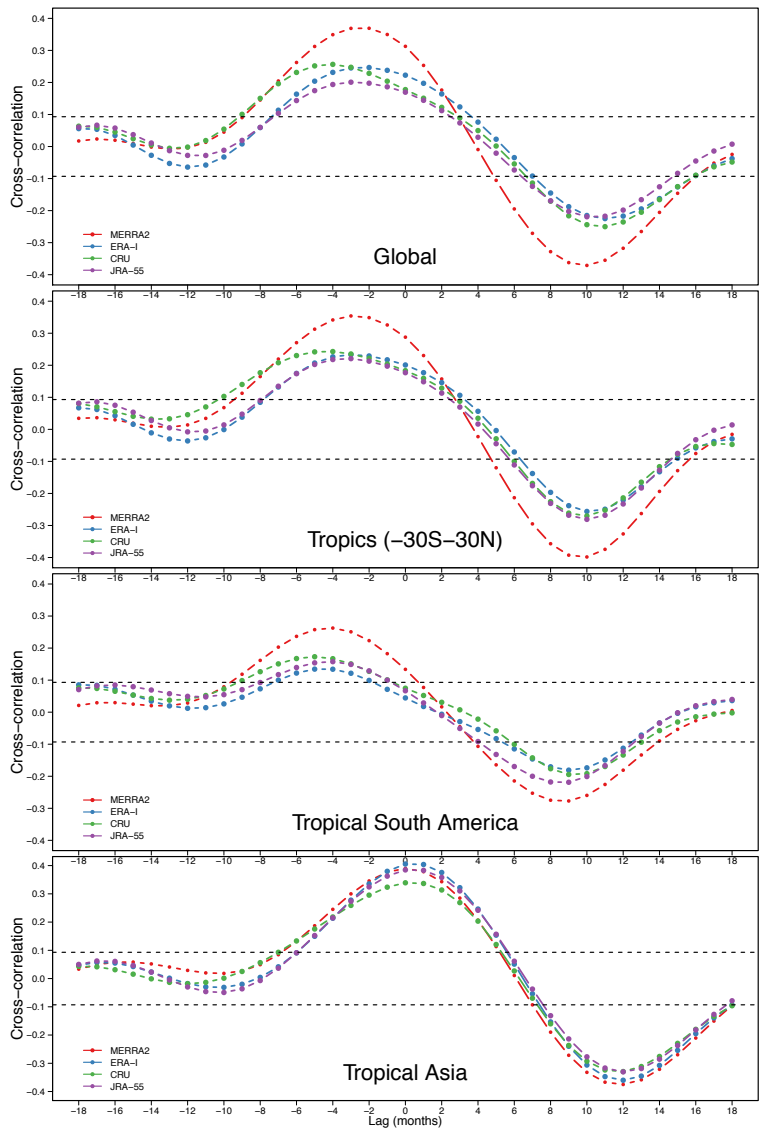
829 \*CLD and WETD are from CRU for comparison

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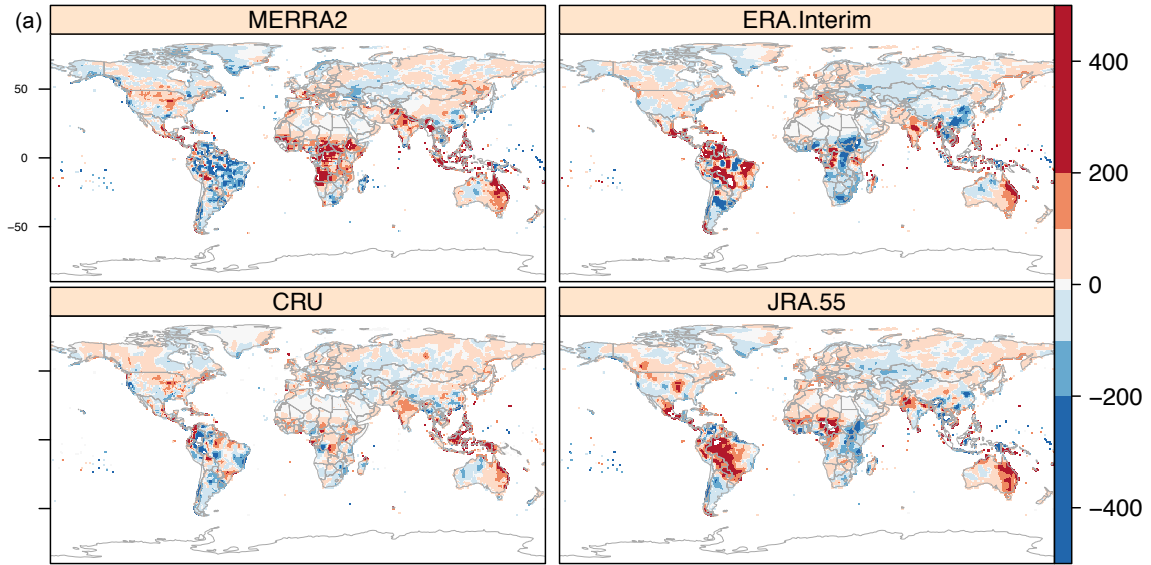
831 Table 2. Summary of mean annual CH<sub>4</sub> emissions of the Tropics (30°S-30°N, denoted  
 832 as TRO), the Northern Extratropics (denoted as NET), and the Southern Extratropics  
 833 (denoted SET) for 2000-2006, and 2007-2014 from simulations with daily  
 834 meteorological forcings MERRA2, ERA-I, and JRA-55 and with a spatial-interpolated  
 835 climate dataset CRU that is based on interpolations from meteorological stations.

Time period	Forcing	eCH <sub>4</sub> (Tg CH <sub>4</sub> yr <sup>-1</sup> )			
		TRO	NET	SET	Global
2000-2006	CRU	138.1	32.3	1.8	172.2
	MERRA2	136.1	32.5	2.1	170.7
	ERA-I	142.3	26.6	1.9	170.9
	JRA-55	141.5	29.8	1.8	173.1
2007-2014	CRU	139.1	33.0	1.7	173.8
	MERRA2	145.6	32.8	1.9	180.3
	ERA-I	148.6	27.0	1.8	177.4
	JRA-55	147.7	31.1	1.8	180.6

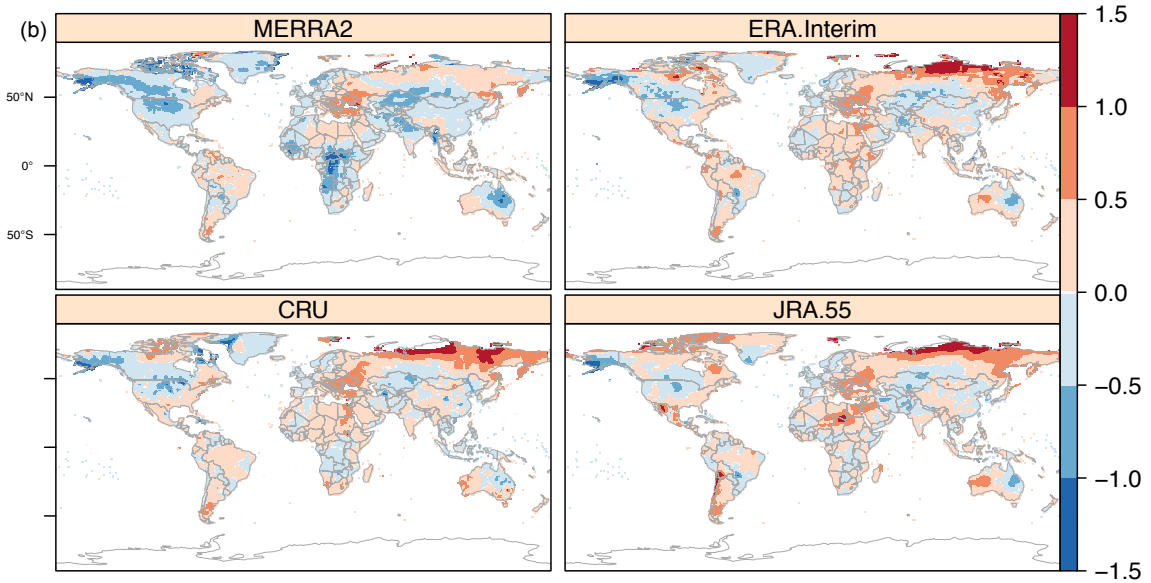
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840 Figure S1. Cross-correlation analysis between ENSO MEI index and instantaneous  
841 growth rate of wetland CH<sub>4</sub> anomalies (calculated as time derivative of  
842 deseasonalized monthly wetland CH<sub>4</sub> emissions) from four simulations with  
843 different forcings (MERRA2, ERA-I, CRU, JRA-55). Dashed horizontal blue lines in all  
844 panels represent the 95% confidence interval.



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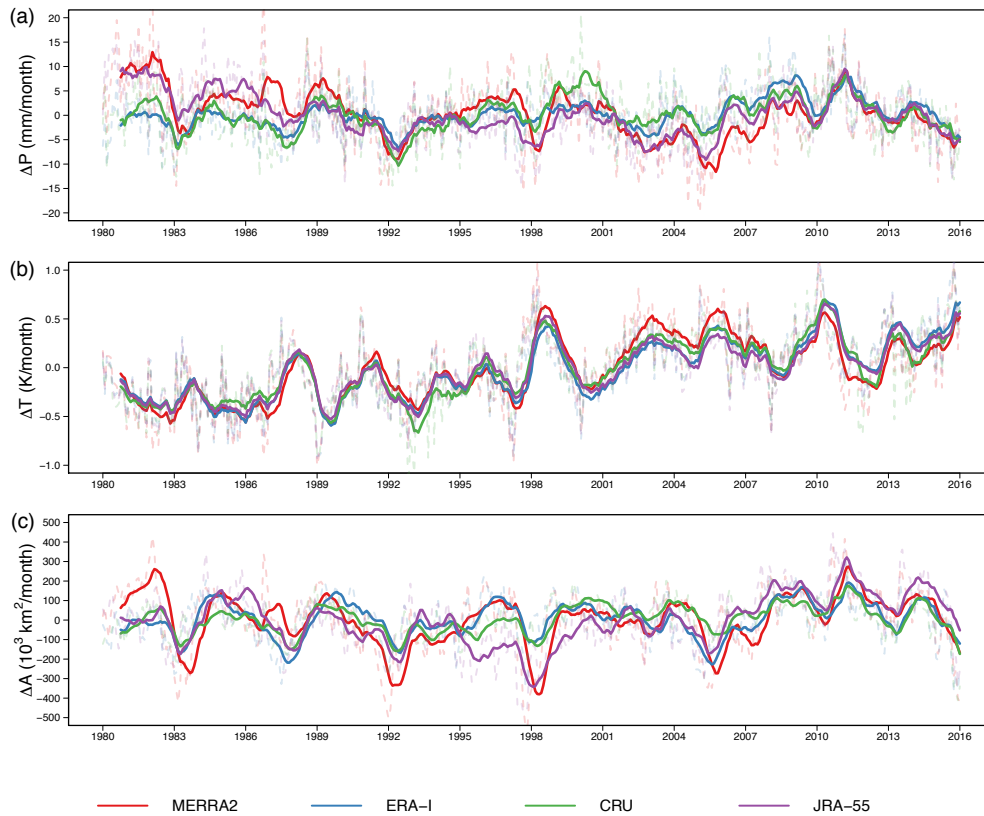
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Figure S2. Spatial distribution of the mean difference in (a) precipitation (Unit: mm yr<sup>-1</sup>) and (b) temperature (Unit: °C yr<sup>-1</sup>) between 2007-2014 and 2000-2006 for MERRA2 and ERA-I.



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Figure S3. Time series of climate variables and simulated wetland area for the monthly anomalies of (a) precipitation ( $\Delta P$ ), (b) temperature ( $\Delta T$ ), and (c) wetland area ( $\Delta A$ ) in the tropics ( $30^{\circ}\text{S}$ - $30^{\circ}\text{N}$ ). Monthly anomalies were estimated relative to corresponding long-term monthly mean (1980-2016). Dashed and solid lines represent the monthly anomaly and 12-month moving average respectively.