

Reconstructions and predictions of the global carbon cycle with an emission-driven Earth System Model

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Key Points:

- The global carbon cycle is well reproduced by MPI-ESM assimilation, which enables global carbon budgeting within a closed Earth system.
- Predictive skill of air-sea CO₂ fluxes is up to 5 years and it is up to 2 years for air-land CO₂ fluxes and the atmospheric carbon growth.
- For the first time, our emission-driven predictions enables prognostic atmospheric CO₂, hence reconstructing and predicting the variations.

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Abstract

The global carbon budget including fluxes of CO₂ between atmosphere, land and ocean, and its atmospheric growth rate show large interannual to decadal variations. Yet, these variations are poorly represented in uninitialized simulations. In a novel approach we reconstruct and predict the global carbon cycle with the decadal prediction system based on the Max Planck Institute Earth system model (MPI-ESM) extended with an interactive carbon cycle. By assimilating atmospheric and oceanic data products into the MPI-ESM, we can well reproduce historical global carbon budget variations with high correlations relative to the assessments from the global carbon project of 0.75, 0.75 and 0.97 for atmospheric CO₂ growth, air-land CO₂ fluxes and air-sea CO₂ fluxes, respectively. Retrospective predictions initializing from the assimilation simulation show the predictive skill of the air-sea CO₂ fluxes up to 5 years, and the air-land CO₂ fluxes and atmospheric carbon growth rate of 2 years.

Plain Language Summary

Reconstructing and predicting the variable global carbon cycle is essential for tracing the fate of carbon and the corresponding climate and ecosystem changes. Reconstructions based on the MPI-ESM emission-driven prediction system by assimilating observational products capture the observed global carbon budget variations in the past decades. Such a fully coupled decadal prediction system with interactive carbon cycle enables representation of the global carbon budget within a closed Earth system and therefore provides an additional line of evidence for the ongoing assessments of the anthropogenic global carbon budget. Retrospective predictions starting from the reconstruction show promising predictive skill for the global carbon cycle up to 5 years for the air-sea CO₂ fluxes and up to 2 years for the air-land CO₂ fluxes and atmospheric carbon growth rate. Our results also suggest predictions based on Earth system models enable reproduction and prediction of the evolution of atmospheric CO₂ concentration changes. The earth system predictions in this study provide valuable inputs for understanding the global carbon cycle and supporting climate relevant policy development.

1 Introduction

The CO₂ fluxes between atmosphere, land and ocean and thus the atmospheric carbon growth rate vary substantially on interannual to decadal time-scales (Peters et al., 2017; Friedlingstein et al., 2019; Landschützer et al., 2019; Friedlingstein et al., 2020). These variations reflect combined effects of internal variability of the global carbon cycle (Li & Ilyina, 2018; Séférian et al., 2018; Spring et al., 2020; Fransner et al., 2020) and its responses to external forcings (McKinley et al., 2020).

To constrain the global carbon cycle of the past and facilitate its prediction and projection into the future, since 2007 the Global Carbon Project (Canadell et al., 2007) assesses the anthropogenic global carbon budget (GCB), i.e., CO₂ emissions and their redistribution among the atmosphere, ocean, and land every year. This assessment is based on data assessments for emissions, observations of the atmospheric CO₂ concentration and single stand-alone model simulations, separately for ocean and land, of CO₂ fluxes. The air-land fluxes are the sum of natural fluxes and the land-use change induced emissions, the GCBs use the bookkeeping approach for the land-use emissions term. The stand-alone simulations on land and ocean use different climatology and thus do not provide an internally consistent estimate of the CO₂ fluxes. Moreover, these stand-alone model simulations of CO₂ fluxes do not exactly match the observations while the variations are well represented via constraining by observation/reanalysis data forcing. Therefore, the global carbon budget is not closed but ends up with a budget imbalance term up to 2 PgC/year (Friedlingstein et al., 2020), which hinders full attribution of the global carbon cycle variations. The budget imbalance could be also attributed to a large part to the mismatch of net biome production between the dynamic global vegetation models (DGVMs) used in the GCBs and inversions that match the atmospheric CO₂ growth rate (Bastos et al., 2020). Both DGVM spread and differences between inversions contributed substantially to the uncertainty of the budget terms on the global and regional scale, respectively (Bastos et al., 2020).

Reconstruction of the variable global carbon cycle within a closed Earth system model (ESM) is of essential value of tracing the fate of carbon and the corresponding climate and ecosystem changes. The decadal prediction systems based on ESMs (Marotzke et al., 2016) show potential to reconstruct and predict the global carbon cycle (Li et al., 2016; Spring & Ilyina, 2020). By assimilating observational products of physical fields,

73 the decadal prediction systems show ability to reproduce the variations of CO₂ fluxes
74 as found in observation-based products. Starting from initial states from the assimila-
75 tion simulation that are close to the real world, decadal prediction systems enable fur-
76 ther multi-year predictions of the global carbon cycle (Li et al., 2016, 2019; Lovenduski,
77 Yeager, et al., 2019; Lovenduski, Bonan, et al., 2019; Ilyina et al., 2021). However, as
78 of now, the state-of-the-art decadal prediction systems are typically forced with prescribed
79 atmospheric CO₂ concentration without interactive carbon cycle, i.e., the feedback of
80 CO₂ fluxes strength to the atmospheric CO₂ variations is ignored. With this conventional
81 model setup, one can only assess the CO₂ fluxes into land and ocean, but not the result-
82 ing variations in atmospheric CO₂ concentration and growth.

83 For the first time, we extend our prediction system from concentration-driven to
84 emission-driven taking into account the interactive carbon cycle and hence enabling prog-
85 nostic atmospheric carbon increment. In this study, we assess the global carbon budget
86 in a simulation with assimilating data products into the model, and further estimate our
87 decadal predictions based on the Max Planck Institute Earth system model (MPI-ESM)
88 relative to GCB2019 (Friedlingstein et al., 2019) and observation-based estimates of the
89 CO₂ fluxes and atmospheric CO₂. The assimilation simulation is designed to reconstruct
90 the evolution of climate and earth system of the real world by incorporating essential
91 fields from observational products into the MPI-ESM. The reconstruction from the fully
92 coupled model simulation (i.e., the assimilation simulation) enables representation of the
93 global carbon budget within a closed Earth system. Therefore, by construction, this ap-
94 proach avoids the budget imbalance term arising from the need to budget carbon fluxes
95 from stand-alone models and observations. Our reconstructions of the carbon budget pro-
96 vide an additional novel estimate, that could be used in addition for a consistent assess-
97 ment of the dominant processes in regulating the global carbon cycle. The assimilation
98 simulation states, which are close to the real world, are then used to start our retrospec-
99 tive prediction simulations (i.e., initialized simulations) aiming to predict the changes
100 of global carbon cycle in the next years by improving the initial states.

2 Materials and Methods

2.1 Model and simulations

We use the MPI-ESM1.2-LR (Mauritsen et al., 2019), which is the low resolution version of MPI-ESM1.2 used for the sixth phase of the Coupled Model Intercomparison Project (CMIP6). The atmospheric horizontal resolution has a spectral truncation at T63 or approximately 200-km grid spacing with 47 vertical levels. The resolution of the ocean model MPIOM is about 150 km with 40 vertical levels. The ocean biogeochemistry component of MPI-ESM is represented by HAMOCC (Ilyina et al., 2013; Paulsen et al., 2017), and the land and vegetation component is represented by JSBACH (Reick et al., 2021).

Similar to our previous prediction system (Li et al., 2016, 2019), we performed 3 sets of simulations, i.e., (i) uninitialized freely historical simulations, (ii) assimilation simulation by nudging the observational signal of climate variations into the model, and (iii) initialized simulations (also refers to as hindcasts or retrospective predictions) starting from the assimilation simulation, to investigate the capacity of our model to reconstruct and predict the global carbon cycle. The assimilation run is needed for the initialized prediction simulations, and the uninitialized simulations are references to compare to and assess the improved predictability due to initialization. The major difference relative to the previous system (Li et al., 2016, 2019) is that this new prediction system is based on emission-driven simulations, which are forced by CO₂ emissions instead of prescribed atmospheric CO₂ concentration. In this way, the atmospheric CO₂ concentration is evolving in response to the interaction with the strength in CO₂ uptake/outgas of the land and ocean. The external forcing is CMIP6 historical extended to the SSP2-4.5 scenario. While the fossil fuel emissions are forced, the land-use change induced emissions are prognostic in the ESMs with LUH2 land use forcing. We use transient land use transitions and included natural disturbances with dynamic vegetation. An ensemble of 10 members is run for the uninitialized historical and initialized prediction simulations. The uninitialized ensembles are generated by starting from different year of the control simulation. The initialized ensembles are generated with lagged 1-day initialization. Note that the initialized 5-year long predictions start annually from November 1st for the period 1960-2018. More details of the simulations are summarized in Table S1.

2.2 Assimilation methods

Similar to our previous concentration-driven decadal prediction systems (Li et al., 2019), the assimilation is done with nudging the ocean 3-D temperature and salinity anomalies from the ECMWF ocean reanalysis system 4 (ORAS4) (Balmaseda et al., 2013) and the atmospheric 3-D full-field temperature, vorticity, divergence, and log surface pressure from ECMWF Re-Analysis ERA40 (Uppala et al., 2005) during the period 1960-1979 and ERA-Interim (Dee et al., 2011) during the period 1980-2018. The sea-ice concentration is nudged towards the National Snow and Ice Data Center (NSIDC) satellite observations (as described in (Bunzel et al., 2016)). The nudging is applied to every model time step but with different relaxation time, i.e., relative longer relaxation time of 10 days for the ocean temperature and salinity and shorter relaxation time of 6 hours, 24 hours and 48 hours for the atmospheric vorticity, temperature and pressure, and divergence, respectively. The chosen variables for assimilation and the respective relaxation time are according to previous investigations of decadal climate prediction based on MPI-ESM (Marotzke et al., 2016). Direct assimilation of the carbon cycle related variables is not included because of the limited available data; in the meanwhile, we found that the global carbon cycle is well represented from the assimilation of only physical variables (Li et al., 2016, 2019; Lovenduski, Yeager, et al., 2019; Lovenduski, Bonan, et al., 2019; Ilyina et al., 2021), and furthermore, our recent study based on a perfect model framework (i.e., based on preindustrial run of the model itself) revealed that direct assimilation of the global carbon cycle only bring trivial improvement of predictive skill of the global carbon cycle (Spring et al., 2021). To avoid spurious upwelling in the equatorial region caused by assimilation as investigated in (Park et al., 2018), we exclude the equatorial band of 5°S - 5°N from data nudging of the ocean data.

2.3 Carbon budget decomposition with CBALONE simulations

The anthropogenic carbon budget is usually decomposed into 5 terms plus an imbalance: the two emissions terms from fossil-fuel and land-use changes, and the three sink terms natural terrestrial sink, ocean sink, and atmospheric growth. The fossil fuel emissions are prescribed as forcing, and terrestrial and ocean carbon sinks and atmospheric growth terms can be directly derived from the ESM. However, directly deducible from an ESM is only the net land-atmosphere exchange, which is the sum of land-use change emissions and the natural terrestrial sink. In order to separate the two land-related fluxes,

164 we use a stand-alone component called CBALONE from JSBACH as a diagnostic for a
165 direct comparison with the global carbon project (Friedlingstein et al., 2019). More de-
166 tails of the method on separating the land-use change induced emission can be found in
167 Loughran et al. (2021). Two simulations, one with and one without land-use change, are
168 conducted with the forcing of the assimilation run. The difference of the two simulations
169 quantify the land-use change induced emission.

170 **2.4 Predictive skill quantification**

171 The initialized simulations are investigated according to their lead time, i.e., how
172 many model years they have been integrated freely after restarting from the assimila-
173 tion simulation (Boer et al., 2016). The time series of initialized simulations at lead time
174 of 1 year (2-5 years) combine the 1st year (2-5 years) predictions from initialized sim-
175 ulations of all the starting years from 1959-2018. Bias correction is an unavoidable topic
176 for decadal predictions due to initial shock, which varies with lead time, therefore, it was
177 recommended to do bias correction when necessary according to the lead time (Boer et
178 al., 2016). In this study, a bias correction is applied for the atmospheric CO₂ concen-
179 tration as shown in Fig. 4.

180 The predictive skill is quantified mainly based on anomaly correlation coefficient,
181 the anomalies are calculated by removing the respective climatology mean state. Here
182 the climatology mean state is based on the ensemble mean of the focus time period, i.e.,
183 1970-2018 for Fig. 1-3 and last 10 years for Fig. 4. For the atmospheric CO₂ concen-
184 tration shown in Fig. 4, which has high correlations close to 1 with observations because
185 of the coherent linear trends, we have also added root mean square error (RMSE) met-
186 ric to investigate the added value of assimilation and initialization. The significance of
187 the predictive skill is tested with a nonparametric bootstrap approach (Goddard et al.,
188 2013).

189 **3 Reconstruction of the global carbon budget**

190 By incorporating observational signals, the assimilation simulation from decadal
191 prediction system based on MPI-ESM captures the evolution of the global carbon cy-
192 cle as well as the climate in observations. The time series from MPI-ESM assimilation
193 simulation in comparison to the GCB2019 is shown in Fig.1.

194 The CO₂ emissions from fossil fuel and industry are in general consistent but with
195 slightly difference in the 1960-1990s between the assimilation simulation (which uses the
196 CO₂ emission forcing provided by CMIP6 for historical and SSP2-4.5 simulations) and
197 GCB2019. This reveals uncertainty in the CO₂ forcings, which could affect the ampli-
198 tude of the atmospheric CO₂ concentration as it is a cumulative quantity. Cumulatively
199 the CMIP6 CO₂ emission forcing is 8.20 PgC higher than that from the GCB2019, which
200 would end up with a 3.86 ppm (by dividing a factor of 2.124 PgC ppm⁻¹ (Ballantyne et
201 al., 2012)) higher atmospheric CO₂ concentration in the simulation with CMIP6 forc-
202 ing than with GCB2019 forcing. This discrepancy of CO₂ emission might explain to some
203 extent that the simulated atmospheric CO₂ concentration is few ppm higher than the
204 NOAA_GML observation (Dlugokencky & Tans, 2020) (Fig. S1). However, this little dif-
205 ference of a few ppm in atmospheric CO₂ concentration magnitude doesn't noticeably
206 affect the variations in the CO₂ fluxes and the corresponding atmospheric carbon incre-
207 ment (see Fig. 1D-F).

208 The land-use change induced emissions diagnosed by CBALONE are within the
209 range of GCB2019 multi-model (including JSBACH) simulations from Dynamic Global
210 Vegetation Models (DGVMs) (Fig.1B). The estimates from bookkeeping models show
211 smaller variations as the DGVMs. Note that the GCBs use the bookkeeping approach
212 for the land-use emissions term. Bookkeeping implies that carbon fluxes are determined
213 from area changes in vegetation types of different vegetation and soil carbon densities,
214 with specific response curves characterizing the evolution of decay and recovery. Car-
215 bon densities may stem from recent observations or models, but are kept fix, i.e. changes
216 in environmental conditions are not accounted for. The DGVMs by contrast (which are
217 used to provide only an uncertainty range around the bookkeeping models in the GCBs)
218 calculate land-use emissions under transient environmental conditions. This implies first
219 that interannual variability in bookkeeping models is only driven by land-use change, not
220 further interactions with climate variability, which makes the DGVM estimates in gen-
221 eral more variable from year to year than the bookkeeping estimates are. Second, it im-
222 plies that the DGVM-based land-use emissions estimates include the so-called "loss of
223 additional sink capacity" (Pongratz et al., 2014), which refers to the carbon that could
224 have been stored on forests additionally over the course of history (e.g., due to the "CO₂-
225 fertilization" effect) if these forests had not been cleared by expansion of agriculture and
226 forestry. This loss of additionally sink capacity generally increases over time and amounts

227 to about 40% ($0.8 \pm 0.3 \text{ PgC yr}^{-1}$) over 2009-2018 (Obermeier et al., 2021). This explains
228 why DGVM estimates in Fig. 1B show higher emissions than bookkeeping estimates in
229 recent decades. The DGVM- and expert-based uncertainty range around the GCB book-
230 keeping estimates is large and MPI-ESM-based land-use change emission estimates have
231 been found to be at the high end of the GCB for all decades by Loughran et al. (2021),
232 consistent with our findings.

233 There is a budget imbalance term resulting from the approach used in GCB2019
234 because the individual budget terms are from separate measurements together with stand-
235 alone ocean and land model simulations (Friedlingstein et al., 2019). In this study, we
236 assimilate each component within a fully coupled ESM considering the interactions. The
237 assimilation ensures evolution of the carbon cycle and climate towards the real world,
238 in the meanwhile, the budget is closed within the Earth system, i.e., no the budget im-
239 balance occurs (Fig. 1C). Therefore, it is more reliable to attribute the global carbon
240 budget variations using the assimilation simulation based on a fully coupled ESM.

241 Atmospheric carbon growth rate and carbon fluxes are reasonably well reproduced
242 in emission-driven assimilation with prognostic atmospheric CO_2 (Fig. 1D-F). The at-
243 mospheric carbon growth and the land carbon sink show more pronounced variations on
244 interannual time scales, however, the ocean carbon sink has more pronounced variations
245 on decadal time scales. These variations are captured in the assimilation with high cor-
246 relations between assimilation and GCB2019 of 0.75, 0.75, and 0.97 for atmospheric growth,
247 land sink, and ocean sink, respectively.

248 The spatial distribution of coherence in carbon fluxes between GCB2019 and the
249 MPI-ESM reconstruction is shown in Fig. S2. The correlation of CO_2 fluxes between re-
250 construction and GCB2019 is high, especially over the ocean. The root mean square de-
251 viation (RMSD) is coherent with the magnitude of carbon fluxes, i.e., with greater val-
252 ues on land than over ocean. The large RMSD is partially due to smoothed magnitude
253 of fluxes in GCB2019 from multi-model mean.

254 In general, the historical global carbon cycle is well reproduced by the MPI-ESM
255 with assimilating observational products, which enables quantification of the global car-
256 bon budget within a closed Earth system. Prediction systems can actually provide internally-
257 consistent values of the ocean and land carbon sink and serve as an additional line of ev-
258 idence for the global carbon budget. A full assimilation simulation spans a longer than

259 the analysis period starting from year 1959 for which the reanalysis data is available, the
260 first 12 years that might be affected by model adjustment were excluded from the anal-
261 yses.

262 **4 Predictability of global carbon cycle**

263 The initialized predictions start from the assimilation states which are close to ob-
264 servations. Therefore, information of observation are incorporated into the prediction
265 system as initial states and they facilitate that the evolution of the global carbon cycle
266 and climate follow the trajectory of the real world for some period encompassing the pre-
267 dictability horizon.

268 As shown in Fig. 2, the initialized simulations at lead time of 2 years still resem-
269 ble the variations well as in the GCB2019 with correlations of 0.49 and even higher. The
270 results from lead time of 1 year is shown in Fig. S3. As for atmospheric carbon growth,
271 the initialized simulations at lead time of 2 years show coherent interannual variations
272 even with a relative smaller correlation (0.49) than that of the historical freely run (0.61),
273 which is mainly contributed by the coherent trends of the freely run and the GCB2019
274 (Fig. 2A).

275 The initialized and uninitialized simulations show a comparably good match to GCB2019
276 with respect to net carbon flux into the ocean (with high correlation of 0.98), it suggests
277 the good representation of the ocean carbon sink variations (especially on decadal time-
278 scale) in the historical free run. This implies that these variations of the globally inte-
279 grated ocean carbon sink are more from external forcing rather than internal variabil-
280 ity (McKinley et al., 2020).

281 The net carbon flux into the land shows higher correlation for initialized simula-
282 tions at lead time of 2 years than that for uninitialized simulations. This indicates the
283 interannual variations are better captured in the initialized model system even after 2
284 years of free integration. This result implies a predictability of the air-land CO₂ flux of
285 at least 2 years.

286 We further quantify the predictive skill of the global carbon cycle (Fig. 3). The cor-
287 relation skill relative to GCB2019 is significant for the lead time of 5 years in atmospheric
288 carbon growth and the ocean carbon sink, however, the skill is lower up to 2 years for
289 the air-land CO₂ flux (Fig. 3A-C). The improved predictive skill of initialized hindcasts

290 comparing to the historical uninitialized run is at lead time of 1 year for atmospheric car-
291 bon growth and at lead time of 2 years for air-land CO₂ flux. The detrended results (Fig.
292 3D-F) are similar to those from the original time series. The correlation of atmospheric
293 carbon growth at a lead time of 2 years in the initialized hindcasts are higher than the
294 uninitialized historical run when detrended. This indicates the contribution of a linear
295 trend to the skill of uninitialized historical runs.

296 From our MPI-ESM1.2-LR initialized hindcasts, we find that predictive skill of air-
297 sea CO₂ flux is relatively high up to 5 years, that of the air-land CO₂ fluxes is up to 2
298 years. This is consistent with previous studies without interactive carbon cycle, i.e., (Ilyina
299 et al., 2021; Lovenduski, Bonan, et al., 2019; Lovenduski, Yeager, et al., 2019). Here we
300 extend the prediction system into emission-driven enabling prognostic CO₂ and the sys-
301 tem keeps the features of predictability. Furthermore, the prognostic CO₂ from the novel
302 emission-driven decadal prediction system suggests predictability as well, and the atmo-
303 spheric CO₂ growth rate shows predictive skill of 2 years in the initialized predictions.

304 **5 Atmospheric CO₂ concentration**

305 Fig. 4 shows time series of atmospheric CO₂ concentration from MPI-ESM sim-
306 ulations together with the NOAA_GML observations for the last decade. As the atmo-
307 spheric CO₂ concentration is an accumulative quantity and shows mainly a linear increas-
308 ing trend, it is necessary to zoom in to visualize the trend slope changes. In addition,
309 the deviation of model simulated atmospheric CO₂ relative to observations in the pre-
310 vious period is accumulated along with the integration of the model, therefore, it ends
311 up with 8ppm higher global atmospheric CO₂ concentration in the model simulation
312 than in the observations (see Fig. S4). In the meanwhile, the NOAA_GML data repre-
313 sents the average of atmospheric CO₂ over marine surface sites (Dlugokencky & Tans,
314 2020), they are slightly smaller than the values on land because of the anthropogenic CO₂
315 emissions are mainly on land. The time series shown in Fig. 4 are bias corrected by re-
316 moving the difference of mean states and linear trends between observation and simu-
317 lations according to Boer et al. (2016).

318 The shown atmospheric CO₂ concentration from assimilation follows quite well the
319 evolution of NOAA_GML observation, however the uninitialized historical run show larger
320 deviation from the observation with root mean square error (RMSE) of 0.72 ppm whereas

321 the RMSE for assimilation is 0.22 ppm (Fig. 4A). The initialized simulations could rep-
322 resent the observed evolution well even at lead time of 5 years, with lower RMSE of 0.46
323 ppm than uninitialized historical run. This result further demonstrate the ability of ESM-
324 based decadal prediction system in reconstructing and predicting the global carbon cy-
325 cle, with only assimilating the physical atmosphere and ocean fields.

326 6 Conclusions

327 For the first time, we extend a decadal prediction system based on MPI-ESM to
328 integrate the interactive carbon cycle, driven by fossil fuel emissions, and hence enabling
329 prognostic atmospheric CO₂. This new setup of assimilation and initialized predictions
330 opens one more dimension of freedom, i.e., enabling prognostic atmospheric CO₂ and the
331 corresponding interactive effects, and represents the global carbon cycle closer to the real
332 world.

333 The variations of atmospheric carbon growth rate and CO₂ fluxes among atmo-
334 sphere, ocean, and land are well reconstructed in our assimilation simulations, with high
335 correlations (0.75, 0.97, and 0.75) with the GCB2019. This enables an internally con-
336 sistent quantification of the global carbon budget within an Earth system model. Fur-
337 thermore, our reconstruction of the global carbon cycle provides an additional line of ev-
338 idence for quantifying the annual global carbon budgets and opens new opportunities
339 in assessing the efficiency of carbon sinks and internally consistent metrics. In partic-
340 ular, this approach eliminates the budget imbalance term that arises in GCBs due to the
341 combination of various, not fully consistent model and data approaches.

342 We also make a step forward and present retrospective predictions of the global car-
343 bon cycle which show predictive skill up to 5 years for air-sea CO₂ fluxes and up to 2
344 years for air-land CO₂ fluxes and the atmospheric carbon growth rate. The variations
345 of atmospheric CO₂ are better reproduced in the assimilation and retrospective predic-
346 tions than in the uninitialized historical simulations with prognostic CO₂ while the trend
347 is better reproduced in the uninitialized simulations.

348 We keep the high predictive power of the prediction system by turning it from concentration-
349 driven to emission-driven, and that still captures atmospheric CO₂ increase pretty well.
350 But the emission-driven decadal prediction system delivers the huge advantage of sim-
351 ulating the land and ocean fluxes in response to fossil-fuel and land use change emissions,

352 including all feedbacks. Further efforts, towards increasing observations to initiate the
353 ESMs and to assess the predictive skills and providing reliable global estimate and spa-
354 tial distribution of anthropogenic and natural emissions, will lead to more reliable re-
355 construction and predictions.

356 We demonstrate that our emission-driven decadal prediction system shows capa-
357 bility to reconstruct and predict the global carbon cycle and atmospheric CO₂ concen-
358 tration variations. This will be a powerful tool in supporting the global carbon stock-
359 taking and policy to compliance with goals of the Paris Agreement. Further multi-model
360 simulations will alleviate dependence of individual model responses and hence demon-
361 strate robust changes of the global carbon cycle.

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375 yses. T.L. ran the CBALONE module simulations. All authors discussed the results and
376 commented on the manuscript at every stage. Data and materials availability: Primary
377 data and scripts used in the analysis that may be useful in reproducing the authors' work
378 are archived by the Max Planck Institute for Meteorology and can be obtained via the
379 institutional repository <http://hdl.handle.net/21.11116/0000-0009-6B84-A>.

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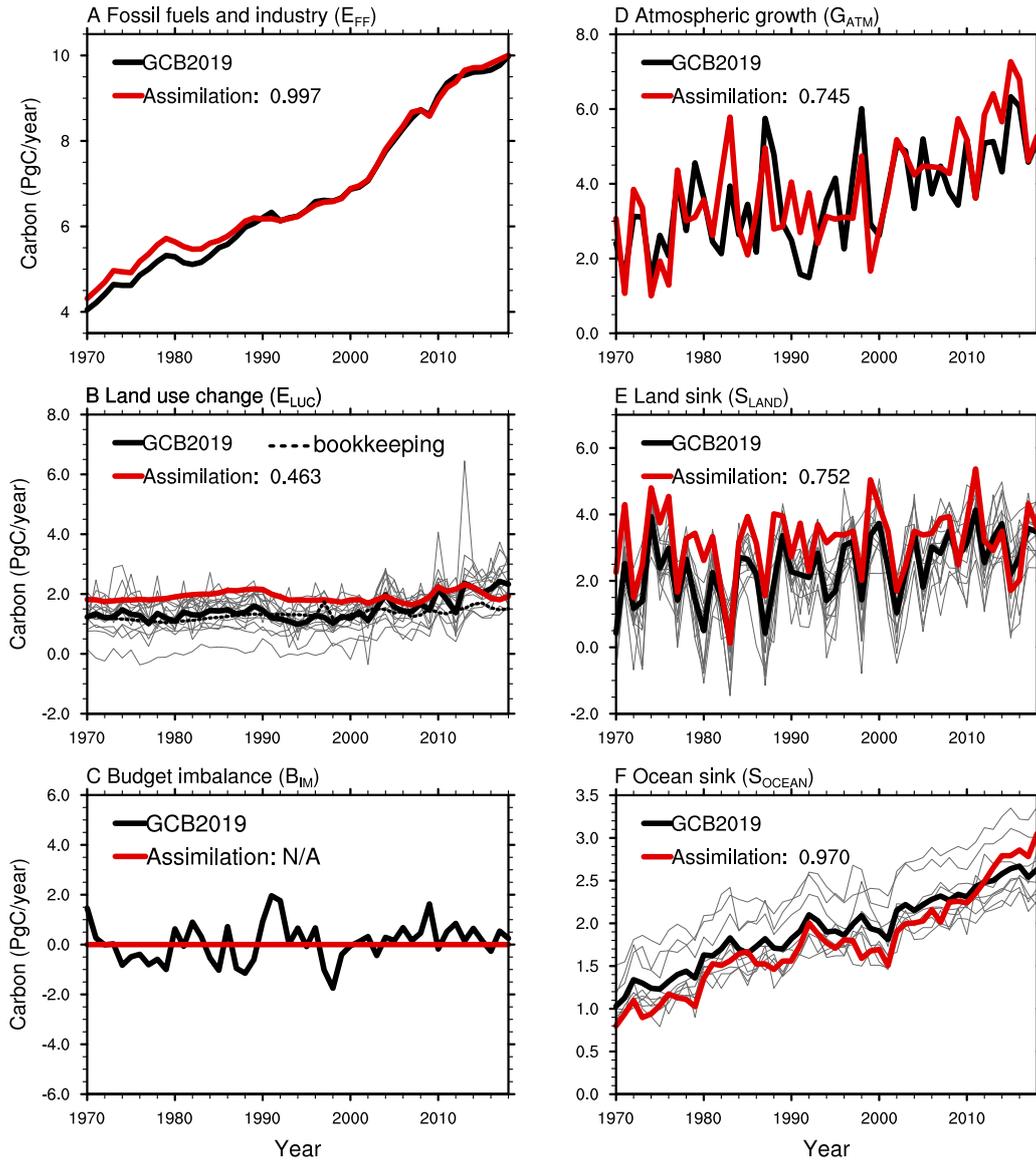


Figure 1. Time series of (A) fossil fuel and industry CO₂ emissions (E_{FF}), (B) emissions from land use change (E_{LUC}), (C) the budget imbalance (B_{IM}) that is not accounted for by the other terms, (D) atmospheric carbon growth rate (G_{ATM}), (E) the natural terrestrial carbon fluxes (S_{LAND}), and (F) air-sea CO₂ fluxes (S_{OCEAN}) from MPI-ESM1.2-LR assimilation in comparison with Global Carbon Budget (GCB 2019 (Friedlingstein et al., 2019)). Emissions (A & B) are positive when they are fluxes into the atmosphere, while sinks (D, E & F) are positive as fluxes into the respective compartment. A positive B_{IM} means a higher sum of emissions than sinks. The thin grey curves in B, E, and F show individual GCB stand-alone model results. The numbers in the legend show the correlation coefficients between assimilation and GCB2019.

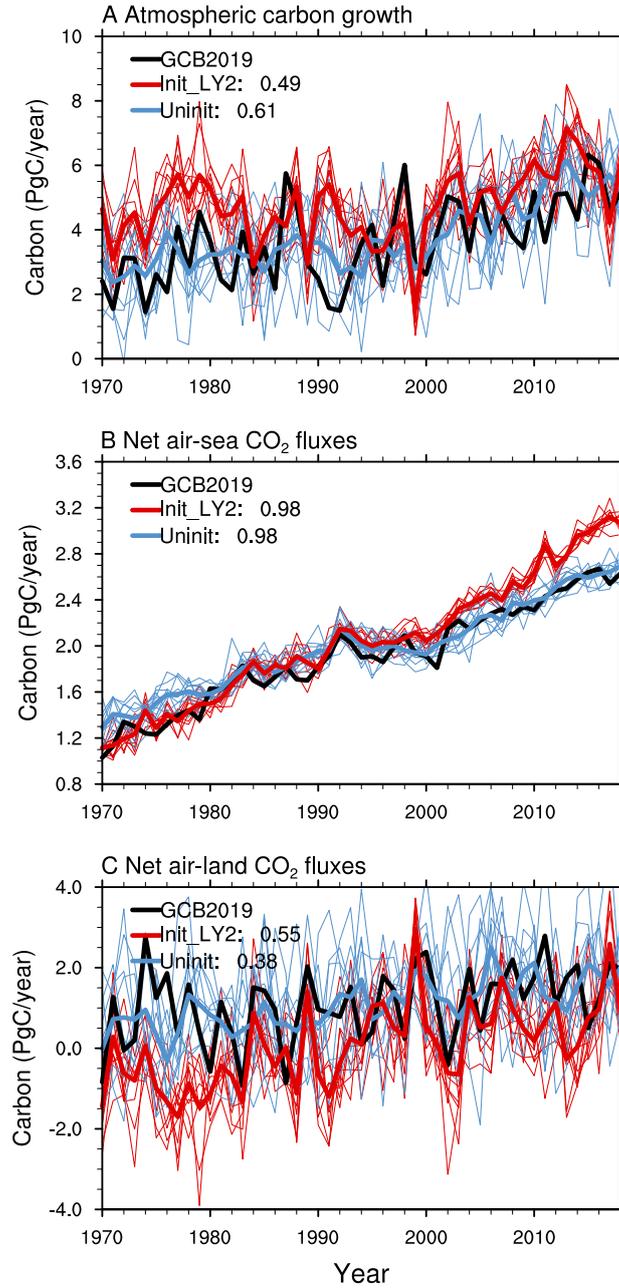


Figure 2. Time series of initialized simulations at lead time of 2 years in atmospheric carbon growth rate, i.e., G_{ATM} (A), net air-sea CO₂ fluxes, i.e., SO_{CEAN} (B) and net air-land CO₂ fluxes, i.e., $ELUC+SLAND$ (C) together with Global Carbon Budget (GCB 2019 (Friedlingstein et al., 2019)). The shown time series are based on annual mean data for the time period from 1970-2018. Positive values in B-C refer to CO₂ fluxes into the ocean or land. The numbers in the legend show the correlation coefficients between the simulations and GCB2019, the ensemble mean data is used for the calculation.

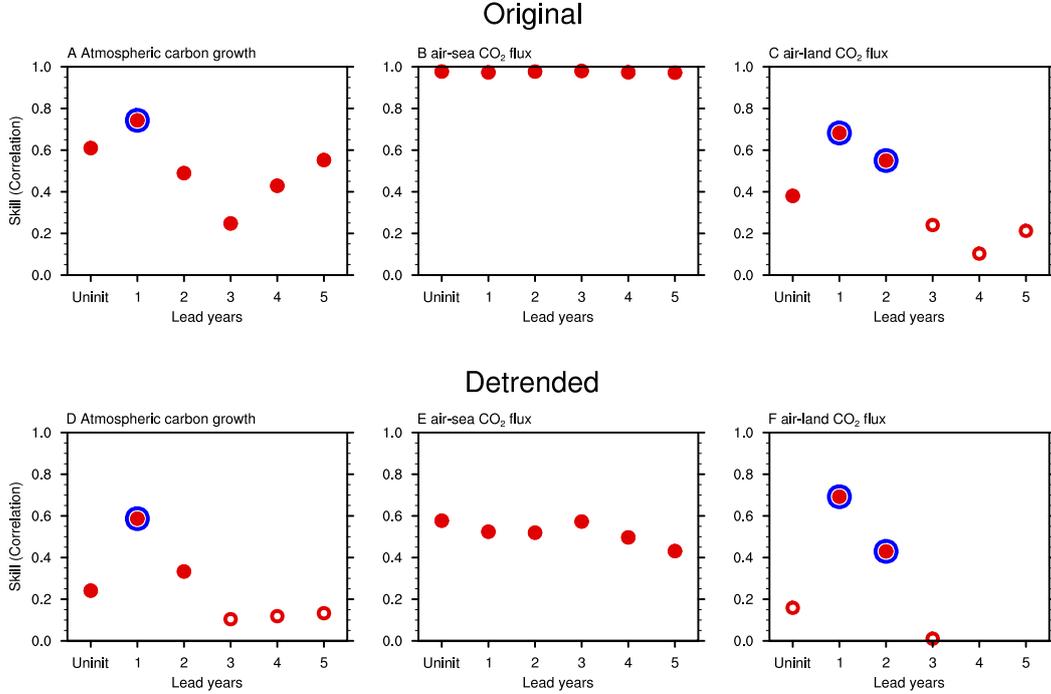


Figure 3. Predictive skill of atmospheric carbon growth rate, i.e., G_{ATM} (A and D), air-sea CO_2 fluxes, i.e., S_{OCEAN} (B and E) and net air-land CO_2 fluxes, i.e., $E_{LUC}+S_{LAND}$ (C and F) reference to Global Carbon Budget (GCB 2019 (Friedlingstein et al., 2019)). A-C show results of anomaly correlation coefficients from the original time series, and D-F show results from the detrended time series with red open circles. All are based on annual mean time series for the time period from 1970-2018. The filled red circles on top of the open red circles show that the predictive skill is significant at 95% confidence level and the additional larger blue circles indicate improved significant predictive skill due to initialization in comparison to the uninitialized simulations. We use a nonparametric bootstrap approach (Goddard et al., 2013) to assess the significance of predictive skill.

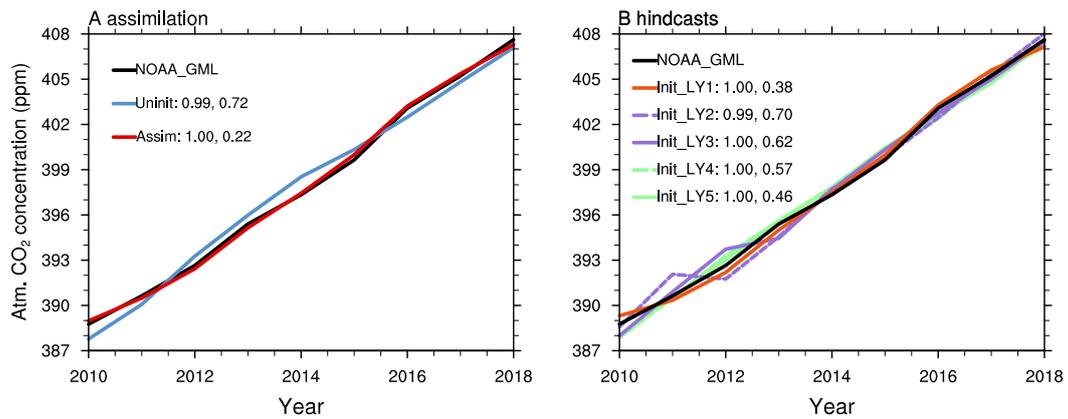


Figure 4. Atmospheric CO₂ concentration from the uninitialized (Uninit) and assimilation (Assim) simulations (A) and initialized simulations at lead time from 1-5 years (Init_LY1 to Init_LY5) (B) in comparing with observations in the last 10 years. The numbers in the figure legend show the correlation (left) and root mean square error (RMSE, right) of the simulations relative to observational data from NOAA_GML (Dlugokencky & Tans, 2020). The time series are bias corrected by removing the difference of mean states and linear trend between observation and simulations according to Boer et al. (2016).