Thanks for the comments. We are carrying out a thorough revision addressing these comments.

RC 1: *Global climate models are of questionable utility in many regions due to poor spatial resolution and a poor reproduction of riverine inputs and other critical determinants of biogeochemical processes. Downscaling approaches are therefore critical in many regions. Zhang and Zhu present a new "downscaling" of CMIP6 model output for the region surrounding the Gulf of Mexico, and they draw conclusions about recent changes in the region's carbon dynamics. The model used by Zhang and Zhu appears equally or more robust than prior models of the regional carbon budget. This is therefore potentially interesting and relevant work. However, in its present form the manuscript is needlessly confusing and misleading and features some potentially major methodological issues. I therefore recommend that the authors carry out a thorough revision of the manuscript text and to clarify methodological issues. The core contribution of this study is to provide updated (and potentially more robust) estimates of carbon fluxes in this region and to estimate temporal trends in variables such as pCO2 and pH. This is a valuable contribution to the literature as these values continue to have high uncertainties, and I hope the authors can address the concerns below.It is highly misleading to call this a "downscaling" of a CMIP6 model. At present, the title, abstract and introduction misrepresent the work in the paper. The title of the manuscript claims this study downscales the global CESM2-WACCM-FV2 model. Conventionally, this should mean that all possible driving data is derived from the global model. Critically, any climate forcings should come from the global model. However, as stated on page 7 of the manuscript, the only things taken from the CESM2-WACCM-FV2 model are the initial conditions and boundary conditions on the geographic boundary. Atmospheric forcings etc. are not taken from the CESM2-WACCM-FV2 model. I therefore view this as a hindcast, where the authors were forced to use the CESM2-WACCM-FV2 model for geographic boundary conditions as a compromise. In no real sense is it a downscaling of a CMIP6 model. This is a major problem for the paper as there are, at present, many inaccurate statements. For example, the abstract claims this: "The model's biogeochemical cycle is driven by the Coupled Model Intercomparison Project 6-Community Earth System Model 2 products (CMIP6-CESM2)…" This is clearly not true, as surface temperature, air PCO2, riverine inputs and most of the variables driving the carbon dynamics do not come from the CMIP6 product.The title, and aims of the paper should therefore be revised.The paper really appears to be a new estimate of carbon fluxes in the region. It should therefore be rewritten accordingly. Critically, the authors should make it clearer how, as claimed, the estimates in this study are more reliable than previous methods. The evidence provided for this are not extensive.*

Response: We acknowledge that the term "downscaling" might not be appropriate, as suggested by reviewers #1 and #2. In this revision, we feature this paper as a hindcast that provided a new estimate of carbon fluxes of the Gulf of Mexico (GoM) and filled the current knowledge gap of the available carbon monitoring data in the GoM. The accuracy of carbon flux estimation in a regional ocean like the GoM is still limited by surface pCO_2 data availability. Our model study, to our knowledge, is the first one in this region to use global products as the boundary condition for biogeochemical fields. Via extensive model-data comparison against three data sources: high-frequency *in situ* buoy measurement, machine learning product based on remote-sensing and underway pCO_2 observations, and CTD transects, our study demonstrates that it is feasible to utilize historical run of the global products to drive a regional coupled physical-biogeochemical model. We will revise all relevant statements. We intend to change the title into "A Re-assessment of the Gulf of Mexico (GoM) Carbon System: Connecting the Gulf of Mexico with the Mississippi River and the Global Ocean".

RC 1: *Output of the CESM2-WACCM-FV2 model are used for both initial and boundary conditions.The authors do not state why they used the CESM2-WACCM-FV2 model for the boundary conditions. Was* *this model more accurate in the region than other CMIP6 models or reanalysis products that are available? This is a critical question, as it is possible the choice has reduced the reliability of the carbon budget estimates. There are also specific issues surrounding the use of this dataset. First, this model can have negative values for nitrate, and presumably other variables. I viewed one of the historical files (http://esgf-data.ucar.edu/thredds/fileServer/esg_dataroot/CMIP6/CMIP/NCAR/CESM2-WACCM-FV2/historical/r1i1p1f1/Omon/no3os/gn/v20191120/no3os_Omon_CESM2-WACCM-FV2_historical_r1i1p1f1_gn_200001-201412.nc) for this model and negative values for nitrate appear very frequently across the boundary. Translating these values into boundary conditions is not a trivial issue as mass conservation etc. is ambiguous. The authors need to explain this thoroughly. Negatives at the boundary also result in average conditions that are far lower than those you would get from the NOAA World Ocean Atlas. Potentially this has been corrected for in some way by the authors, but if it has not it is not clear if the treatment of the boundary conditions is sensible. Likewise, there are negative values in the first time step in 2000, which the authors presumably used in some way to generate their initial conditions.The authors state on p. 19 that this study's estimates of air-sea CO2 fluxes are "more reliable than previous GoM model studies". However, without showing whether the boundary conditions are reliable it is difficult to assess this claim. This is especially true, given the authors state that Xue et al. 2016 used over-simplified boundary conditions. There is therefore real potential that the boundary conditions used here are no more reliable than those in Xue et al.*

Response: We did a thorough examination of available global ocean carbon-related climatology/ reanalysis products for the potential to be used as the regional model boundaries. And we argue that the current model boundaries setting is a better choice. It should be noted that the GoM region has very limited observations of dissolved inorganic carbon (DIC) and total alkalinity (TA) available, and observational data along different depths are even fewer and has limited spatial and temporal coverage. This is the primary reason many global climatology products have no coverage in the GoM region, e.g., Mapped Observation-Based Oceanic DIC monthly climatology from the Max-Planck-Institute for Meteorology (MOBO-DIC_MPIM) (NCEI Accession 0221526) (Keppler et al. 2020); or only contain surface carbon variables, e.g., global gridded data set of the surface ocean carbonate system OceanSODA-ETHZ (v2021,NCEI Accession 0220059) (Gregor and Gruber, 2020), Climatological Distributions of pH, pCO_2, Total CO_2, Alkalinity, and CaCO3 Saturation in the Global Surface Ocean (NCEI Accession 0164568) (Takahashi et al. 2017), the partial pressure of carbon dioxide collected from Surface underway observations in the world-wide oceans (NCEI Accession 0161129) (Bakker et al. 2017), an observation-based global monthly gridded sea surface pCO_2 product (NCEI Accession 0160558) (Landschützer et al., 2017), and a global ocean pCO_2 climatology combining open ocean and coastal areas (NCEI Accession 0209633) (Landschützer et al. 2020).

Thus global ocean climatology products are not suitable to be used as the boundary for a regional model since data along the vertical direction are needed for the model boundary. The most updated global monthly climatology of TA (NCEI Accession 0222470) (Broullón et al. 2020b) and DIC (NCEI Accession 0222469) (Broullón et al. 2020a) offer 12-month climatology with a 1°x1° spatial resolution and 102 depth levels, this product can potentially be used as a static DIC, TA boundary for the regional model. However, these products utilized a neural network approach to achieving full data coverage for the 3-dimensional global ocean. They used pCO_2 from LDEOv2016 (Takahashi, Sutherland, Kozyr, 2017) and TA from Broullón et al. (2019) to compute DIC surface values to increase the surface coverage in the training data for the machine learning model (Broullón et al. 2020a,b). Therefore, we should be aware that the generated global monthly climatology products are not purely observation interpolations but rather a machine learning model product with many untested assumptions. And the calculated DIC values do not necessarily match the field observations even if the temperature, salinity, TA, and pCO_2 source data used for the calculations are accurate. Although the global climatology products include grided estimates in the GoM region over 12 months, the products are ultimately derived from limited observations that cannot support such variation in space and time without data augmentation. We argue that the GCMs based on biogeochemical processes, earth system circulations, and conservation schemes are more reliable than the neural network machine learning model used to generate the climatology product.

CMIP6 participating GCMs consume enormous research resources and generate unprecedented knowledge on global carbon system evolution with a whole-ecosystem conservation perspective. Utilizing GCMs results in a refined regional model extends their research value, especially in regards to bridging GCMs product with *in situ* field observations. With the interannual variation estimated by GCMs, the regional model should take advantage of global models by using dynamic boundaries that reflect climate oscillations and carbon accumulation in oceanic waters. The choice of CESM2-WACCM-FV2 model among other global climate models is primarily based on the global model's horizontal resolution in the GoM region and the availability of nutrients and carbon variables. By comparing a number of global models (Table A1), we conclude that the CESM2-WACCM-FV2 by NCAR is among the best modeling resolution in the Gulf of Mexico region- it contains all essential nutrients and carbon variables available and has a natural focus on the US waters.

We can use a static climatology product boundary or like Xue et al. (2016) use an empirical salinity–temperature–DIC–alkalinity relationships to prescribe the model DIC and TA boundaries. However, using a static boundary or an over-simplified boundary like Xue et al. (2016) would reduce the value of the current study. As shown in Fig. A1 the World Ocean Atlas nitrate product (Boyer et al. 2018) not only does not provide a dynamic boundary with interannual variability but also contains very limited supporting observational data at the domain boundaries, both horizontal and vertically. Therefore we would refrain from using WOA or other climatology as the regional model boundaries.

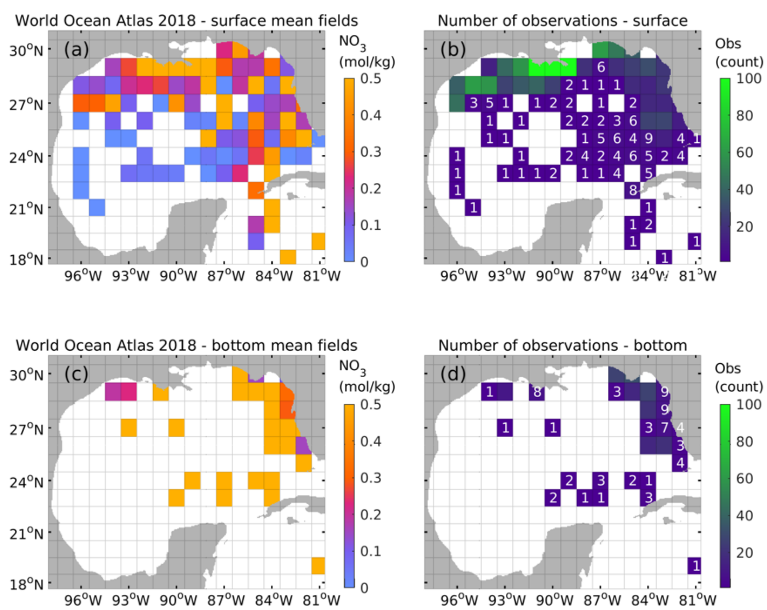

Figure A1. World Ocean Atlas 2018 NO3 product mean fields (a) surface, (c) bottom and all available observation counts (b) surface, (d) bottom incorporated in the product. (note: for observation counts below 10, a single-digit number is shown; for observation counts > 100 same color grade is shown as that of 100)

Table A1. Summary of CMIP6 GCMs considered for regional boundaries

Model Name	Institution	Resolution (m)	NH4	NO3
CESM2	NCAR	124214.044	available	not available
CESM2-FV2	NCAR	124214.044	available	available
CESM2-WACCM	NCAR	124214.044	available	not available
CESM2-WACCM-FV2	NCAR	124214.044	available	available
MPI-ESM1-2-LR	MPI	176531.166	available	available
MPI-ESM1-2-HR	MPI	53841.4877	not available	available
MPI-ESM-1-2-HAM	HAMMOZ-Consortium	176531.166	available	available
ACCESS-ESM1-5	CSIRO	147378.349	available	available
CMCC-ESM2	CMCC	140351.946	available	available
CanESM5	CCCma	140351.946	available	available
IPSL-CM6A-LR	IPSL	140352.354	available	available
IPSL-CM6A-LR-INCA	IPSL	140352.354	available	available

Translating negative tracer values into boundary conditions from the global model product is indeed a question to be considered when implementing the regional model. Out-of-bound tracer value is a common occurrence to all numerical modeling and is related to the tracer advection scheme used. Numerical schemes for tracer transport and mixing ideally satisfy high-order accuracy, conservation, and boundedness. However, boundedness is generally not strictly imposed as most numerical schemes give priority to the former two desirable properties. Commonly-used approaches to enforce tracer boundedness either compromise accuracy or conservation. Minor occurrences of out-of-bound tracer value *per se* should not debase the credibility and reliability of GCMs, which have to meet stringent modeling requirements (finer grid resolution and smaller time step can reduce the occurrence of negative tracer values, but balancing the computational cost and model complexity dissuades such implementation). The negative concentration of tracers can be corrected with a mass conservative and non-diffusive scheme by balancing the value from the nearest grid points in a way that conserves the tracer mass. Most negative tracer data for NO3 happens in the middle of loop current where there is a sudden change in bathymetry and loop current takes a sharp turn as a result of the combined stresses. Along the southern boundary of our model (around latitude 16.7387 N), we notice negative tracer values rarely happen (Table A2).

Table A2. GCMs Tracer NO3 value range along GoM boundary

Model Name	Institution	NO3 range in GoM southern boundary [min, max], unit: mol m^{-3}	NO3 range in GoM eastern boundary [min, max], unit: mol m^{-3}
CESM2-FV2	NCAR	[0, 0.026418]	[-0.00033723, 0.026207] (1.34 % negative tracer values)
CESM2-WACCM-FV2	NCAR	[0, 0.025887]	[-0.00025584, 0.025676](0.98 % negative tracer values)
MPI-ESM1-2-LR	MPI	[0, 0.023258]	
MPI-ESM1-2-HR	MPI	[0, 0.020868]	
MPI-ESM-1-2-HAM	HAMMOZ-Consortium	[0, 0.022392]	
ACCESS-ESM1-5	CSIRO	[0, 0.073462]	
CMCC-ESM2	CMCC	[0, 0.048223]	
CanESM5	CCCma	[0, 0.06836]	
IPSL-CM6A-LR	IPSL	[0, 0.041679]	
IPSL-CM6A-LR-INCA	IPSL	[0, 0.041748]	

RC1: *Only a single year is used for model spin up. It is not clear if the model will really have settled down by that point. Many regional models require 5 years to spin up, so one year is possibly questionable, especially given model output is used for temporal trend analysis.*Starting conditions are *used from the CESM2-WACCM-FV2 model, and quasi-equilibrium conditions for this model will differ (perhaps quite dramatically) from the regional model. The authors justify using a one-year spin up by saying "the global model has been well stabilized up to the year 2000 from its 'pre-industry' experiment". This does not say much about the stability of the regional model used. Given the issues mentioned above about negative nitrate values in the global model, it seems questionable whether the starting conditions are close to a stable state in the regional model. Furthermore, it is plausible that riverine inputs are drastically better resolved in the regional model than the global model. This is particularly important given the conclusion of the importance of the carbon inputs from the Mississippi River.*

The spin-up timing issue is also particularly relevant for the "no rivers" experiment. This experiment essentially removes rivers at the start of 2000, but assumes that the model is effectively spun-up to "river-free" conditions by the end of 2000. The authors need to show that this is credible. Otherwise, some of the results in the experiments section may not be robust.

Response: The regional model has the benefit of swift spin-up compared with the global model due to higher spatial resolution, smaller time-step, and relatively high momentum in the GoM region. The biogeochemical model typically completes its spin-up in one year (e.g. Große, Fennel, Laurent, 2019;

Laurent and Fennel, 2019; Laurent et al., 2021). To address the reviewer's comment about the spin-up time, especially for the "no rivers" experiment, we added the spin-up comparison results of the "no rivers" experiment to assure that a one-year spin-up is necessary and further spin-up beyond one year do not gain additional benefits. We used the 9-year spin-up result as the control and assumed spinning up for nine years was adequate for the regional model. Then we check the difference between the model results of different spin-up times to that of the 9-year spin-up result (as Diff). For the interest of the carbon model, ocean surface DIC and TA concentration differences are plotted in detail in Figs. A2 and A3.

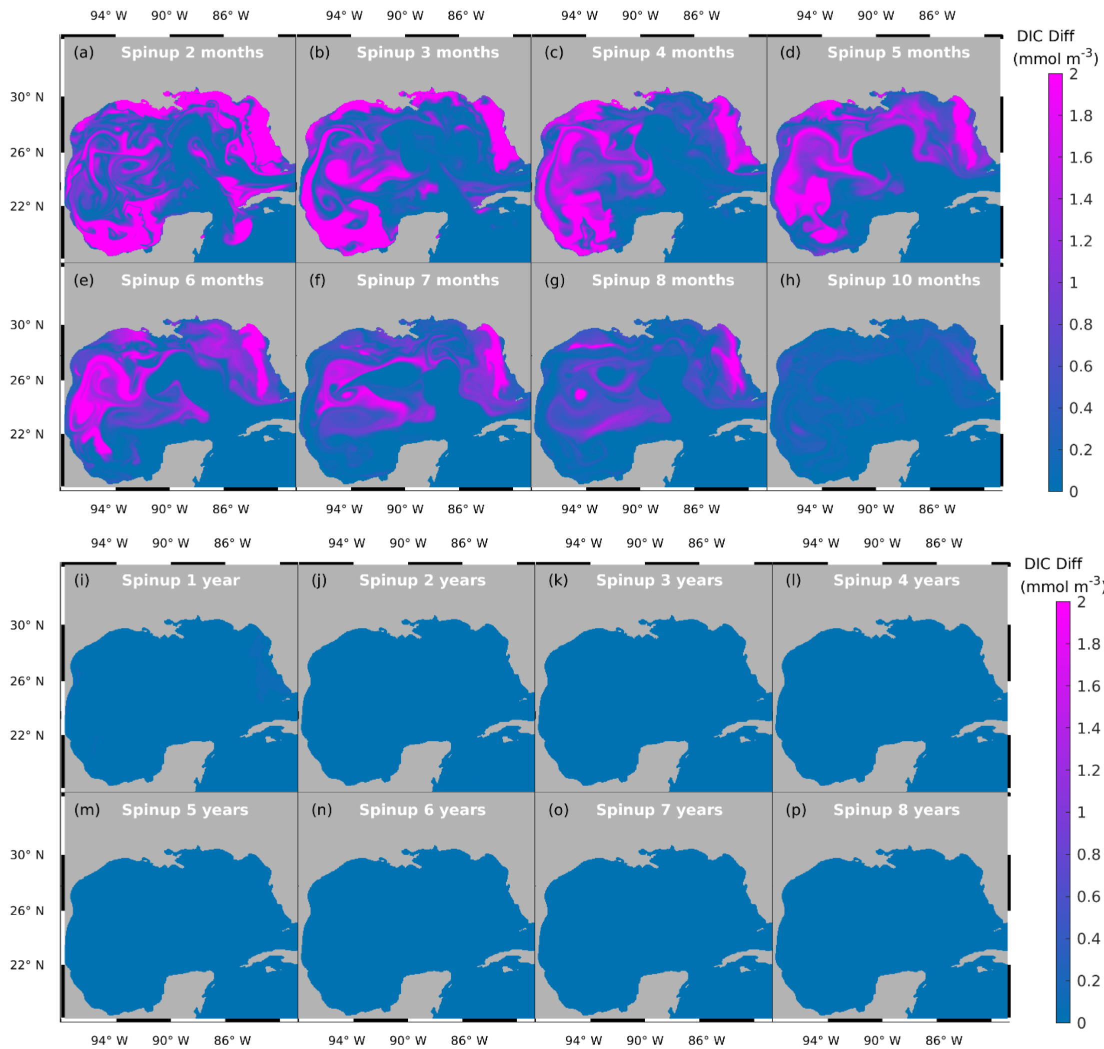

Figure A2. Ocean surface DIC difference between nine-year spin-up NoR experiment and NoR experiment spinning up for (a) 2 months (b) 3 months (c) 4 months (d) 5 months (e) 6 months (f) 7 months (g) 8 months (h) 10 months (i) 1 year (j) 2 years (k) 3 years (l) 4 years (m) 5 years (n) 6 years (o) 7 years (p) 8 years.

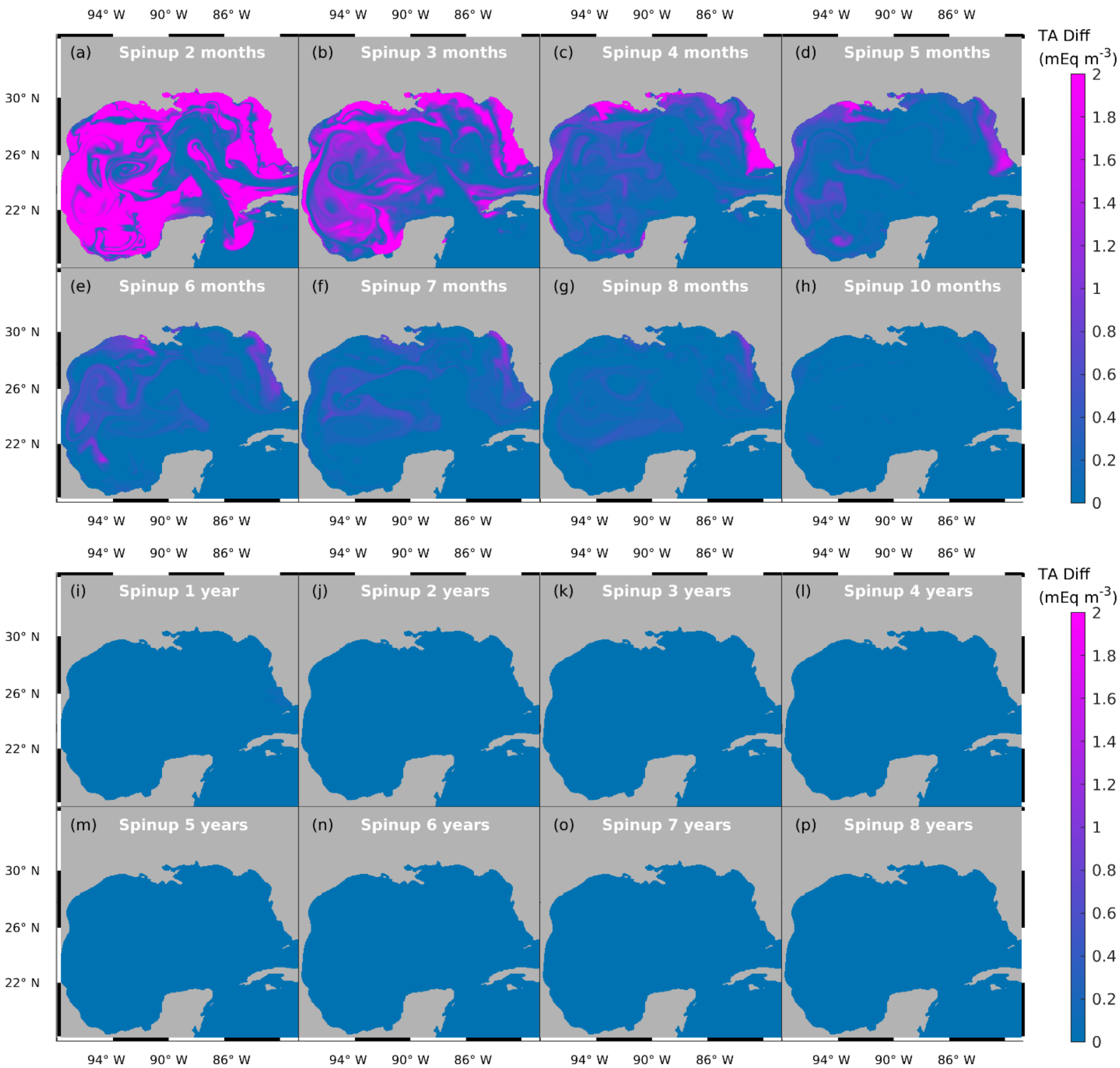

Figure A3. Ocean surface TA difference between nine-year spinup NoR experiment and NoR experiment spinning up for (a) 2 months (b) 3 months (c) 4 months (d) 5 months (e) 6 months (f) 7 months (g) 8 months (h) 10 months (i) 1 year (j) 2 years (k) 3 years (l) 4 years (m) 5 years (n) 6 years (o) 7 years (p) 8 years.

RC1: *Overall, the model seems to do a reasonable job compared with observations. However, at present the model validation lacks rigorous statistics and is purely visual. There are 3 figures comparing model results and observations. However, there is a failure to show how close the model is to observations. I recommend the authors add correlation coefficients, RMSE and bias values for model-observation comparisons where relevant. These should give reasonable results based on the figures. This is particularly important for figure 5 comparing surface pCO2 between model and observation/ML model. The authors should also consider carrying out a similar analysis of pCO2 for the global climate model used to help assess the reliability of the boundary and initial conditions.*

Response: Two types of observations are used as the standard for model evaluations, namely the high-frequency buoy measurements of surface *pCO_2* and CTD measurements of DIC and TA in the GoM. We plan to introduce the following statistics to the revision.

$$skill = 1 - \frac{\sum_{i=1}^{N}(d_i - \Im[m_i])^2}{\sum_{i=1}^{N}(d_i - c_i)^2} \tag{A1}$$

(Zhang et al., 2012)

The model skill is a metric that evaluates the improvement gain in the high-resolution regional model compared with that of the climatology/ global model. A skill value of 1 indicates significant model improvement, and a value of 0 indicates no improvement. We will also employ commonly used statistical metrics such as correlation coefficient (R), Root Mean Square Error (RMSE), and the standard deviation (STD) to evaluate the model performance.

Taylor diagram can assess the model's ability to capture spatial patterns with regard to a given set of reference data. The Taylor Skil Score (TSS) will be used to rank models in capturing the spatial pattern of sea surface *pCO_2*, according to both STD and R value defined by equation (A2).

$$TSS = \frac{4(1+R)^2}{\left(\frac{\sigma_o}{\sigma_m} + \frac{\sigma_m}{\sigma_o}\right)^2 (1+R_0)^2} \tag{A2}$$

(Babaousmail et al., 2021)

where σ_o and σ_m are the STD of observation and model, respectively. The value of TSS range from 0 to 1, with values close to 1 corresponding to better performance.

The equations of Bias, RMSE and R are given as follows:

$$Bias = \sum_{i=1}^{N}(M_i - O_i) \tag{A3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - O_i)^2} \tag{A4}$$

$$R = \frac{Cov(M,O)}{\sigma_M \sigma_O} \tag{A5}$$

where M stands for model output, and O stands for observation; Cov refers to the coverance, and σ indicates the standard deviation.

We provide the model-data comparison at the two coastal buoy locations to demonstrate our model is outperforming the other products in the coastal and shelf waters (Fig. A4). Comparison of monthly climatology among various global models, the remote sensing-based machine learning products by Chen et al. (2019), and the model by Gomez et al. (2020) indicated that our model could better capture the seasonal variability in surface *pCO_2* at these two locations. We thank Dr. Chuanmn Hu from USF and Dr. Fabian Gomez from NOAA for providing us with their model data.

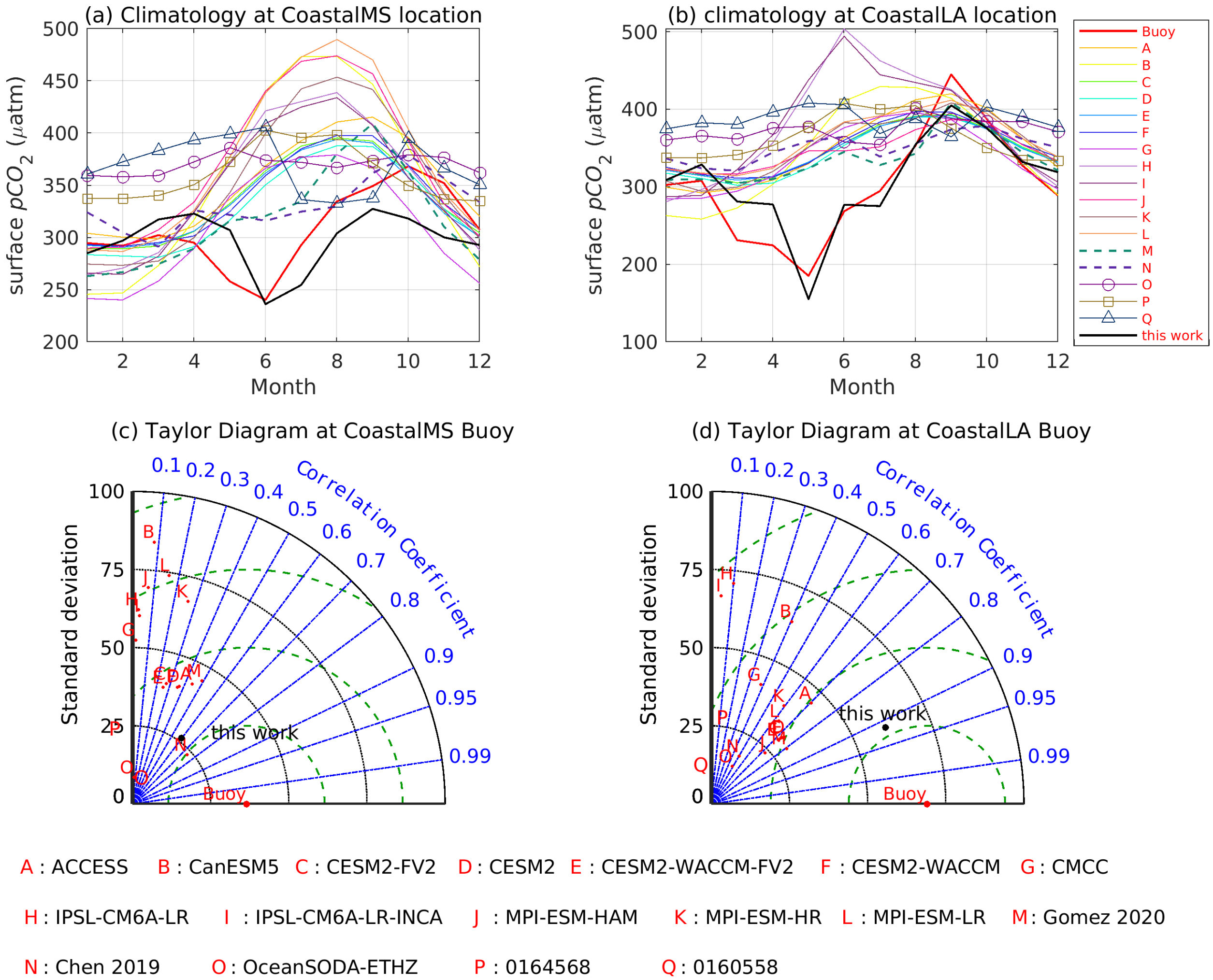

Figure A4. Comparison of sea surface pCO_2 from Global Climate Models (GCMs) (A though L), global ocean climatology products (O,P,Q), regional ocean model products (M,N) at two buoy sites. Climatology at the two buoy locations of CMIP6 models and Gomez et al. (2020) are calculated by multiyear averaging from 2000-2014 model surface results. Climatology at the two buoy locations of Chen et al. (2019) is calculated from their ML surface pCO_2 product (from 2002-07 to 2017-12). Climatology from NCEI Accession 0164568, NCEI Accession 0160558 contains 12-month estimates of surface pCO_2 and were used directly. Monthly climatology of OceanSODA-ETHZ and this work are calculated from 2017-07 to 2019-12 for CoastalLA buoy, and from 2011-03 to 2017-05 for CoastalMS buoy. Buoy raw observations have a frequency of ~ 3 hours, monthly averages are used in Fig. A4 to be compared with monthly model estimates.

RC1: *I recommend the authors ensure that all figures are colour-blind friendly. At least 7 of the figures are not. Figure 11 is very difficult to understand. Double y-axes should generally be avoided, and in this case they just serve to confuse. The axis units are also not stated.*

Response: We will avoid using pure red and pure green in the color scheme and adopt colour-blind friendly color schemes. Thanks for the recommendation and reminder. We will remove double y-axes in Fig. 11 and re-organize the data in a more readable visualization format.

RC1: *At present, the results section includes discussion and the discussion includes results. Comparisons of the results with other studies (p. 19) should be moved to the discussion. Furthermore, the sensitivity analysis should be in the results section, not the results.*

Response: We will re-organize and place the comparison with other studies in the discussion section and the presentation of sensitivity analysis from the perturbed runs in the result section. Our second reviewer also gave this suggestion.

RC1: *The forcing data used is of varying temporal resolution, and some of it (such as oxygen) is only available as a climatology. The authors should clarify which driving data is actually changing during the 2001-2019 time period, and which are essentially unchanging. At present it is not fully clear what can and cannot be driving the temporal trends in carbon fluxes etc.*

To what extent are the riverine inputs climatological? P. 7 states "Missing river alkalinity values are interpolated from climatological values, and missing river DIC values are calculated from pH and alkalinity…" An indication of how well varying riverine inputs are represented would clarify this.

The driving data sets mostly seems to be the best available, so minor clarifications are only needed.

Response: In Table A3 we listed the frequency of the forcing data prepared for the regional model.

Table A3. Model Forcing Frequency

Forcing Name	Data Source	Frequency used
Wind	CFSR;CFSv2	6-hourly
Precipitation	CFSR;CFSv2	6-hourly
Longwave Radiation	CFSR;CFSv2	6-hourly
Shortwave Radiation	CFSR;CFSv2	6-hourly
Humidity	CFSR;CFSv2	6-hourly
Air Temperature	CFSR;CFSv2	6-hourly
Air Pressure	CFSR;CFSv2	6-hourly

In Table A4 we listed the frequency of the boundary data prepared for the regional model.

Table A4. Model Boundary Frequency

Boundary Variable	Data Source	Frequency used
u, v, ubar, vbar, zeta, temp,salt	HYCOM	daily
NO3, NH4, PO4, Si(OH)4, DIC, TA, diatom, small phytoplankton, microzooplankton, mesozooplankton, Pzooplankton, CalC, DOC	CESM2-WACCM-FV2	monthly
Oxygen	WOA	static climatology
DON, PON, opal	small positive value	constant

A total of 47 rivers (Brazos; Colorado; Guadalupe; Neches; Nueces; Rio Grande; Sabine; W San Jacinto; E San Jacinto; Trinity; Atchafalaya; Calcasieu; Mermetau; Mississippi; Pearl; Vermilion; Pascagoula; Fish river; Mobile; Perdido; Escambia; Yellow; Choctawhatchee; Apalachicola; Ochlockonee; Steinhatchee; Suwannee; Withlacoochee; Crystal river; Chassahowitzka; Pithlachascotee; Anclote river; Hillsborough; Alafia; Manatee; Myakka; Peace; Caloosahatchee; Harney; San Fernando; Sotola Marina; Panuco; Tecolutla; Jamapa; Papaloapan; Coatzacoalcos; Usumacinta) are included in the model. USGS station 7381495, 7381600, 7373420, 7374000, 7374525 are used for alkalinity, DIC data for MARS. For all other rivers in the domain, mean climatological DIC and TA values are used due to limited data availability.

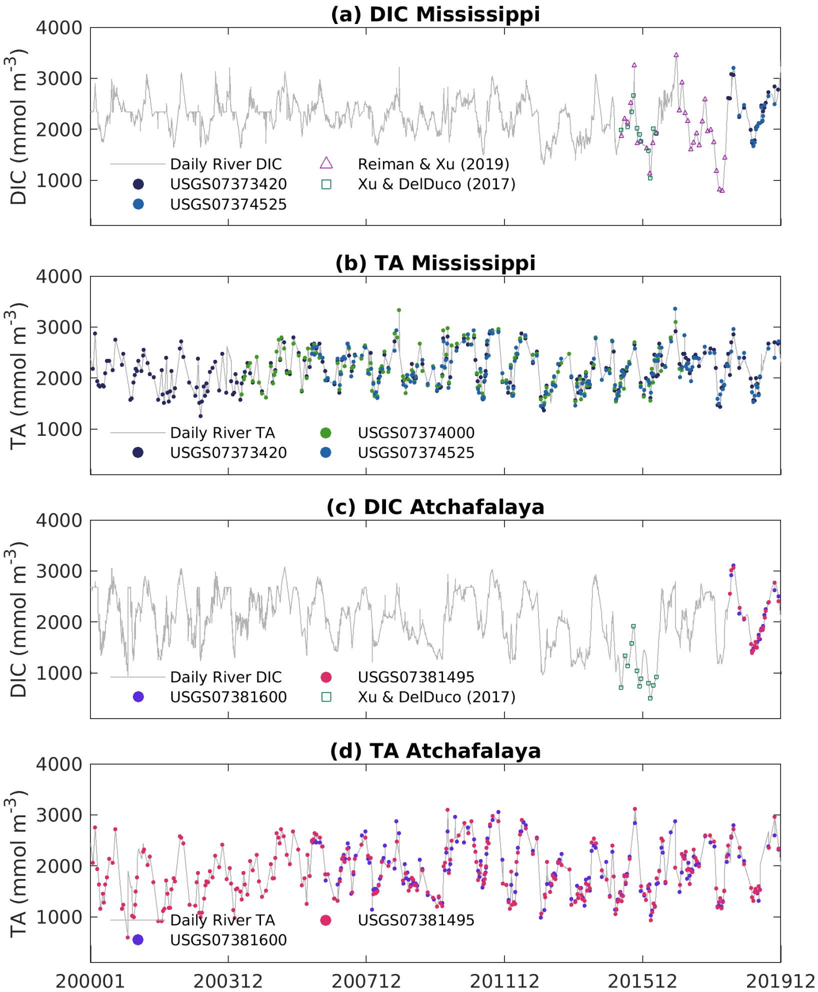

Figure A5. River DIC, TA concentration prescribed in the model. Grey lines are the interpolated daily concentration values; colored data points are raw data collected from multiple sources.

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