APPENDIX A

Technical Memorandum on Modeling

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1. Introduction

This technical memorandum supports the petition filed by Environmental Defense Fund, Natural Resources Defense Council, et al. seeking reconsideration of EPA's final rule "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards," 91 Fed. Reg. 7,686 (Feb. 18, 2026).The Final Rule's futility rationale relied on entirely new modeling and other technical analyses that EPA performed after the period for public comment on the proposed rule closed. The novel technical analysis projects GHG emissions from US on-road vehicles and the impacts of such emissions on Global Mean Surface Temperature (GMST) and Global Sea Level Rise (GSLR). As we explain in the accompanying petition, EPA's futility analysis is arbitrary and capricious for many reasons. To address the errors in EPA's approach, EDF has conducted our own analysis. A description of the methodology and results of that analysis are presented below.

2. Vehicle Scenario Modeling

a. Recreating EPA's vehicle emission projections (Scenario A)

In order to critique EPA's futility analysis, we first needed to obtain EPA's emissions inputs, which in turn are used in the temperature and sea level rise modeling. Ordinarily, such emissions inputs and the relevant emissions modeling files are simply provided by the Agency. In this Final Rule, EPA also provided certain documentation and modeling files to accompany its Regulatory Impacts Analysis.[3] In support of its futility analysis, however, EPA provided extremely limited documentation. This documentation is insufficient for the public to reproduce EPA's results or to fully know what the Agency actually did.

First, although EPA purported to model total US vehicle GHG emissions from 2027 through 2100, EPA only provided CO2 emissions input data for 3 of those years: 2027, 2050, and 2100. In other words, EPA provided key numerical emissions data for only 4% of the years (3 out of 74 years) that it modeled, leaving it to the public to reconstruct emissions data for the remaining 96% of years (71 out of 74 years). EDF needed to recreate the annual emissions in order to model the temperature, sea level, and damages associated with EPA's scenario, which we term Scenario A in this memorandum.

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[3] *See, e.g.*, EPA, Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act Regulatory Impact Analysis, EPA-420-R-26-002 ("RIA"); EPA, Updated modeling assumptions and tools for "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act" Final Rule, Docket No. EPA-HQ-OAR-2025-0194-31054 ("EPA Modeling Memo"); EPA, Projected Criteria, Air Toxics, and GHG Emissions Impacts for the "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act" Final Rule, Docket No. EPA-HQ-OAR-2025-0194-31055 ("EPA Emissions Memo"). Commenters raised significant objections to EPA's draft Regulatory Impacts Analysis accompanying the proposal, demonstrating that such analysis was fundamentally flawed in many ways. This memorandum does not further address EPA's Regulatory Impacts Analysis.

Second, EPA purported to run two models to estimate vehicle emissions: OMEGA and MOVES5.R2. EPA's Temperature Memo (hereafter "Memo")[4] states that it used the same "OMEGA model version and inputs" as Scenario A1. EDF used the CO_2 emission projections for light- and medium-duty vehicles (LMDVs) from the corresponding physical effects file in the "Modeling Memo Attachments" folder provided by the EPA Docket Center upon request.[5]

For heavy-duty emissions, EPA did not provide any modeling files. In the "Modeling Memo Attachments" folder, there is a file labeled "20251117_151129_hdp3_physical_effects.csv" but the file is blank and empty.[6] Instead, the Agency gave only a cursory, one sentence explanation of how it applied the MOVES model, claiming that "[e]missions of the same gases from on-road heavy-duty vehicles (HDV) are estimated using MOVES5.R1."[7] However, this explanation appears wrong. As described in the separate EPA Modeling Memo, MOVES5.R1 is the model for the No Action case and MOVES5.R2 is the model for the Action case. Given the context, we have assumed EPA meant MOVES5.R2 since that is the relevant model.

However, when we calculated the heavy-duty Class 4 to 8 CO_2 emissions from MOVES5.R2, they did not match the three values EPA provided for 2027, 2050, and 2100. See Table 1 for the comparison of the emissions. We also assessed Class 2b-8 emissions, and they also do not match EPA's provided values. (Note that the table uses 2055 in lieu of 2100, as MOVES5.R2 does not model year 2100, and EPA asserts it held emissions constant between 2055 and 2100.)

Table 1: CO_2 emissions for calendar years 2027, 2050, and 2055 from MOVES5.R2 by regulatory class (million metric tons)

RegClass	Reg Class Name	2027	2050	2055*
41	Class 2b/3	116	117	123
42	Class 4/5	30	27	28
46	Class 6/7	37	25	25
47	Class 8	337	327	337
48	Urban Bus	3	3	3
49	Gliders	4	0	0
	MOVES5.R2 Class 4-8	412	381	393
	MOVES5.R2 Class 2b-8	527	498	516
	EPA HDV Emissions from Memo	450	550	564

*The value EPA provides is for 2100. Since EPA states they held emissions constant between 2055 and 2100, this is also the emissions value EPA used for 2055.

[4] EPA, Technical Memo on: Temperature, CO_2 Concentration, and Sea Level Rise Impacts of Greenhouse Gas Emissions from U.S. Motor Vehicles for the "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act" Final Rule, Docket No. EPA-HQ-OAR-2025-0194-31105 ("Memo").

[5] Memo at 1-2.
Documents attached to EPA Docket ID: EPA-HQ-OAR-2025-0194 provided by the EPA Docket Center upon request, file location within the folder \Modeling Memo Attachments\LMHDV\A1\20251117_151129_a1\20251117_151129_a1\20251117_151129_lmdv_physical_effects_by_annum.csv
From EPA's description, it is unclear if the Agency included CH_4 and N_2O in its modeling, and the Agency only appears to present results for CO_2. We further explain this issue in the accompanying petition. For Scenario A, we only modeled CO_2.

[6] Connected to EPA Docket ID: EPA-HQ-OAR-2025-0194, file location: \Modeling Memo Attachments\LMHDV\A1\20251117_151129_a1\20251117_151129_a1\20251117_151129_hdp3_physical_effects.csv

[7] Memo at 2.

MOVES5.R2 provides annual emissions. However, given we could not get the MOVES5.R2 emissions to match EPA's stated CO2 values, and given our objective of matching EPA's modeling for emissions as accurately as possible, we chose not to use the annual emissions produced by MOVES5.R2. Instead, we linearly interpolated emissions from 2027 to 2050. Because EPA states it held the emissions constant after 2055, we also linearly interpolated between 2050 and 2055 using the 2100 value as the 2055 value. In order to continue modeling EPA's scenario through 2200, we assumed flat emissions for Scenario A as EPA did between 2055 and 2100.

b. Additional vehicle emission scenarios (Scenarios B and C)

As we explain in the petition, EPA's modeling makes numerous erroneous and irrational choices. To address these errors, EDF modeled two additional scenarios, identified as Scenario B and Scenario C.

Scenario B ("Today's Fleet") assumes vehicle emissions do not improve further than where they are currently. All future model years are assumed to have the same per-vehicle emissions rate as approximately MY2025. We use MY2025 because this is the most recent year with sufficiently available reported data. Electric vehicle adoption rates remain constant.

Scenario C ("Pre-GHG Protection Fleet") assumes that U.S. vehicle fleet composition and per-vehicle emissions rates as of approximately the time of the 2009 Endangerment Finding extend in perpetuity, with total emissions increasing proportionally to VMT. This scenario attempts to remove the emission reductions that occurred since EPA began regulating onroad vehicle GHG emissions.

To model these two scenarios, EDF ran MOVES5.R2 to project the emissions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) from all onroad vehicle classes[8] for calendar years 2009 through 2060 aggregated at both national and annual levels.[9] We split out GHG emissions for each calendar year by vehicle class,[10] model year (MY), and fuel type. EDF used MOVES5.R2 outputs for vehicle populations and vehicle miles travelled (VMT) for these same vehicle groupings.

Because MOVES5.R2 only allows modeling to 2060, we developed VMT growth rates that we used to model emissions in 2061 through 2200. EDF determined the average annual absolute growth in light-duty, medium-duty, and heavy-duty VMT between 2050 and 2060 in MOVES5.R2. We increased GHG emissions in 2061 and beyond using only these growth amounts. The annual VMT growth used was 0.38% of 2050 VMT for light-duty vehicles, 1.01% of 2050 VMT for medium-duty vehicles, and 0.67% of 2050 VMT for heavy-duty vehicles.[11]

[8] All onroad vehicle classes in MOVES5 are regClassID 11 through 49, or motorcycles through heavy-duty tractor trailers.

[9] GHG emissions are not as sensitive to climatic conditions as evaporative and some other exhaust emissions, like those of volatile organic compounds (VOC), which are dominated by cold start emissions. Therefore, GHG emissions using national and annual ambient temperatures produce reasonable estimates. Running MOVES5 using monthly averages is both substantially more time consuming and would produce only slightly higher emissions results, underscoring the conservative nature of our approach.

[10] In MOVES5.R2 these are defined as sourceID and regClassID and we refer to them throughout using vehicle class as shorthand.

[11] EDF assumed constant growth, not a growth rate. So the increase in VMT each year between 2061 and 2200 was the same absolute number increase in miles.

We next developed model year specific emissions factors for each of our two scenarios. For Scenario B, EDF modeled EV sales as constant at approximately current levels—10% for light-duty vehicles[12] (regClassID = 20 or 30), 2% for medium-duty vehicles (regClassID=41), and no ZEV sales for heavy-duty vehicles (regClassID>41).[13] We left GHG emissions per mile from internal combustion engine vehicles constant at their 2027 MOVES5.R2 levels but increased their portion of VMT to account for our assumed lower and constant ZEV levels (in the case of light- and medium-duty vehicles) or no ZEVs (in the case of heavy-duty vehicles).[14] In addition, by adjusting emissions in 2061 and later only through VMT growth, we ensure that average GHG emissions per mile likewise remain constant over this timeframe.

For Scenario C, we assumed no ZEVs in the fleet. To derive GHG emissions per mile from internal combustion engine vehicles, EDF compared GHG emission factors for model years 2007-2014 for each vehicle class and fuel combination and selected the model year with the highest level of CO2 emissions per mile ("circa 2009 emissions factor"). Because of the Great Recession, vehicle sales dropped significantly in 2008 and 2009. Compared to 2006, total vehicle sales in 2008 and 2009 were 21% and 38% lower, respectively.[15] Because the Great Recession likely changed the fleet make up, especially for light-duty vehicles (i.e., likely more sales of lower emitting small and cheaper cars and fewer higher emitting, more expensive SUVs), we chose the highest CO2 emissions rate for a range of years. Additionally, in the MOVES5 data, some of the MD and HD categories have a sharp uptick in emissions rate starting in MY2010 which appears to be an upgrade in methodology EPA used in MOVES5 to estimate emissions rather than a change in the actual vehicles. We believe using the higher values avails ourselves of the updates to MOVES and more accurately represents vehicles from around that time period.

We then applied the CO2, CH4, and N2O emission factors for the model year with the highest emissions to all 2009 and later model year vehicles.[16] As in Scenario B, we hold GHG emissions per mile from internal

[12] We further apportioned the 10% EVs between Battery Electric Vehicles (BEVs), representing 8% of vehicles, and plug-in-hybrid electric vehicles (PHEVs), representing 2% of vehicles, using outputs of EPA's OMEGA compliance model. We assumed PHEVs would operate roughly two-thirds of the time on grid electricity, meaning a single PHEV effectively represents 67% of a BEV and 33% of an internal combustion engine vehicle. Thus, modeling a fleet in MOVES with 8% BEVs and 2% PHEVs, is equivalent to a fleet with 9.4% BEVs. The share of time PHEVs spend running on electricity is determined by the size of the battery. 67% represents a PHEV with a real world 50-mile electric range. This is likely higher than the current PHEV sales but data is sparse on electric range. Thus, we made a conservative assumption reflecting a slightly cleaner fleet than had we used a lower electric operation factor and yielding smaller projected emissions impacts attributable to U.S. vehicles.

[13] According to the Alliance for Automotive Innovation's Get Connected EV Quarterly Report for Q4 2025, EV sales in the US accounted for 9.6% of LD sales in 2025 with 1.7% PHEVs and 7.9% BEVs. There is less data available for MD and HD EV sales. For MDVs, EDF previously estimated MD EV sales at 6% using Atlas Public Policy and CALSTART data. See Comment submitted by Environmental Defense Fund (EDF) (Part 1 of 3), EPA-HQ-OAR-2025-0194-3046 ("EDF EF Tech Comments"). MOVES5.R2 projects MD EV sales at 0.6% of total new vehicles in 2027 rising to around 2% by around 2030. Given the uncertainty in the data, EDF chose 2% EV sales for MDVs. CALSTART's Zeroing in on Zero-Emission Trucks dashboard reports 2024 HD EV sales as 0.4% of total sales and for the first six months of 2025, that value dropped to 0.2%. For the sake of model simplicity, EDF estimated HD EV sales at 0%. https://www.autosinnovate.org/posts/papers-reports/Get%20Connected%20EV%20Quarterly%20Report%202025%20Q4.pdf https://calstart.org/zio-zets/#zet-dashboard

[14] To ensure GHG emissions per mile from conventional vehicles remained constant where we capped ZEV sales at levels lower than MOVES5.R2 would otherwise project, EDF multiplied the GHG emissions from each vehicle class-fuel-MY combination by the ratio of (1.0 minus our assumed light-, medium-, and heavy-duty ZEV sales described above) over (1.0 minus the ZEV sales level in MOVES5.R2). EDF determined the BEV and fuel cell vehicle (FCV) sales fractions for each vehicle class and MY in MOVES5.2 using the output from our MOVES5.R2 run (fuelTypeID=9).

[15] https://fred.stlouisfed.org/series/TOTALSA

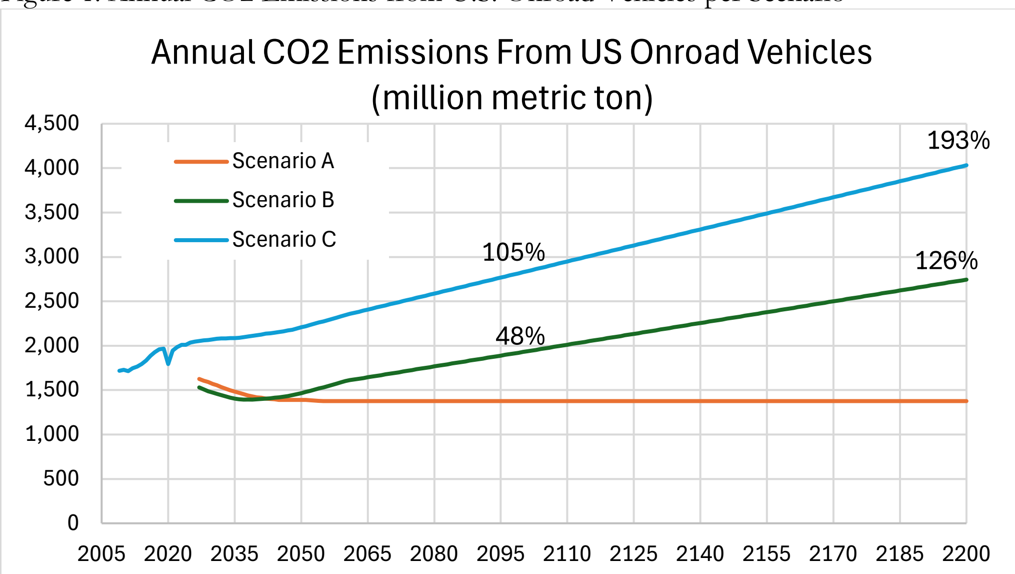
[16] We did this by multiplying the emissions of each vehicle class-fuel combination for model years 2009 and later by the ratio of the circa-2009 emission factor to the emission factor MOVES5.R2 projected for that model year. EDF did this for all the calendar years between 2009 and 2060.

combustion engine vehicles constant (though, in this case at circa-2009 levels) but increase their portion of VMT to account for the fact that Scenario C includes no ZEV sales in any of the vehicle classes.[17] The circa-2009 emission factors for selected vehicle class-fuel combinations are shown in Tables A1-A4 reproduced in the addendum to this memorandum.

As shown in Figure 1, the annual CO2 emissions for Scenario B is 48% higher in 2100 and 126% higher in 2200 compared to Scenario A. Scenario C annual CO2 emissions are more than double Scenario A in 2100 and nearly triple in 2200.

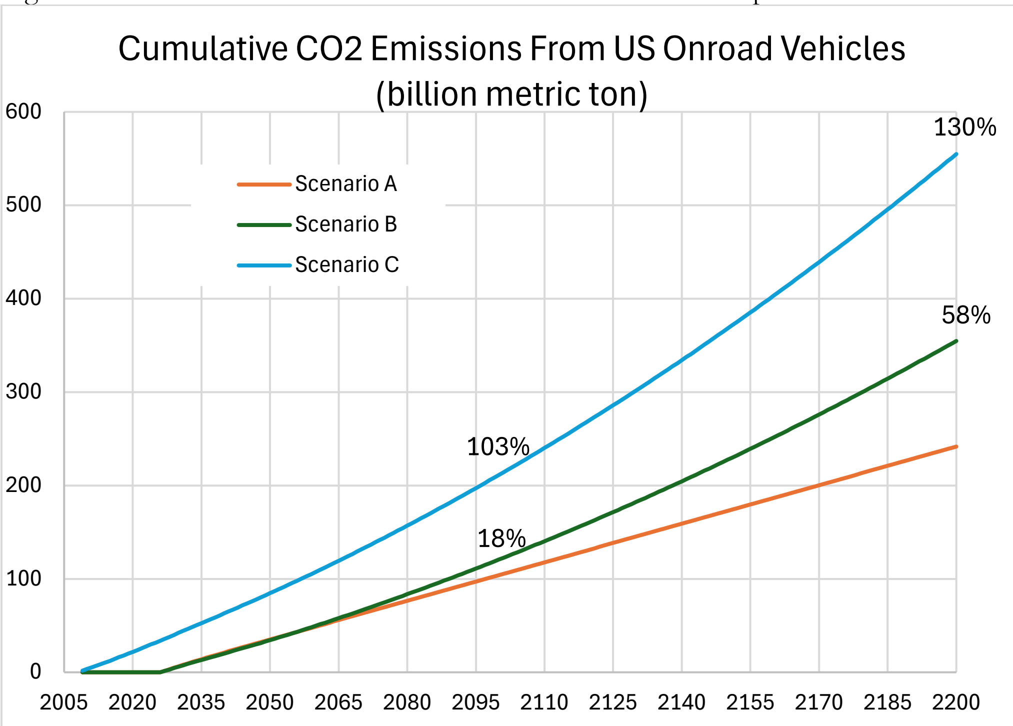
When comparing cumulative emissions (Figure 2), Scenario B is 18% higher in 2100 and 58% higher in 2200. Scenario C, when comparing cumulative emissions back to 2009, has more than double the CO2 emissions compared to Scenario A by 2100 and 130% higher cumulative emissions in 2200. Each year of emissions for CO2, CH4, and N2O are in Table A5 at the end of the memo.

Figure 1: Annual CO2 Emissions from U.S. Onroad Vehicles per Scenario



[17] Similar to our approach in Scenario B, described above, EDF divided the GHG emissions from each vehicle class-fuel-MY combination by (1.0 minus the ZEV sales level in MOVES5.2). This held the GHG emissions per mile from conventional vehicles at their circa-2009 MY levels, but increased their portion of VMT to account for no ZEV sales.

Figure 2: Cumulative CO2 Emissions from U.S. Onroad Vehicles per Scenario



c. Share of emissions from new vehicles for Scenario A

EDF calculated the share of emissions from new vehicles (MY2027+) for Scenario A (Table 2). We used MY and CY outputs from MOVES5.R2 to calculate the share of emissions from MY2027+ vehicles for calendar year 2027 through 2060. We summed the total emissions from MY2027+ vehicles for each calendar year and then divided that by the total emissions from all onroad vehicles. MOVES5 assumes all vehicles turnover within 41 years (year 0 to year 40). Since not all vehicles turned over by 2060, EDF assumed linear interpolation from 98.9% of all emissions from MY2027+ vehicles in 2060 to 100% in 2068.

Table 2: Share of annual and cumulative CO2 emissions from MY2027+ vehicles for Scenario A, cumulative relative to 2027

	Annual	Cumulative
2027	7.0%	7.0%
2030	26.6%	16.8%
2040	75.8%	43.6%
2050	94.3%	61.2%
2075	100.0%	80.2%
2100	100.0%	86.8%
2150	100.0%	92.1%
2200	100.0%	94.4%

The LMDV CO2 projections from OMEGA and MOVES5.R2 are slightly different but because OMEGA outputs do not provide a breakdown by MY and CY for the emissions, we used MOVES5.R2. The difference in the share of emissions from MY2027+ vehicles should be negligible.

3. Global Mean Surface Temperature (GMST) and Global Sea Level Rise (GSLR) modeling

As with EPA's emissions modeling, the Final Rule's modeling of temperature and sea level using FaIR and BRICK rise did not provide the public with sufficient information to reproduce the Agency's results. To begin with, EPA did not provide any of the modeling files for FaIR and BRICK, even though the Agency presumably used such files and had them in its possession. Nor did EPA provide many of the parameters required to run these models or even inform the public of the version of BRICK that the Agency used. Moreover, as already explained in the prior section, EPA did not provide the public with its emissions data or MOVES modeling files, and we did our best to reconstruct the inputs based on the scant documentation EPA provided. As a result of the Agency's lack of transparency for the emissions inputs, FaIR, and BRICK, we were unable to reproduce the exact temperature and sea level numbers presented in the Final Rule. Nonetheless, our Scenario A—which is meant to reproduce EPA's modeling—projected temperature and sea level impacts similar to and consistent with EPA's Final Rule. As explained further in the petition, we believe that comparing the results in Scenarios A-C reasonably illustrates EPA's failure to adequately account for the climate change impacts of US vehicle GHGs and the arbitrary nature of EPA's reliance on only one modeling scenario.

The framework EPA used to model the impact of US vehicle emissions was to run a scenario with global emissions based on SSP2-4.5 and then run a scenario where EPA removed US vehicle emissions from global emissions (i.e., subtracted US onroad vehicle CO2 from global CO2 emissions for each year). To calculate the "contribution" from US onroad vehicles, EPA subtracted the run without vehicles from the baseline run. We have replicated EPA's general framework. We ran four scenarios, Baseline and the Baseline minus Scenarios A, B, and C, respectively, for each of the modeling steps included below. For CO2 concentration, GMST, and GSLR, we present the results as EPA did: (1) the total global increase under SSP2-4.5 "Baseline", (2) the total global increase under SSP2-4.5 less the vehicle emissions "Minus Scen X GHG Emissions", and the contribution of the vehicle emissions calculated by subtracting (2) from (1). Table 3 details the global CO2, CH4, and N2O emissions and the US onroad vehicle emissions contribution for each scenario for a subset of years.

Table 3: Global GHG emissions (million metric tons/year) and contributions by scenario

	2009	2027	2050	2100	2150	2200
Global CO2[18]	31,459	39,633	42,961	14,483	9,655	4,924
Global CH4	364.2	396.0	357.2	295.2	237.5	180.9
Global N2O	10.55	11.94	12.59	8.73	8.21	7.70
Scenario A CO2	-	1,626	1,390	1,376	1,376	1,376
Scenario B CO2	-	1,529	1,467	1,930	2,337	2,744
Scenario B CH4	-	1.131	0.333	0.830	1.048	1.266
Scenario B N2O	-	0.077	0.074	0.094	0.118	0.142
Scenario B CO2e		1,553	1,495	1,978	2,398	2,818
Scenario C CO2	1,719	2,054	2,207	2,828	3,430	4,033
Scenario C CH4	0.250	0.223	0.546	1.325	1.670	2.016
Scenario C N2O	0.066	0.096	0.104	0.136	0.171	0.207
Scenario C CO2e	1,743	2,085	2,250	2,901	3,523	4,144

*CO2e values calculated with a global warming potential (GWP) on a 100-year time horizon based on the Fifth Assessment Report with the GWP for CH4 equal to 28 and N2O equal to 265.[19]

a. FaIR

i. FaIR Modeling

The Finite Amplitude Impulse Response (FaIR) model is a reduced-complexity, open-source climate model that translates greenhouse gas emissions into atmospheric concentrations, radiative forcing, and global temperature changes. EDF used FaIR v2.2.0, initialized over 1750-2200 with default species properties, emissions, and radiative forcing imported from RCMIP for the SSP2-4.5 scenario. A calibrated ensemble of parameter sets was imported (v1.4.1), and solar radiative forcing was modified to remain constant from 2022 onwards, consistent with what EPA appears to do based on the Memo. Custom emissions trajectories were imported and subtracted from the baseline emissions. All state variables were initialized to baseline conditions, and stochastic variability was enabled using configuration-specific parameters with unique seeds. Simulations were then executed across the full ensemble.

ii. FaIR Results

This section shows the results of running our baseline and three vehicle emissions scenarios in the FAIR model.

1. CO2 Concentration

The tables below show the estimated impact of U.S. vehicle emissions on global CO2 concentrations through 2200 and under the three scenarios.

Table 4 includes the estimated median CO2 concentrations from 2009 to 2200 for the baseline and each of the scenarios with the 95% confidence interval in parentheses.

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[18] This is only fossil fuel CO2 emissions (FFI) and not Agriculture, Forestry, and Other Land Use (AFOLU) emissions.

[19] https://ghgprotocol.org/sites/default/files/Global-Warming-Potential-Values%20%28Feb%2016%202016%29_1.pdf

Table 4: Absolute global CO2 concentrations (ppm), by scenario. Median (95% confidence interval)

	Baseline	minus Scen. A veh. GHG emissions	minus Scen. B veh. GHG emissions	minus Scen. C veh. GHG emissions
2009	385.7 (384.5-387.2)	385.7 (384.5-387.2)	385.7 (384.5-387.2)	385.7 (384.5-387.2)
2027	433.6 (430.8-437.1)	433.6 (430.8-437.1)	433.6 (430.8-437.1)	430.6 (427.9-434.0)
2050	504.8 (499.0-512.8)	501.6 (495.9-509.4)	501.7 (496.0-509.5)	497.5 (491.9-505.1)
2100	599.7 (586.9-617.8)	590.0 (577.6-607.5)	588.3 (576.0-605.7)	580.2 (568.2-597.1)
2150	618.9 (603.1-642.9)	602.8 (587.8-625.6)	597.5 (582.8-620.0)	584.8 (570.8-606.3)
2200	634.4 (616.1-664.6)	611.9 (594.9-640.1)	601.1 (584.6-628.3)	583.0 (567.6-608.5)

Table 5 shows the change in global CO2 concentrations for Scenario A and Scenario B. As shown, Scenario B results in a greater increase in global median CO2 concentrations by 2100 than Scenario A and the gap continues to increase through 2200, by which time the vehicle emissions associated with Scenario B has resulted in a 33 ppm increase in CO2 concentrations compared to 23 ppm for the vehicle emissions associated with Scenario A.

Table 5: Change in global CO2 concentrations (ppm) relative to 2027 for Scenario A and B. Median (95% confidence interval) (% contribution)

	2027 Baseline	Scen. A contribution	Scen. B contribution
2050	+71.2 (68.2-75.6)	3.2 (3.1-3.3) (4.5%)	3.1 (3.0-3.3) (4.4%)
2100	+166.1 (156.0-180.7)	9.7 (9.3-10.4) (5.9%)	11.4 (10.9-12.1) (6.9%)
2150	+185.2 (172.2-205.8)	16.1 (15.2-17.3) (8.7%)	21.4 (20.3-23.0) (11.5%)
2200	+200.8 (185.2-227.4)	22.5 (21.2-24.5) (11.2%)	33.3 (31.4-36.3) (16.6%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2027

Table 6 shows the impact of U.S. vehicle emissions on global median CO2 concentrations in Scenario C. By 2050, the contribution of U.S. vehicles to the global CO2 concentration increase since 2009 would be more than 6% and by 2200, that share would increase to over 20%.

Table 6: Change in global CO2 concentrations (ppm) relative to 2027 for Scenario C. Median (95% confidence interval) (% contribution)

	2009 Baseline	Scen C contribution
2027	+47.9 (46.4-49.9)	3.1 (3.0-3.1) (6.4%)
2050	+119.1 (114.6-125.5)	7.3 (7.1-7.7) (6.2%)
2100	+214.0 (202.4-230.6)	19.5 (18.6-20.8) (9.1%)
2150	+233.1 (218.6-255.7)	34.1 (32.3-36.6) (14.6%)
2200	+248.7 (231.6-277.3)	51.4 (48.4-56.1) (20.7%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2009

2. *Temperature*

The tables below show the estimated impact of U.S. vehicle emissions on global mean surface temperature (GMST) through 2200 under the three vehicle emission scenarios.

Table 7 shows estimated temperatures between 2009 and 2200 relative to pre-industrial (1850-1900) temperatures for the baseline and each of the three scenarios, with the 95% confidence interval shown in parentheses.

Table 7: Global Mean Surface Temperature (deg C) relative to pre-industrial levels (1850-1900), by scenario. Projected median temperature (95% Confidence Interval)

	Baseline	minus Scen. A veh. GHG emissions	minus Scen. B veh. GHG emissions	minus Scen. C veh. GHG emissions
2009	0.871 (0.538-1.245)	0.871 (0.538-1.245)	0.871 (0.538-1.245)	0.871 (0.538-1.245)
2027	1.405 (0.937-1.961)	1.405 (0.937-1.961)	1.405 (0.937-1.961)	1.391 (0.926-1.943)
2050	1.983 (1.324-2.887)	1.969 (1.314-2.869)	1.969 (1.314-2.869)	1.947 (1.299-2.839)
2100	2.886 (1.850-4.405)	2.839 (1.821-4.340)	2.831 (1.816-4.329)	2.791 (1.789-4.264)
2150	3.201 (2.079-5.186)	3.120 (2.026-5.060)	3.096 (2.007-5.019)	3.026 (1.962-4.918)
2200	3.383 (2.170-5.823)	3.263 (2.097-5.659)	3.205 (2.061-5.572)	3.105 (1.994-5.405)

Table 8 shows the contribution in increased surface temperature relative to 2027 for Scenarios A and B. The table shows that Scenario A and Scenario B contribute to the same change in temperature in 2050, relative to a 2027 baseline. However, by 2100, and even more so by 2200, Scenario B temperature change is far higher than Scenario A.

Table 8: Change in Global Mean Surface Temperature (deg C) relative to 2027 for Scenarios A and B. Median (95% Confidence Interval) (% contribution)

	2027 Baseline	Scen. A contribution	Scen. B contribution
2050	+0.578 (0.387-0.926)	0.014 (0.010-0.020) (2.4%)	0.014 (0.010-0.020) (2.4%)
2100	+1.481 (0.914-2.443)	0.045 (0.031-0.065) (3.0%)	0.053 (0.036-0.077) (3.6%)
2150	+1.796 (1.142-3.225)	0.079 (0.053-0.119) (4.4%)	0.106 (0.071-0.157) (5.9%)
2200	+1.979 (1.233-3.861)	0.115 (0.076-0.179) (5.8%)	0.170 (0.113-0.260) (8.6%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2027

Table 9 shows that if EPA had never adopted vehicle GHG emissions standards, climate emissions from the U.S. vehicle fleet could drive up global mean surface temperature by 0.094 degrees C in 2100 and 0.269 degrees C in 2200, or 10%, relative to a 2009 baseline. This is approximately 0.169 degrees F in 2100 and 0.484 degrees F in 2200.

Table 9: Change in Global Mean Surface Temperature (deg C) relative to 2009 for Scenario C. Median (95% Confidence Interval) (% contribution)

	2009 Baseline	Scen. C contribution
2027	+0.534 (0.399-0.717)	0.015 (0.011-0.020) (2.7%)
2050	+1.112 (0.786-1.643)	0.036 (0.025-0.051) (3.2%)
2100	+2.015 (1.313-3.160)	0.094 (0.064-0.138) (4.7%)
2150	+2.330 (1.541-3.941)	0.173 (0.115-0.259) (7.4%)
2200	+2.513 (1.632-4.578)	0.269 (0.178-0.414) (10.7%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2009

EPA includes in the Final Rule an "illustrative 50%" scenario where the Agency divides all of the temperature and sea level contributions in half. As we explain in the petition, it is arbitrary to divide modeled contributions in half. Nonetheless, consistent with EPA's approach, we also present below the temperature impacts from our own modeling divided in half.

Table 10: Change in Global Mean Surface Temperature (deg C) relative to 2027 for **50%** of Scenarios A and B. Median (95% Confidence Interval) (% contribution)

	2027 Baseline	Scen. A contribution	Scen. B contribution
2050	+0.578 (0.387-0.926)	0.007 (0.005-0.010) (1.22%)	0.007 (0.005-0.010) (1.22%)
2100	+1.481 (0.914-2.443)	0.023 (0.015-0.033) (1.52%)	0.027 (0.018-0.038) (1.80%)
2150	+1.796 (1.142-3.225)	0.040 (0.026-0.060) (2.21%)	0.053 (0.035-0.079) (2.94%)
2200	+1.979 (1.233-3.861)	0.058 (0.038-0.090) (2.92%)	0.085 (0.057-0.130) (4.30%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2027

Table 11: Change in Global Mean Surface Temperature (deg C) relative to 2009 for **50%** of Scenario C. Median (95% Confidence Interval) (% contribution)

	2009 Baseline	Scen. C contribution
2027	+0.534 (0.399-0.717)	0.007 (0.005-0.010) (1.37%)
2050	+1.112 (0.786-1.643)	0.018 (0.013-0.025) (1.64%)
2100	+2.015 (1.313-3.160)	0.047 (0.032-0.069) (2.34%)
2150	+2.330 (1.541-3.941)	0.086 (0.057-0.130) (3.71%)
2200	+2.513 (1.632-4.578)	0.134 (0.089-0.207) (5.35%)

*% contribution calculated as the absolute contribution in each year divided by the absolute increase in the baseline in that year relative to 2009

b. BRICK

The BRICK sea-level modeling was conducted by Tony Wong at Rochester Institute of Technology, one of the two original lead authors and current manager of the development of the model. The full explanation of his methodology and results are copied into Appendix D and can be found at https://arxiv.org/abs/2604.13446. Below we present select summary tables.

Table 12: Global Sea Level Rise (cm) relative to pre-industrial levels (1850-1900), by scenario. Median (95% Confidence Interval)

	Baseline	minus Scen. A veh. GHG emissions	minus Scen. B veh. GHG emissions	minus Scen. C veh. GHG emissions
2009	10.1 (6.0-15.3)	10.1 (6.0-15.3)	10.1 (6.0-15.3)	10.1 (6.0-15.3)
2027	15.6 (10.6-22.5)	15.6 (10.6-22.5)	15.6 (10.6-22.5)	15.5 (10.5-22.5)
2050	27.2 (18.4-53.6)	27.0 (18.4-53.5)	27.0 (18.4-53.5)	26.8 (18.3-52.2)
2100	91.3 (42.5-179.4)	89.7 (42.0-176.5)	89.5 (41.9-176.3)	87.5 (41.4-174.2)
2150	177.9 (68.6-330.0)	174.7 (67.2-324.9)	174.3 (66.9-323.8)	170.5 (65.7-318.5)
2200	268.5 (95.6-475.1)	260.4 (90.5-467.6)	259.1 (89.8-464.9)	252.6 (87.5-456.1)

Table 13: Change in Global Sea Level Rise (cm) relative to 2027 for Scenario A and B. Median (95% Confidence Interval) (% contribution)

	2027 Baseline	Scen A contribution	Scen B contribution
2050	+11.4 (6.0-32.7)	0.07 (0.04-1.04) (0.6%)	0.07 (0.04-1.03) (0.6%)
2100	+76.1 (29.9-160.7)	1.45 (0.40-5.16) (1.9%)	1.61 (0.44-5.82) (2.1%)
2150	+163.6 (55.4-309.3)	3.61 (1.16-12.73) (2.2%)	4.28 (1.43-17.32) (2.6%)
2200	+253.8 (82.1-454.1)	6.39 (2.35-21.18) (2.5%)	8.32 (3.12-29.34) (3.3%)

Table 14: Change in Global Sea Level Rise (cm) relative to 2009 for Scenario C. Median (95% Confidence Interval) (% contribution)

	2009 Baseline	Scen C contribution
2027	+5.5 (2.5-9.3)	0.04 (0.03-0.08) (0.72%)
2050	+17.0 (9.6-41.0)	0.29 (0.15-2.23) (1.7%)
2100	+81.0 (33.3-169.0)	3.57 (0.91-9.65) (4.4%)
2150	+167.8 (59.0-317.4)	8.25 (2.58-30.40) (4.9%)
2200	+260.5 (85.6-463.4)	14.37 (5.17-60.30) (5.5%)

As with temperature impacts, we observe significantly greater sea level rise impacts from Scenario B and C relative to Scenario A. For example, by 2100, we observe sea level rise of 1.61 cm and 3.57 cm in Scenario B and C, respectively, compared to only 1.45 cm in Scenario A (Tables 12, 13, 14). We observe the highest modeled sea level rise of 14.37 cm in 2200 in Scenario C, nearly ten times the 2100 projected impacts in Scenario A. 14.37 cm is approximately 5.66 inches, or nearly half a foot of sea level rise.

EPA includes in the Final Rule an "illustrative 50%" scenario where they divide all of the temperature and sea level contributions in half. As we explain in the petition, it is arbitrary to divide modeled contributions in half. Nonetheless, consistent with EPA's approach, we also present below the sea level rise impacts from our own modeling divided in half.

Table 15: Change in Global Sea Level Rise (cm) relative to 2027 for 50% of Scenario A and B. Median (95% Confidence Interval) (% contribution)

	2027 Baseline	Scen A contribution	Scen B contribution
2050	+11.4 (6.0-32.7)	0.04 (0.02-0.52) (0.30%)	0.04 (0.02-0.52) (0.30%)
2100	+76.1 (29.9-160.7)	0.73 (0.20-2.58) (0.95%)	0.81 (0.22-2.91) (1.05%)
2150	+163.6 (55.4-309.3)	1.81 (0.58-6.37) (1.10%)	2.14 (0.72-8.66) (1.30%)
2200	+253.8 (82.1-454.1)	3.20 (1.18-10.59) (1.25%)	4.16 (1.56-14.67) (1.65%)

Table 16: Change in Global Sea Level Rise (cm) relative to 2009 for 50% of Scenario C. Median (95% Confidence Interval) (% contribution)

	2009 Baseline	Scen C contribution
2027	+5.5 (2.5-9.3)	0.02 (0.02-0.04) (0.36%)
2050	+17.0 (9.6-41.0)	0.15 (0.08-1.12) (0.85%)
2100	+81.0 (33.3-169.0)	1.79 (0.46-4.83) (2.20%)
2150	+167.8 (59.0-317.4)	4.13 (1.29-15.20) (2.45%)
2200	+260.5 (85.6-463.4)	7.19 (2.59-30.15) (2.75%)

In addition to the global sea level modeling, Wong also preformed local sea level modeling to better understand how changes in sea level will impact American communities, specifically in the Gulf of Mexico. Further discussion of the methods are included in Appendix D and at https://arxiv.org/abs/2604.13446.

Given the limited time available to develop this modeling, and for ease of interpretation, only two of the FaIR-BRICK model runs were "downscaled" to understand their impacts at the local level: the "Maximum

Likelihood Estimate" (MLE), and the run with the median in 2100, "Med2100". The MLE is the simulation that we can think of as the simulation that best matches the historical sea-level observations. Med2100 is the simulation that yields the median global sea-level rise in the year 2100 in the baseline scenario. This "Med2100" simulation is significant because it is a middle-of-the-road outcome globally, where half the simulations project higher sea levels in 2100, and half project lower sea levels, making Med2100 a good summary of central tendency. Together, these two simulations provide a relatively simple and scientifically sound way to understand both a central outcome (Med2100) and a well-fitting, physically consistent outcome (MLE), without needing to examine hundreds of model simulations individually, which would have been infeasible in the limited time available.[20] Both MLE and Med2100, and the range between them, provide reasonable ways to understand the potential sea level rise impacts attributable the US vehicle emissions policy changes.

Table 17 below shows the MLE and Med2100 for the global baseline, the Gulf Coast baseline and for each of the three scenarios. Modeling of local sea level rise along the U.S. coast of the Gulf of Mexico demonstrates that the Gulf is projected to suffer substantially greater local sea level rise impacts than the global average. For example, assuming EPA's emissions inputs (Scenario A), we project that the impact of U.S. vehicle emissions on local sea level rise in the Gulf could reach 3.7 cm by 2100, far exceeding the global average impact of 1.45 cm. By 2200, we find that the impact on Gulf local sea level rise could rise up to 55.5 cm, considering a scenario where EPA never regulated vehicle GHGs (Scenario C). This is equivalent to 21.9 inches, or over 1.5 feet—a truly staggering amount of sea level rise.

Table 17: Baseline global mean sea level rise (GMSLR) and local mean sea level rise (LMSLR) for the U.S. Gulf of Mexico Coast (cm), shown relative to 2030 for consistency with how downscaling was done, which used a 10-year timestep. Gulf Coast baseline is the mean local mean sea level for all 178 US Gulf of Mexico coastal segments, relative to 2030, in each of the two downscaled simulations, MLE and Med2100. Scenarios A, B, and C are given as the reduction in LMSLR relative to the Gulf Coast baseline scenario.

	GMSLR relative to 2030		Gulf Coast baseline		Scenario A		Scenario B		Scenario C	
	MLE	Med2100	MLE	Med2100	MLE	Med2100	MLE	Med2100	MLE	Med2100
2050	11.2	8.76	12	12	0.1	0.1	0	0.1	0.2	0.2
2100	47.4	78.3	53	92	2.8	3.7	2.8	3.8	3.4	6.5
2150	106.2	164.3	121	190	12.5	4.8	15.1	5.1	20.9	8.7
2200	181.7	249.7	205	286	20.1	6.2	26.5	7.3	55.5	12.1

4. Damages modeling

In the novel futility analysis EPA conducted in the Final Rule, EPA only considered how US onroad vehicle GHG emissions would impact global mean surface temperature and global sea level rise. In doing so, EPA failed to consider how that temperature and sea level increase would directly impact Americans' public health and welfare. This section, we illustrate how EPA could have quantified damages through the social cost of GHGs (SC-GHGs). We present this analysis for Scenario A based on EPA's emissions inputs, as well as for the higher emissions values in the two additional Scenarios B and C described above. We also present a

[20] We believe EPA took the median projected value in each modeled year, from among the 841 simulations run in FaIR and BRICK. We believe that the MLE and Med2100 methods represent technically more robust ways to think about local sea level rise impacts, because they rely on a single, consistent simulation across all years. The location of the ice melt, Greenland or Antarctica, makes a large difference on the resulting local sea level rise because of the impacts of gravity. Using one consistent set of parameters ensures we do not jump half way through from an ensemble run with high levels of Greenland melt to a run with high levels of Antarctic melt which would mean very different outcomes for local sea level. To be consistent with EPA's approach, we also projected global sea level rise using the method we believe EPA used.

quantification of damages from Jessica Wentz based on a framework developed by Abram et al. These analyses further demonstrate that EPA cannot reasonably base its futility finding on the analysis in the Final Rule and that its finding is arbitrary and capricious.

The purpose of this analysis is to highlight that EPA's new futility methodology—of comparing proportional global mean surface temperature and global sea level rise projections to alleged and unsupported *de minimis* thresholds—is fundamentally absurd as it obscures the very thing for which EPA claims to rely on it: determining whether vehicle GHG emission standards have or could have meaningful impacts on U.S. health and welfare dangers from climate change. To the contrary, EPA's sole focus on the intermediate metrics of temperature and sea level masks massive and catastrophic impacts to human health and welfare endpoints. We do not intend this analysis to provide definitive quantifications of harm or to define specific modeling tools that EPA should have used.[21] These critiques are additional to the public comments, which presented robust demonstrations of the health and welfare harms from vehicle GHGs and the corresponding benefits of GHG emission standards.

a. Global Social Cost of GHGs

i. Methodology

EDF used the social cost of greenhouse gas estimates included in the November 2023 EPA's "Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances."[22] We calculated the social cost associated with CO_2 for Scenario A and CO_2, CH_4, and N_2O for Scenarios B and C. We converted the values into 2024$ and discounted all three scenarios to 2027.

ii. Results

Under a 2% discount rate, Tables 18 and 19 show that Scenario A would impose an estimated $23.3 trillion in global climate costs by 2200 while Scenario B would be even costlier at nearly $30 trillion. And if EPA had never adopted GHG emissions standards (Scenario C), the cost of global climate damages could reach $39 trillion by 2200 (Table 20).

Table 18: Climate Costs from Scenario A CO2 Emissions (trillion 2024$)

	2.50%	2.0%	1.5%
2050	$4.5	$7.3	$12.7
2100	$10.1	$17.6	$32.0
2150	$11.9	$21.7	$41.9
2200	$12.4	$23.3	$46.6

Table 19: Climate Costs from Scenario B CO2, CH4, and N2O Emissions (trillion 2024$)

	2.50%	2.0%	1.5%
2050	$4.4	$7.3	$12.6
2100	$11.5	$20.2	$37.1
2150	$14.3	$26.7	$52.5
2200	$15.3	$29.6	$61.3

[21] We are not providing new modeling of the other impacts of repealing the GHG program, such as increased fuel consumption or criteria pollutant harms. As commenters explained, those impacts are enormous and further demonstrate the benefits and reasonableness of the GHG program.

[22] EPA, Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, 2023. https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf

Table 20: Climate Costs from Scenario C CO2, CH4, and N2O Emissions (trillion 2024$)

	2.50%	2.0%	1.5%
2050	$6.5	$5.0	$9.0
2100	$16.9	$25.1	$47.4
2150	$21.1	$34.3	$69.1
2200	$22.5	$38.9	$81.5

b. Abram et al. Framework

Since the promulgation of the final rule, other experts have also examined EPA's futility analysis and concluded that EPA's emissions inputs and global mean surface temperature and global sea level rise changes are associated with massive health and welfare impacts. For example, Jessica Wentz (2026) published an analysis based on the quantification framework based on Abram et al. (2025) and concluded that the 0.037°C global mean surface temperature increase projected by EPA for 2100 corresponds with large concrete harms, including "(i) approximately 48.5 million additional people exposed to unprecedented extreme heat; (ii) approximately 33.4 million additional people left outside of the human climate niche, and (iii) the death of an additional ~ 1.5 billion coral colonies in the Great Barrier Reef during every future mass bleaching event."[23] This analysis, based on distinct methods, further shows that that EPA's analytical approach to futility arbitrarily obscures massive harms.[24]

[23] Jessica Wentz, Responding to EPA's Claim that U.S. Motor Vehicle Emissions Have a "De Minimis" Impact on Climate-Related Harms, *Climate Change: A Sabin Center Blog* (Feb. 20, 2026), https://blogs.law.columbia.edu/climatechange/2026/02/20/responding-to-epas-claim-that-u-s-motor-vehicle-emissions-have-a-de-minimis-impact-on-climate-related-harms/; Abram, N.J., Maher, N., Perkins-Kirkpatrick, S. *et al.* Quantifying the regional to global climate impacts of individual fossil fuel projects to inform decision-making. *npj Clim. Action* **4**, 92 (2025). https://doi.org/10.1038/s44168-025-00296-5.

[24] Another recent study highlighted how such assessing damages over the longer term, such as through the year 2300, provide a fuller accounting of damages. See Burke, M., Zahid, M., Diffenbaugh, N.S. et al. Quantifying climate loss and damage consistent with a social cost of carbon. Nature 651, 959–966 (2026). https://doi.org/10.1038/s41586-026-10272-6. This study further highlights that looking solely at global temperature and sea level rise impacts in the 2050 and 2100 timeframes can obscure the full harms to health and welfare.

Addendum A

Table A1: Circa-2009 GHG Emission Factors for Gasoline-Fueled Vehicles (g/mile)					
Model Year	sourceTypeID	RegClassID	CO2	Methane	N2O
2007	11	10	395	0.15	0.003
2007	21	20	390	0.02	0.006
2007	31	30	558	0.02	0.008
2007	32	30	548	0.02	0.008
2010	31	41	887	0.04	0.037
2010	32	41	907	0.04	0.037
2010	52	41	1103	0.04	0.100
2010	53	41	1046	0.02	0.022
2010	54	41	1114	0.03	0.020
2010	41	42	1912	0.08	0.033
2010	42	42	1829	0.07	0.030
2010	43	42	1368	0.05	0.035
2010	52	42	1183	0.08	0.100
2010	53	42	1115	0.03	0.022
2010	54	42	1199	0.05	0.020
2010	41	46	2033	0.10	0.033
2010	42	46	1947	0.09	0.030
2010	43	46	1501	0.06	0.035
2013	51	46	2092	0.09	0.007
2011	52	46	1495	0.09	0.027
2011	53	46	1388	0.04	0.006
2010	54	46	1493	0.07	0.020
2009	41	47	1618	0.05	0.033
2009	42	47	1547	0.05	0.030
2009	52	47	1499	0.09	0.100
2009	53	47	1387	0.03	0.022
2010	54	47	1881	0.09	0.020

Table A2: Circa-2009 GHG Emission Factors for Diesel Vehicles (g/mile)					
Model Year	sourceTypeID	RegClassID	CO2	Methane	N2O
2009	21	20	425	0.09	0.001
2007	31	30	791	0.10	0.001
2007	32	30	779	0.10	0.001
2009	31	41	828	0.09	0.015
2009	32	41	846	0.09	0.016
2009	52	41	1149	0.13	0.021
2009	53	41	1070	0.07	0.020
2009	54	41	1186	0.07	0.022
2010	41	42	1549	0.06	0.213
2010	42	42	1510	0.05	0.208
2009	43	42	1254	0.08	0.023
2009	52	42	1172	0.13	0.022
2009	53	42	1093	0.07	0.021
2009	54	42	1192	0.07	0.022
2010	41	46	1773	0.05	0.244
2010	42	46	1719	0.05	0.236
2010	43	46	1365	0.04	0.187
2010	51	46	1829	0.05	0.252
2010	52	46	1321	0.07	0.181
2010	53	46	1234	0.03	0.170
2010	54	46	1323	0.04	0.182
2010	61	46	1839	0.05	0.253
2007	62	46	1764	0.12	0.033
2010	41	47	1896	0.10	0.261
2010	43	47	1489	0.08	0.204
2010	51	47	1962	0.09	0.270
2010	52	47	1615	0.12	0.221
2010	53	47	1505	0.07	0.207
2010	54	47	1610	0.08	0.221
2010	61	47	1971	0.08	0.272
2010	62	47	1969	0.07	0.268
2010	42	48	1818	0.09	0.250
2010	61	49	1855	0.00	0.003
2010	62	49	1865	0.00	0.002

Table A3: Circa-2009 GHG Emission Factors for CNG-Fueled Vehicles (g/mile)					
Model Year	sourceTypeID	RegClassID	CO2	Methane	N2O
2010	41	47	1697	29.06	0.115
2010	43	47	1352	25.00	0.125
2010	51	47	1785	30.31	0.091
2010	52	47	1486	27.74	0.368
2010	53	47	1394	25.48	0.077
2010	61	47	1705	22.93	0.078
2012	62	47	1669	18.57	0.040
2010	42	48	1616	25.83	0.106

Table A4: Circa-2009 GHG Emission Factors for E85-Fueled Vehicles (g/mile)					
Model Year	sourceTypeID	RegClassID	CO2	Methane	N2O
2007	21	20	381	0.04	0.006
2007	31	30	546	0.04	0.008
2007	32	30	536	0.04	0.008

Table A5: Annual CO2, CH4, N2O and CO2e emissions from US onroad vehicles

All units million metric tons

	Scen A	Scen B				Scen C			
	CO2	CO2	CH4	N2O	CO2e	CO2	CH4	N2O	CO2e
2009						1,719	0.250	0.066	1,743
2010						1,730	0.232	0.064	1,753
2011						1,714	0.221	0.064	1,737
2012						1,748	0.205	0.066	1,772
2013						1,765	0.198	0.068	1,788
2014						1,792	0.195	0.071	1,817
2015						1,835	0.193	0.073	1,860
2016						1,889	0.195	0.078	1,915
2017						1,928	0.192	0.080	1,955
2018						1,959	0.192	0.082	1,986
2019						1,965	0.188	0.083	1,992
2020						1,795	0.167	0.081	1,821
2021						1,945	0.181	0.089	1,974
2022						1,985	0.190	0.090	2,014
2023						2,010	0.191	0.091	2,039
2024						2,009	0.198	0.092	2,039
2025						2,033	0.208	0.093	2,064
2026						2,045	0.215	0.094	2,076
2027	1,626	1,529	0.131	0.1	1,553	2,054	0.223	0.096	2,085
2028	1,606	1,507	0.134	0.077	1,532	2,059	0.229	0.096	2,091
2029	1,591	1,488	0.137	0.077	1,513	2,065	0.235	0.097	2,097
2030	1,572	1,472	0.140	0.077	1,497	2,072	0.239	0.098	2,105
2031	1,554	1,457	0.145	0.077	1,482	2,078	0.244	0.098	2,111

2032	1,533	1,442	0.150	0.077	1,467	2,081	0.250	0.099	2,114
2033	1,518	1,427	0.154	0.076	1,452	2,082	0.255	0.099	2,116
2034	1,499	1,416	0.158	0.076	1,440	2,085	0.261	0.099	2,119
2035	1,485	1,406	0.162	0.075	1,430	2,086	0.267	0.099	2,120
2036	1,468	1,398	0.164	0.075	1,423	2,089	0.273	0.100	2,123
2037	1,454	1,395	0.168	0.075	1,419	2,095	0.280	0.100	2,130
2038	1,441	1,394	0.173	0.075	1,419	2,103	0.289	0.100	2,137
2039	1,430	1,395	0.179	0.075	1,419	2,110	0.300	0.101	2,145
2040	1,420	1,398	0.187	0.074	1,423	2,119	0.315	0.101	2,155
2041	1,414	1,401	0.195	0.074	1,426	2,127	0.331	0.101	2,163
2042	1,405	1,405	0.205	0.074	1,431	2,135	0.350	0.101	2,172
2043	1,399	1,409	0.215	0.074	1,435	2,142	0.369	0.102	2,179
2044	1,395	1,413	0.227	0.074	1,439	2,147	0.390	0.102	2,185
2045	1,391	1,419	0.241	0.074	1,445	2,154	0.412	0.102	2,193
2046	1,389	1,426	0.256	0.074	1,452	2,162	0.435	0.102	2,201
2047	1,389	1,434	0.273	0.074	1,461	2,171	0.459	0.102	2,211
2048	1,388	1,443	0.292	0.074	1,471	2,181	0.485	0.103	2,222
2049	1,390	1,454	0.312	0.074	1,483	2,194	0.514	0.103	2,236
2050	1,390	1,467	0.333	0.074	1,495	2,207	0.546	0.104	2,250
2051	1,388	1,479	0.356	0.074	1,508	2,220	0.581	0.104	2,264
2052	1,385	1,491	0.380	0.074	1,522	2,234	0.618	0.105	2,279
2053	1,383	1,504	0.406	0.074	1,535	2,247	0.659	0.105	2,293
2054	1,380	1,518	0.433	0.074	1,550	2,261	0.703	0.105	2,309
2055	1,376	1,531	0.463	0.075	1,564	2,275	0.751	0.106	2,324
2056	1,376	1,545	0.496	0.075	1,579	2,289	0.802	0.106	2,340
2057	1,376	1,560	0.531	0.075	1,594	2,303	0.858	0.107	2,355
2058	1,376	1,574	0.570	0.075	1,610	2,317	0.917	0.107	2,371
2059	1,376	1,589	0.611	0.075	1,626	2,332	0.981	0.107	2,388
2060	1,376	1,604	0.655	0.075	1,642	2,346	1.048	0.107	2,404
2061	1,376	1,612	0.659	0.076	1,650	2,358	1.055	0.108	2,416
2062	1,376	1,620	0.664	0.076	1,659	2,370	1.062	0.109	2,429
2063	1,376	1,628	0.668	0.076	1,667	2,382	1.069	0.110	2,441
2064	1,376	1,636	0.672	0.077	1,676	2,394	1.076	0.110	2,454
2065	1,376	1,644	0.677	0.077	1,684	2,406	1.083	0.111	2,466
2066	1,376	1,653	0.681	0.078	1,692	2,418	1.090	0.112	2,479
2067	1,376	1,661	0.686	0.078	1,701	2,431	1.097	0.112	2,491
2068	1,376	1,669	0.690	0.079	1,709	2,443	1.103	0.113	2,503
2069	1,376	1,677	0.694	0.079	1,718	2,455	1.110	0.114	2,516
2070	1,376	1,685	0.699	0.080	1,726	2,467	1.117	0.115	2,528
2071	1,376	1,693	0.703	0.080	1,734	2,479	1.124	0.115	2,541
2072	1,376	1,701	0.707	0.081	1,743	2,491	1.131	0.116	2,553
2073	1,376	1,710	0.712	0.081	1,751	2,503	1.138	0.117	2,566
2074	1,376	1,718	0.716	0.082	1,760	2,515	1.145	0.117	2,578

2075	1,376	1,726	0.720	0.082	1,768	2,527	1.152	0.118	2,590
2076	1,376	1,734	0.725	0.083	1,776	2,539	1.159	0.119	2,603
2077	1,376	1,742	0.729	0.083	1,785	2,551	1.166	0.120	2,615
2078	1,376	1,750	0.734	0.084	1,793	2,563	1.173	0.120	2,628
2079	1,376	1,759	0.738	0.084	1,802	2,575	1.179	0.121	2,640
2080	1,376	1,767	0.742	0.085	1,810	2,587	1.186	0.122	2,653
2081	1,376	1,775	0.747	0.085	1,818	2,599	1.193	0.122	2,665
2082	1,376	1,783	0.751	0.086	1,827	2,611	1.200	0.123	2,677
2083	1,376	1,791	0.755	0.086	1,835	2,623	1.207	0.124	2,690
2084	1,376	1,799	0.760	0.087	1,843	2,635	1.214	0.124	2,702
2085	1,376	1,807	0.764	0.087	1,852	2,647	1.221	0.125	2,715
2086	1,376	1,816	0.769	0.088	1,860	2,659	1.228	0.126	2,727
2087	1,376	1,824	0.773	0.088	1,869	2,671	1.235	0.127	2,740
2088	1,376	1,832	0.777	0.089	1,877	2,683	1.242	0.127	2,752
2089	1,376	1,840	0.782	0.089	1,885	2,696	1.249	0.128	2,764
2090	1,376	1,848	0.786	0.089	1,894	2,708	1.255	0.129	2,777
2091	1,376	1,856	0.790	0.090	1,902	2,720	1.262	0.129	2,789
2092	1,376	1,864	0.795	0.090	1,911	2,732	1.269	0.130	2,802
2093	1,376	1,873	0.799	0.091	1,919	2,744	1.276	0.131	2,814
2094	1,376	1,881	0.803	0.091	1,927	2,756	1.283	0.132	2,827
2095	1,376	1,889	0.808	0.092	1,936	2,768	1.290	0.132	2,839
2096	1,376	1,897	0.812	0.092	1,944	2,780	1.297	0.133	2,851
2097	1,376	1,905	0.817	0.093	1,953	2,792	1.304	0.134	2,864
2098	1,376	1,913	0.821	0.093	1,961	2,804	1.311	0.134	2,876
2099	1,376	1,921	0.825	0.094	1,969	2,816	1.318	0.135	2,889
2100	1,376	1,930	0.830	0.094	1,978	2,828	1.325	0.136	2,901
2101	1,376	1,938	0.834	0.095	1,986	2,840	1.332	0.137	2,914
2102	1,376	1,946	0.838	0.095	1,995	2,852	1.338	0.137	2,926
2103	1,376	1,954	0.843	0.096	2,003	2,864	1.345	0.138	2,938
2104	1,376	1,962	0.847	0.096	2,011	2,876	1.352	0.139	2,951
2105	1,376	1,970	0.851	0.097	2,020	2,888	1.359	0.139	2,963
2106	1,376	1,979	0.856	0.097	2,028	2,900	1.366	0.140	2,976
2107	1,376	1,987	0.860	0.098	2,037	2,912	1.373	0.141	2,988
2108	1,376	1,995	0.865	0.098	2,045	2,924	1.380	0.142	3,001
2109	1,376	2,003	0.869	0.099	2,053	2,936	1.387	0.142	3,013
2110	1,376	2,011	0.873	0.099	2,062	2,949	1.394	0.143	3,025
2111	1,376	2,019	0.878	0.100	2,070	2,961	1.401	0.144	3,038
2112	1,376	2,027	0.882	0.100	2,079	2,973	1.408	0.144	3,050
2113	1,376	2,036	0.886	0.101	2,087	2,985	1.414	0.145	3,063
2114	1,376	2,044	0.891	0.101	2,095	2,997	1.421	0.146	3,075
2115	1,376	2,052	0.895	0.102	2,104	3,009	1.428	0.147	3,088
2116	1,376	2,060	0.899	0.102	2,112	3,021	1.435	0.147	3,100
2117	1,376	2,068	0.904	0.103	2,121	3,033	1.442	0.148	3,112

2118	1,376	2,076	0.908	0.103	2,129	3,045	1.449	0.149	3,125
2119	1,376	2,084	0.913	0.103	2,137	3,057	1.456	0.149	3,137
2120	1,376	2,093	0.917	0.104	2,146	3,069	1.463	0.150	3,150
2121	1,376	2,101	0.921	0.104	2,154	3,081	1.470	0.151	3,162
2122	1,376	2,109	0.926	0.105	2,163	3,093	1.477	0.152	3,175
2123	1,376	2,117	0.930	0.105	2,171	3,105	1.484	0.152	3,187
2124	1,376	2,125	0.934	0.106	2,179	3,117	1.490	0.153	3,199
2125	1,376	2,133	0.939	0.106	2,188	3,129	1.497	0.154	3,212
2126	1,376	2,141	0.943	0.107	2,196	3,141	1.504	0.154	3,224
2127	1,376	2,150	0.947	0.107	2,205	3,153	1.511	0.155	3,237
2128	1,376	2,158	0.952	0.108	2,213	3,165	1.518	0.156	3,249
2129	1,376	2,166	0.956	0.108	2,221	3,177	1.525	0.156	3,262
2130	1,376	2,174	0.961	0.109	2,230	3,189	1.532	0.157	3,274
2131	1,376	2,182	0.965	0.109	2,238	3,201	1.539	0.158	3,286
2132	1,376	2,190	0.969	0.110	2,247	3,214	1.546	0.159	3,299
2133	1,376	2,198	0.974	0.110	2,255	3,226	1.553	0.159	3,311
2134	1,376	2,207	0.978	0.111	2,263	3,238	1.560	0.160	3,324
2135	1,376	2,215	0.982	0.111	2,272	3,250	1.566	0.161	3,336
2136	1,376	2,223	0.987	0.112	2,280	3,262	1.573	0.161	3,349
2137	1,376	2,231	0.991	0.112	2,289	3,274	1.580	0.162	3,361
2138	1,376	2,239	0.996	0.113	2,297	3,286	1.587	0.163	3,373
2139	1,376	2,247	1.000	0.113	2,305	3,298	1.594	0.164	3,386
2140	1,376	2,256	1.004	0.114	2,314	3,310	1.601	0.164	3,398
2141	1,376	2,264	1.009	0.114	2,322	3,322	1.608	0.165	3,411
2142	1,376	2,272	1.013	0.115	2,331	3,334	1.615	0.166	3,423
2143	1,376	2,280	1.017	0.115	2,339	3,346	1.622	0.166	3,436
2144	1,376	2,288	1.022	0.116	2,347	3,358	1.629	0.167	3,448
2145	1,376	2,296	1.026	0.116	2,356	3,370	1.636	0.168	3,460
2146	1,376	2,304	1.030	0.116	2,364	3,382	1.643	0.169	3,473
2147	1,376	2,313	1.035	0.117	2,372	3,394	1.649	0.169	3,485
2148	1,376	2,321	1.039	0.117	2,381	3,406	1.656	0.170	3,498
2149	1,376	2,329	1.044	0.118	2,389	3,418	1.663	0.171	3,510
2150	1,376	2,337	1.048	0.118	2,398	3,430	1.670	0.171	3,523
2151	1,376	2,345	1.052	0.119	2,406	3,442	1.677	0.172	3,535
2152	1,376	2,353	1.057	0.119	2,414	3,454	1.684	0.173	3,547
2153	1,376	2,361	1.061	0.120	2,423	3,467	1.691	0.174	3,560
2154	1,376	2,370	1.065	0.120	2,431	3,479	1.698	0.174	3,572
2155	1,376	2,378	1.070	0.121	2,440	3,491	1.705	0.175	3,585
2156	1,376	2,386	1.074	0.121	2,448	3,503	1.712	0.176	3,597
2157	1,376	2,394	1.078	0.122	2,456	3,515	1.719	0.176	3,610
2158	1,376	2,402	1.083	0.122	2,465	3,527	1.725	0.177	3,622
2159	1,376	2,410	1.087	0.123	2,473	3,539	1.732	0.178	3,634
2160	1,376	2,418	1.092	0.123	2,482	3,551	1.739	0.179	3,647

2161	1,376	2,427	1.096	0.124	2,490	3,563	1.746	0.179	3,659
2162	1,376	2,435	1.100	0.124	2,498	3,575	1.753	0.180	3,672
2163	1,376	2,443	1.105	0.125	2,507	3,587	1.760	0.181	3,684
2164	1,376	2,451	1.109	0.125	2,515	3,599	1.767	0.181	3,697
2165	1,376	2,459	1.113	0.126	2,524	3,611	1.774	0.182	3,709
2166	1,376	2,467	1.118	0.126	2,532	3,623	1.781	0.183	3,721
2167	1,376	2,475	1.122	0.127	2,540	3,635	1.788	0.184	3,734
2168	1,376	2,484	1.126	0.127	2,549	3,647	1.795	0.184	3,746
2169	1,376	2,492	1.131	0.128	2,557	3,659	1.801	0.185	3,759
2170	1,376	2,500	1.135	0.128	2,566	3,671	1.808	0.186	3,771
2171	1,376	2,508	1.140	0.129	2,574	3,683	1.815	0.186	3,784
2172	1,376	2,516	1.144	0.129	2,582	3,695	1.822	0.187	3,796
2173	1,376	2,524	1.148	0.129	2,591	3,707	1.829	0.188	3,808
2174	1,376	2,533	1.153	0.130	2,599	3,719	1.836	0.188	3,821
2175	1,376	2,541	1.157	0.130	2,608	3,732	1.843	0.189	3,833
2176	1,376	2,549	1.161	0.131	2,616	3,744	1.850	0.190	3,846
2177	1,376	2,557	1.166	0.131	2,624	3,756	1.857	0.191	3,858
2178	1,376	2,565	1.170	0.132	2,633	3,768	1.864	0.191	3,871
2179	1,376	2,573	1.175	0.132	2,641	3,780	1.871	0.192	3,883
2180	1,376	2,581	1.179	0.133	2,650	3,792	1.877	0.193	3,895
2181	1,376	2,590	1.183	0.133	2,658	3,804	1.884	0.193	3,908
2182	1,376	2,598	1.188	0.134	2,666	3,816	1.891	0.194	3,920
2183	1,376	2,606	1.192	0.134	2,675	3,828	1.898	0.195	3,933
2184	1,376	2,614	1.196	0.135	2,683	3,840	1.905	0.196	3,945
2185	1,376	2,622	1.201	0.135	2,692	3,852	1.912	0.196	3,958
2186	1,376	2,630	1.205	0.136	2,700	3,864	1.919	0.197	3,970
2187	1,376	2,638	1.209	0.136	2,708	3,876	1.926	0.198	3,982
2188	1,376	2,647	1.214	0.137	2,717	3,888	1.933	0.198	3,995
2189	1,376	2,655	1.218	0.137	2,725	3,900	1.940	0.199	4,007
2190	1,376	2,663	1.223	0.138	2,734	3,912	1.947	0.200	4,020
2191	1,376	2,671	1.227	0.138	2,742	3,924	1.954	0.201	4,032
2192	1,376	2,679	1.231	0.139	2,750	3,936	1.960	0.201	4,045
2193	1,376	2,687	1.236	0.139	2,759	3,948	1.967	0.202	4,057
2194	1,376	2,695	1.240	0.140	2,767	3,960	1.974	0.203	4,069
2195	1,376	2,704	1.244	0.140	2,776	3,972	1.981	0.203	4,082
2196	1,376	2,712	1.249	0.141	2,784	3,984	1.988	0.204	4,094
2197	1,376	2,720	1.253	0.141	2,792	3,997	1.995	0.205	4,107
2198	1,376	2,728	1.257	0.142	2,801	4,009	2.002	0.206	4,119
2199	1,376	2,736	1.262	0.142	2,809	4,021	2.009	0.206	4,132
2200	1,376	2,744	1.266	0.142	2,818	4,033	2.016	0.207	4,144

APPENDIX B

Technical Memorandum on the EPA Final Rule's Reliance on Global Average Temperature and Sea Level Rise Metrics

L. Delta Merner, Carly A. Phillips, Carlos Martinez and Rachel Cleetus
Union of Concerned Scientists

Memo Outline:

1) Introduction
2) Limitations of Averaging Over Spatial Scales
3) Limitations of Averaging Over Temporal Scales
4) Limitations of Ignoring Non-Linearities
5) Global Average Temperatures are the Wrong Metric for Health Impacts
6) Summary

I. Introduction

This technical memorandum supports the petition filed by Environmental Defense Fund, Natural Resources Defense Council, et al. seeking reconsideration of EPA's final rule "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards," 91 Fed. Reg. 7,686 (Feb. 18, 2026). This memo examines how EPA's recent use of global mean surface temperature (GMST) and global mean sea level (GMSL) as the only metrics to assess the impacts of climate change is contrary to the scientific consensus which shows that seemingly "small" increases in GMST and GMSL translate into profound, non-linear, and compounding[1] risks for the human health and welfare of Americans. We highlight that: (1) global average temperatures and global mean sea level rise do not account for regional variations in the U.S., which in many cases are much higher than global averages; (2) global average temperatures mask true risks to people's health and well-being because they fail to take into account climate-driven temperature extremes such as heatwaves, which are increasing in frequency and duration and are a known driver of climate-related morbidity and mortality; and (3) overlapping climate impacts can lead to compounding and cascading impacts that magnify risks to people's health and welfare—interactions that are often obscured by mean global temperature and sea level values.

Drawing on recent data, scientific reports, and peer-reviewed literature, we demonstrate that global averages obscure critical regional disparities that impact communities and economies across the country. For example, the U.S. East and Gulf Coasts are experiencing accelerating sea-level rise

[1] Singh D. et al. 2023. Focus on compound events. In Fifth National Climate Assessment. Crimmins A.R. et al (eds) USGCRP, Washington, DC, USA.

rates that significantly exceed the global mean due to ocean dynamic changes and land subsidence.[2,3] Simultaneously, many regions of the United States are warming faster than the global average, such as arctic Alaska, which has warmed at three times the global rate since 1980,[4] driving cascading ecological and infrastructural failures.[5] New England in the Northeast U.S. is also warming much more and faster than most parts of the world.[6,7] Furthermore, reliance on GMST and GMSL metrics fails to capture the intensification of local extreme weather events—hurricanes, droughts, and floods—which serve as the primary vectors for health impacts and economic disruption from climate change.[8,9,10,11] Studies also show that compounding and cascading climate risks, including those from extreme heat and sea level rise, worsen impacts on human health infrastructure and the economy.[12,13] **We argue that relying solely on global averages is a fundamentally flawed way to estimate the threat to the health and welfare of people in the U.S. and the benefits of limiting those threats.**

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[13] Ebi, Kristie L. 2025. "Understanding the Risks of Compound Climate Events and Cascading Risks." *Dialogues on Climate Change* 2 (1): 33–37. https://doi.org/10.1177/29768659241304857.

II. Limitations of Averaging Over Spatial Scales

The most significant flaw in using global averages to assess U.S. risk is the assumption of uniformity with regards to both GMST and GMSL. Sea level is not a flat bathtub that rises evenly everywhere.[14,15] It is a dynamic surface influenced by gravity, ocean currents, wind patterns, and vertical land motion. Further complicating this, the relationship between sea level and temperature is non-linear, and the rate of SLR has been accelerating faster than predicted due to thermal expansion and accelerating land ice loss.[16] Consequently, the U.S. coastline is experiencing rates of change that diverge sharply from the global mean (Fig. 1).[17,18]

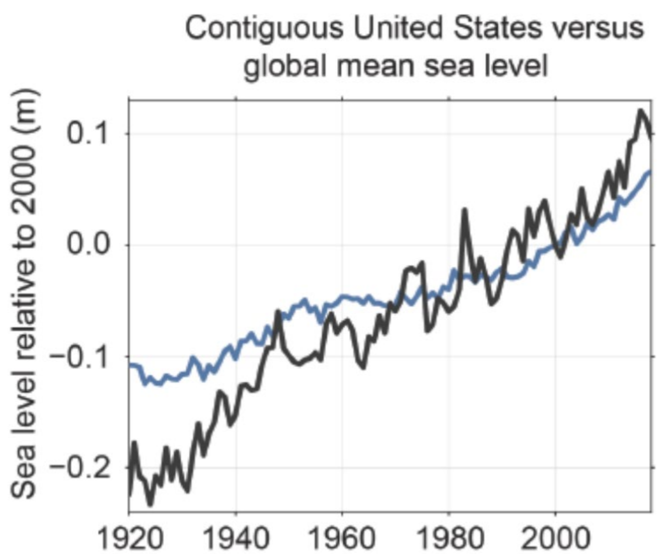

Figure 1 - GMSL change (blue line) as shown in a) with the annual average relative sea level change measured by tide gauges around the contiguous United States (black line; with a linear regression estimate of 28 cm of sea level rise from 1920 to 2020).[19,20]

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14 NASA Sea Level Change. n.d. "Are Sea Levels Rising the Same All over the World, as If We're Filling a Giant Bathtub?" https://sealevel.nasa.gov/faq/9/are-sea-levels-rising-the-same-all-over-the-world-as-if-were-filling-a-giant-bathtub/.

15 Fasullo, John T., and R. Steven Nerem. 2018. "Altimeter-Era Emergence of the Patterns of Forced Sea-Level Rise in Climate Models and Implications for the Future." *Proceedings of the National Academy of Sciences* 115 (51): 12944–49. https://doi.org/10.1073/pnas.1813233115.

16 Druckenmiller, et al. *Arctic Report Card.*

17 Fasullo, et al. *Altimeter-Era.*

18 May, Christine L., Mark S. Osler, Hilary F. Stockdon, et al. 2023. *Chapter 9 : Coastal Effects. Fifth National Climate Assessment.* Edited by Allison R. Crimmins, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Brooke C. Stewart, and Thomas K. Maycock. U.S. Global Change Research Program. https://doi.org/10.7930/NCA5.2023.CH9.

19 Sweet et al. 2022. *Global and Regional Sea Level Rise.*

20 Frederikse, Thomas, Felix Landerer, Lambert Caron, et al. 2020. "The Causes of Sea-Level Rise since 1900." *Nature* 584 (7821): 393–97. https://doi.org/10.1038/s41586-020-2591-3.

Accelerated Sea Level Rise on the East and Gulf Coasts

Recent analysis on sea level rise for U.S. coastal communities show that the East and Gulf Coasts are consistently hotspots for sea-level rise .[21,22,23] A 2025 study by the Woods Hole Oceanographic Institution found that the rate of relative sea-level rise - measured relative to the local land surface - along the U.S. coast has more than doubled in the past 125 years, increasing from approximately 1.7 millimeters per year in 1900 to over 4.3 millimeters per year in 2024.[24] This rate is well above the global average for sea-level rise **of ~3.1 mm/year** observed in recent decades[25].

The William & Mary Virginia Institute of Marine Science 2024 Sea Level Report Cards, which analyze data from 36 U.S. coastal communities, confirm this acceleration which can be compared to the global average. The report cards show that sea level rise acceleration rates began increasing notably around 2013-2014 along the East and Gulf Coasts.[26] Most sea level projections are based on an understanding of average global sea level rise, but these local report cards demonstrate that the reality for U.S. coastal communities diverges significantly from global averages due to regional factors. Along the East and Gulf Coasts, land subsidence, changes in ocean currents, and glacial isostatic adjustment creates hotspots where relative sea level rise can exceed global averages. For instance, Grand Isle, Louisiana, is currently experiencing a rise rate of 7.72 mm/year, while Rockport, Texas, and Norfolk, Virginia, face rates of 6.71 mm/year and 5.14 mm/year, respectively—far outpacing the global mean of approximately 3.1 mm/year. [27,28] Other regions may experience slower rates. Such spatial variability means communities face divergent risks that global projections do not capture.

Disproportionate Warming Rates

Many regions of the U.S. are experiencing disproportionate warming rates compared to the global average. For most years since the 1970s, the average surface temperature in the U.S. has risen faster than the global average temperature.[29,30] The 5th US National Climate Assessment states that the

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21 Boon, John D., Molly Mitchell, Jon Derek Loftis, and David L. Malmquist. 2018. *Anthropocene Sea Level Change: A History of Recent Trends Observed in the U.S. East, Gulf, and West Coast Regions.* https://doi.org/10.21220/V5T17T.

22 Sallenger, Asbury H., Kara S. Doran, and Peter A. Howd. 2012. "Hotspot of Accelerated Sea-Level Rise on the Atlantic Coast of North America." *Nature Climate Change* 2 (12): 884–88. https://doi.org/10.1038/nclimate1597.

23 Sweet et al. 2022. *Global and Regional Sea Level Rise*

24 Piecuch. *Rate of U.S. Coastal Sea-Level Rise*

25 Sweet et al. 2022. *Global and Regional Sea Level Rise*

26 Boon et al 2018. *Anthropocene Sea Level Change*

27 Sweet et al. 2022. *Global and Regional Sea Level Rise*

28 Boon et al 2018. *Anthropocene Sea Level Change*

29 U.S. Environmental Protection Agency. (2024). Climate change indicators in the United States (Fifth ed., EPA 430-R-24-003). www.epa.gov/climate-indicators

30 Jay, A.K., A.R. Crimmins, C.W. Avery, T.A. Dahl, R.S. Dodder, B.D. Hamlington, A. Lustig, K. Marvel, P.A. Méndez-Lazaro, M.S. Osler, A. Terando, E.S. Weeks, and A. Zycherman, 2023: Ch. 1. Overview: Understanding risks, impacts, and responses. In: *Fifth National Climate Assessment*. Crimmins, A.R., C.W.

continental U.S. has warmed 60% faster than the global average since 1970.[31] This is in part due to land areas warming faster than oceans, but also results from regional climate dynamics. This means that the historical and projected warming that Americans experience where they live is inherently higher than the 'global average' temperatures commonly reported (Fig. 2).

For example, Alaska is warming significantly faster than the global average (Fig.2). This phenomenon is called arctic amplification and is driven by the loss of reflective sea ice and snow that drives the Arctic region to warm significantly faster than the global average. When bright, reflective ice melts, it exposes darker ocean waters that absorb more heat from the sun, creating a feedback loop that accelerates warming. The smallest peak sea ice extent in the 47-year satellite record occurred in March 2025.[32]

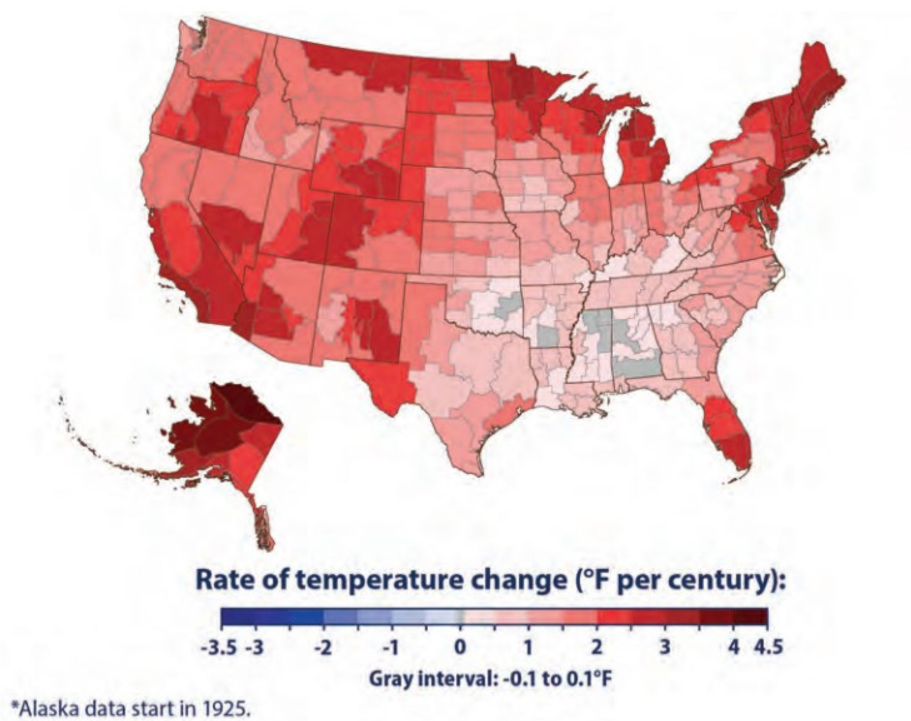

Figure 2 – Rate of Temperature change in the U.S. between 1901 and 2023 for the contiguous 48 states and between 1925 and 2023 for Alaska. The data are shown for climate divisions, as defined by NOAA.[33]

Avery, D.R. Easterling, K.E. Kunkel, B.C. Stewart, and T.K. Maycock, Eds. U.S. Global Change Research Program, Washington, DC, USA.

[31] Marvel, Kate, Wenying Su, Roberto Delgado, et al. 2023. *Chapter 2 : Climate Trends. Fifth National Climate Assessment*. Edited by Allison R. Crimmins, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Brooke C. Stewart, and Thomas K. Maycock. U.S. Global Change Research Program. https://doi.org/10.7930/NCA5.2023.CH2.

[32] NOAA in the Arctic. 2025. "Arctic Report Card: Update for 2025." https://arctic.noaa.gov/report-card/report-card-2025/.

[33] U.S. Environmental Protection Agency. *Climate change indicators in the United States.*

Findings from the 2025 Arctic Report Card, released by NOAA, confirm that the Arctic, globally, has warmed more than three times faster than the rest of the planet since 1980.[34] For the period of October 2024 through September 2025, the Arctic experienced its warmest temperatures on record since measurements began in 1900. The last ten years in the Arctic are the ten warmest on record, with annual temperatures increasing at more than double the global rate since 2006 (Fig. 3).[35]

The Alaska Climate Research Center reported 2025 as one of Alaska's warmest years in the past 100, with northern Alaska exhibiting warming consistent with this broader Arctic pattern.[36] Elevated temperatures throughout the year contributed to diminished spring snowpack, earlier snowmelt, and increased wildfire risk, with Interior Alaska experiencing the most pronounced effects.[37]

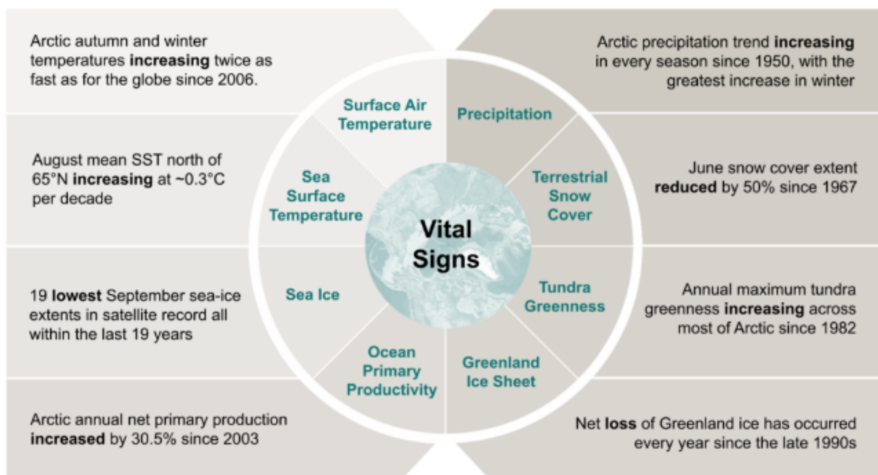

Fig. 1. Arctic Report Card Vital Signs with selected noteworthy trends and observations. The ARC annually reports on eight Vital Sign topics. Vital Sign data records vary in length based on dataset availability and considerations to methodological continuity. The historical record periods are used when computing ranked observations. When reporting anomalies, Vital Signs currently use 1991-2020 as the 30-year reference period, except for Tundra Greenness (2000-24) and Ocean Primary Productivity (2003-24).

Figure 3 - Summary of key Arctic "Vital Signs" showing major environmental changes. Indicators include temperature, precipitation, snow cover, sea ice, ocean productivity, tundra greenness, and the Greenland Ice Sheet. Overall, the Arctic is warming rapidly, with declining ice and snow and increasing precipitation and vegetation.[38]

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[34] NOAA. *Arctic Report Card.*
[35] NOAA. *Arctic Report Card.*
[36] *2025 Alaska Annual Climate Report*. 2025. Alaska Climate Research Center: The Alaska State Climate Center. https://akclimate.org/data/annual-reports/.
[37] *2025 Alaska Annual Climate Report.*
[38] NOAA. *Arctic Report Card.*

Another example is in the U.S. Northeast, the fastest warming region in the contiguous U.S.[39] Many Northeast states including Maine,[40] New Jersey,[41] and Rhode Island,[42] have had a 3°F (~1.7°C) to 4°F (~2.2°C) increase in their average temperature since the early 20th Century, nearly twice the rate of global average warming. Studies attribute this amplified regional warming to a combination of anthropogenic-influenced factors: rapid ocean warming across the Northeast continental shelf and consequent regional atmospheric circulation changes,[43] decreasing snow cover that amplify land-warming,[44] and the disproportionate warming of nighttime and winter temperatures relative to daytime and summer temperatures in higher latitudes.[45]

III. Limitations of Averaging Over Temporal Scales

There are also limitations when averaging GMST and GMSL over temporal scales to assess U.S. risk. Mean temperatures alone cannot capture changes in extremes; extremes are impacted by changes to their mean and distribution. Therefore, averaging GMST over a specific time-period may not account for the distributional shifts of extreme events over that period. In fact, data show that GMST masks the increase in heat-related extremes, including multi-day heatwaves, which are consequential for heat- related adverse health outcomes.[46]

For example, in the United States, the annual number of heatwaves has doubled since the 1980s and the heatwave season has increased threefold in length since the 1960s.[47] A recent study of heat-related mortality among older adults in the United States drives home the disproportionate consequences of climate impacts, finding: "…heat waves are driving a substantial increase in deaths

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39 Karmalkar, Ambarish V., and Raymond S. Bradley. 2017. "Consequences of Global Warming of 1.5 °C and 2 °C for Regional Temperature and Precipitation Changes in the Contiguous United States." *PLOS ONE* 12 (1): e0168697. https://doi.org/10.1371/journal.pone.0168697

40 Maine Climate Council Scientific and Technical Subcommittee; Fernandez, Ivan; Marvinney, Robert; Arnold, Susie; Bacon, Linda; Barton, Andrew; Beal, Brian; Birkel, Sean; Black, Russell; Contosta, Alix; Cross, Amanda; Daigneault, Adam; Danielson, Thomas; Dickson, Stephen; DiFranco, Jeanne; Elias, Susan; Hodgkins, Glenn; Hubbell, Brian; Kelley, Joe; Kersbergen, Rick; Koehler, Glen; Lincoln, Rebecca; Livingston, William; Lombard, Pamela; Lyon, Bradfield; Pershing, Andrew; Price, Nichole; Rubin, Jonathan; Salisbury, Joseph; Simons-Legaard, Erin; Slovinsky, Peter; Steneck, Robert; Stockwell, Sally; Wahle, Richard; Wason, Jay; Weiskittel, Aaron; and Wilson, Carl, "Scientific Assessment of Climate Change and Its Effects in Maine" (2020). Climate Change. 1. https://digitalcommons.library.umaine.edu/maine_env_climate/1

41 Davies, Kathryn, Anthony J. Broccoli, James B. Shope, et al. 2025. *State of the Climate: New Jersey 2024*. Rutgers University. Application/pdf. https://doi.org/10.7282/00000539.

42 Runkle, J., K.E. Kunkel, D.R. Easterling, B.C. Stewart, S.M. Champion, L.E. Stevens, R. Frankson, W. Sweet, and J. Spaccio, 2022: Rhode Island State Climate Summary 2022. NOAA Technical Report NESDIS 150-RI. NOAA/NESDIS, Silver Spring, MD, 4 pp.

43 Karmalkar, et al. *Drivers of Exceptional Coastal Warming.*

44 Young and Young. *Decreasing Snow Cover.*

45 Marvel, et al. *Climate Trends.*

46 Davariashtiyani, Ali, Mohsen Taherkhani, Seyyedfaridoddin Fattahpour, and Sean Vitousek. 2023. "Exponential Increases in High-Temperature Extremes in North America." *Scientific Reports* 13 (1): 19177. https://doi.org/10.1038/s41598-023-41347-3.

47 Bell, Michelle L., Antonio Gasparrini, and Georges C. Benjamin. 2024. "Climate Change, Extreme Heat, and Health." *New England Journal of Medicine* 390 (19): 1793–801. https://doi.org/10.1056/NEJMra2210769.

among older US adults each year, with disproportionate impacts on Black and low income communities, while neighborhoods with more green space see lower death rates."[48] According to the study, "Across the contiguous USA from 2000–18, the 8307 observed heat waves were associated with an estimated 17,603 excess deaths."[49]

For example, since 1993, global sea level has risen by 4 inches[50] (10 centimeters), and the rate of rise has doubled over the past 30 years (Fig. 4).[51,52] In 2024, global sea level rose at a rate of 0.23 inches (0.59 cm) per year, more than 30% more than the expected rate of 0.17 inches (0.43 cm).[53] According to a NASA-led analysis, this spike was driven largely by thermal expansion—the physical expansion of seawater as it warms. In a typical year, melting ice contributes the majority of sea-level rise, with thermal expansion accounting for about one-third. However, in 2024, as the warmest year on record, this ratio flipped: two-thirds of the rise came from thermal expansion.[54] **This phenomenon illustrates that the relationship between temperature and sea level is not static over space or time**. As the ocean absorbs excess heat, the water expands. Even a "small" average temperature increase in the upper ocean layers results in a measurable, accelerating rise in sea level.

Furthermore, temperature and sea-level exhibit time-dependent responses; temporal averaging of GMST and GMSL dampens their evolving relationships, feedbacks, and underlying dynamics.

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48 Healy, James P., Edgar Castro, Mahdieh Danesh Yazdi, et al. 2026. "Heat Waves and Annual Mortality among Older Adults (Aged ≥65 Years) in the USA." *The Lancet Planetary Health* 10 (2): 101432. https://doi.org/10.1016/j.lanplh.2026.101432.

49 Healy, et al. *Heat Waves and Annual Mortality*.

50 Lee, Jane J. 2025. "NASA Analysis Shows Unexpected Amount of Sea Level Rise in 2024." NASA Sea Level Change, NASA's Jet Propulsion Laboratory, March 13. https://sealevel.nasa.gov/news/282/nasa-analysis-shows-unexpected-amount-of-sea-level-rise-in-2024/.

51 Hamlington, Benjamin D., Severine Fournier, Philip R. Thompson, and Marta Marcos. 2025. "Sea Level Rise in 2024." *Nature Reviews Earth & Environment* 6 (4): 246–48. https://doi.org/10.1038/s43017-025-00667-w.

52 Hamlington, B. D., A. Bellas-Manley, J. K. Willis, et al. 2024. "The Rate of Global Sea Level Rise Doubled during the Past Three Decades." *Communications Earth & Environment* 5 (1): 601. https://doi.org/10.1038/s43247-024-01761-5.

53 Lee. *NASA Analysis*.

54 Lee. *NASA Analysis*.

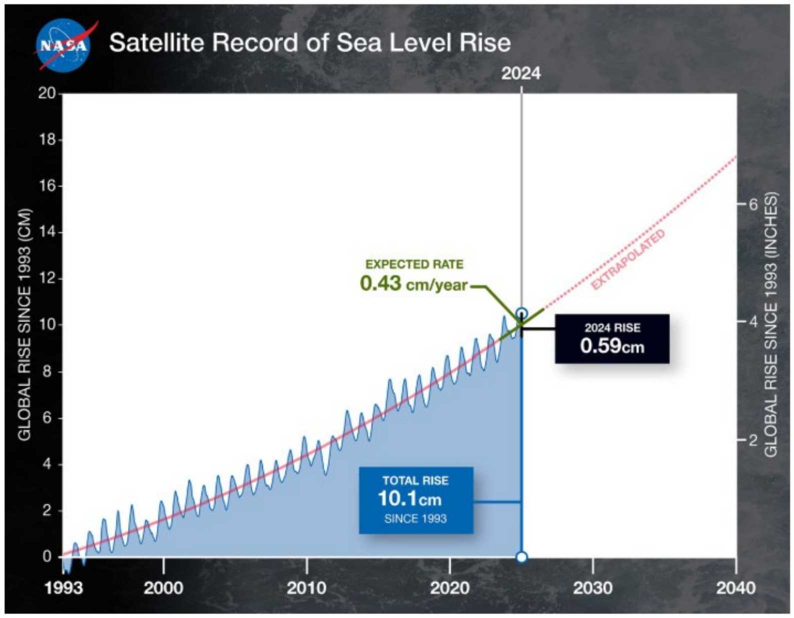

Figure 4 - Satellite-derived record of global mean sea level rise from 1993 to 2024 as measured by five satellites. The blue curve shows observed sea level change with seasonal variability, while the solid red line indicates the long-term trend, which has accelerated over time. The dotted red line indicates the trajectory of this increase. By 2024, global sea level has risen approximately 10.1 cm since 1993, with a recent annual increase of about 0.59 cm. The dotted red line represents extrapolated future rise, compared with an expected rate of 0.43 cm per year.[55]

IV. Limitations of Ignoring Non-Linearities

Limitations of Global Mean Metrics in Assessing Regional Climate Risk

In regulatory and policy discourse, descriptions of climate change that focus solely on increases in GMST and GMSL can misrepresent these changes as manageable despite strong evidence that small increments of change in global averages trigger disproportionate and potentially disruptive changes in regional climate dynamics, extreme weather frequency and/or intensity, and ecosystem stability. Many climate systems are non-linear, and the impacts of climate change are not distributed evenly across the globe.[56,57,58,59] Domestic regulatory policies must account for the discrepancy between global average impacts and the local reality for Americans. While the globe, on average, may warm by a specific margin, parts of the U.S. are experiencing temperature changes that are two to three

[55] Lee. *NASA Analysis.*
[56] Sadai, Shaina, Ambarish V. Karmalkar, David Pollard, et al. 2025. "Antarctic Meltwater Alters Future Projections of Climate and Sea Level." *Nature Communications* 16 (1): 9271. https://doi.org/10.1038/s41467-025-64438-3.
[57] Rivas, María Dolores Gadea, and Jesús Gonzalo. 2026. "Regional Heterogeneity and Warming Dominance in the United States." *PLOS Climate* 5 (2): e0000808. https://doi.org/10.1371/journal.pclm.0000808.
[58] Young and Young. *Decreasing Snow Cover.*
[59] Climate Central. 2025. "Earth Day: Fastest-Warming U.S. Cities and States." April 16. https://www.climatecentral.org/climate-matters/earth-day-fastest-warming-us-cities-and-states#cm-license.

times more severe.[60,61] Similarly, while global average sea levels rise at a seemingly moderate pace, specific American coastlines are facing accelerated flooding and inundation that threaten critical infrastructure, public health, and economic stability much sooner than global models suggest.[62,63,64,65]

The relationship between GMST and extreme weather frequency and/or intensity is governed by non-linear dynamics in the climate system. Incremental increases in atmospheric and oceanic heat content produce disproportionate changes in the distribution of weather events, such as elevated probabilities of extreme events relative to baseline conditions.[66] This phenomenon is well-documented in peer-reviewed literature, where small shifts in mean temperature correspond to non-linear increases in the frequency of threshold-exceeding events, including heat waves, heavy precipitation, drought conditions, and hydroclimate volatility.[67,68,69,70]

The impact of sea-level rise (SLR) on flooding is often exponential, not linear. As noted in peer-reviewed research, a small increase in the baseline sea level dramatically increases the frequency of high-tide flooding.[71,72] What was once a 1-in-100-year flood event can become a 1-in-10-year event with only a few inches of rise. Sea level acts as a rising floor, such that storm surges and high tides start from a higher baseline, allowing them to breach defenses that were previously sufficient.

Research published in *Scientific Reports* demonstrated that coastal flooding frequency is doubling every few years in many locations—including US Gulf Coast, East Coast, and Caribbean

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60 Druckenmiller, et al. *Arctic Report Card.*
61 Young and Young. *Decreasing Snow Cover.*
62 Piecuch. *Rate of U.S. Coastal Sea-Level Rise.*
63 Dangendorf, Sönke, Noah Hendricks, Qiang Sun, et al. 2023. "Acceleration of U.S. Southeast and Gulf Coast Sea-Level Rise Amplified by Internal Climate Variability." *Nature Communications* 14 (1): 1935. https://doi.org/10.1038/s41467-023-37649-9.
64 Gilmore, Elisabeth A., Carolyn Kousky, and Travis St.Clair. 2022. "Climate Change Will Increase Local Government Fiscal Stress in the United States." *Nature Climate Change* 12 (3): 216–18. https://doi.org/10.1038/s41558-022-01311-x.
65 Hino, Miyuki, Samanthe Tiver Belanger, Christopher B. Field, Alexander R. Davies, and Katharine J. Mach. 2019. "High-Tide Flooding Disrupts Local Economic Activity." Science Advances 5 (2): eaau2736. https://doi.org/10.1126/sciadv.aau2736.
66 IPCC. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. Chapter 12.
67 Diffenbaugh, Noah S., and Filippo Giorgi. 2012. "Climate Change Hotspots in the CMIP5 Global Climate Model Ensemble." *Climatic Change* 114 (3–4): 813–22. https://doi.org/10.1007/s10584-012-0570-x.
68 IPCC. *Impacts, Adaptation and Vulnerability.*
69 Swain, Daniel L., Andreas F. Prein, John T. Abatzoglou, et al. 2025. "Hydroclimate Volatility on a Warming Earth." *Nature Reviews Earth & Environment* 6 (1): 35–50. https://doi.org/10.1038/s43017-024-00624-z.
70 Mearns, Linda O., Richard W. Katz, and Stephen H. Schneider. 1984. "Extreme High-Temperature Events: Changes in Their Probabilities with Changes in Mean Temperature." *Journal of Climate and Applied Meteorology* 23 (12): 1601–13. https://doi.org/10.1175/1520-0450(1984)023%253C1601:EHTECI%253E2.0.CO;2.
71 Vitousek, Sean, Patrick L. Barnard, Charles H. Fletcher, Neil Frazer, Li Erikson, and Curt D. Storlazzi. 2017. "Doubling of Coastal Flooding Frequency within Decades Due to Sea-Level Rise." *Scientific Reports* 7 (1): 1399. https://doi.org/10.1038/s41598-017-01362-7.
72 Sweet et al. 2022. *Global and Regional Sea Level Rise.*

territories— due to sea-level rise, even without increases in storm intensity.[73,74] This research highlights how even 10 cm of SLR doubles flooding potential along the west coast of the US, including Seattle, San Francisco and Los Angeles,[75] highlighting that the "magnitude" of the rise is less relevant than the "frequency" of the resulting impact. A rise of a few inches can double or triple the number of days a coastal community is inundated, leading to chronic infrastructure degradation, mold growth in homes, and disruption of local economies. Related research highlights how even smaller amounts of sea level rise, between 1 and 10 cm, can lead to outsized impacts by increasing the frequency of coastal floods.[76] This underscores why looking at GLSR alone is not sufficient to understand how that change will impact Americans.

Regional Variation in Extreme Weather Event Trends

A focus on only GMST and GSLR fails to account for how changes in those metrics will lead to more frequent and intense extreme weather, the primary way that climate change harms human health and welfare. Americans do not experience "global averages"; they experience hurricanes, droughts, rainfall, heatwaves, wildfires, and floods. Climate change is contributing to the increase in frequency, duration, and/or intensity of these types of events, regardless of the magnitude of the shift in global averages. For example, data show that heatwaves are increasing in frequency and duration, especially in the western U.S. and Southeast.[77]

Similarly, warmer ocean temperatures provide more energy for hurricanes, leading to stronger, wetter, and slower-moving hurricanes.[78,79] In 2024, the U.S. experienced 27 separate weather and climate disasters with costs exceeding $1 billion each (Fig. 5).[80] Over the last decade (2015–2024), the U.S. has been impacted by 190 such disasters, costing approximately $1.4 trillion and killing more than 6,300 people (Fig. 5).[81]

These extreme events are not random; they are symptomatic of a changing climate, which is not fully captured by expressions of global mean temperatures.

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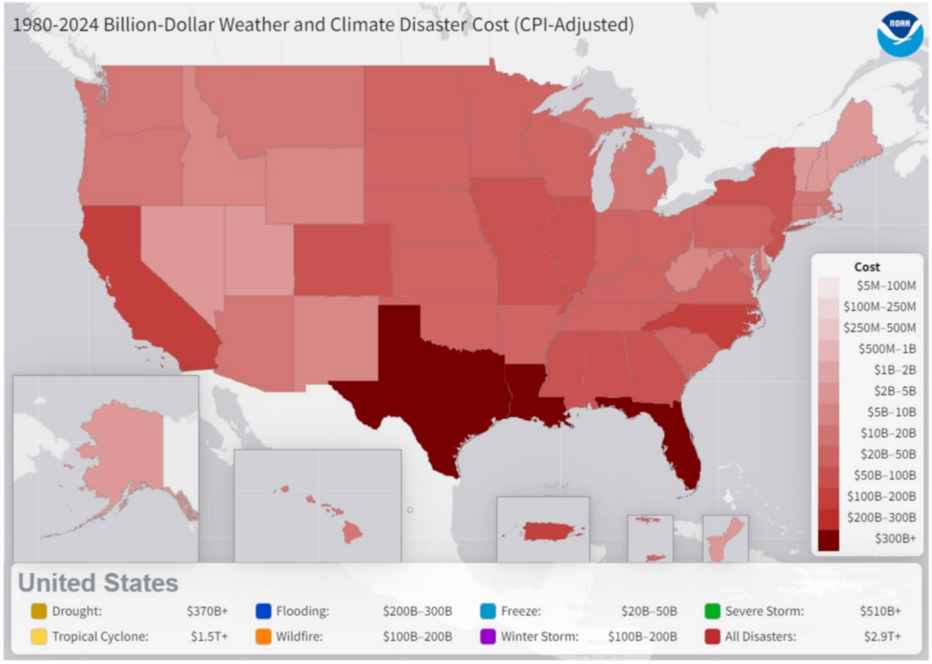
73 Sweet et al. 2022. *Global and Regional Sea Level Rise.*
74 Vitousek et al. *Doubling of Coastal Flooding.*
75 Vitousek et al. *Doubling of Coastal Flooding.*
76 Taherkhani, M., Vitousek, S., Barnard, P.L., Frazer, N., Anderson, T.A., and Charles H. Fletcher. 2020. "Sea-level rise exponentially increases coastal flood frequency." *Scientific Reports* 10, 6466. https://doi.org/10.1038/s41598-020-62188-4
77 Committee on Anthropogenic Greenhouse Gases and U.S. Climate: Evidence and Impacts, Climate Crossroads, Board on Atmospheric Sciences and Climate, et al. 2025. *Effects of Human-Caused Greenhouse Gas Emissions on U.S. Climate, Health, and Welfare*. National Academies Press. https://doi.org/10.17226/29239.
78 Kossin, James P. 2018. "A Global Slowdown of Tropical-Cyclone Translation Speed." *Nature* 558 (7708): 104–7. https://doi.org/10.1038/s41586-018-0158-3.
79 Gilford, Daniel M., Joseph Giguere, and Andrew J. Pershing. 2024. "Human-Caused Ocean Warming Has Intensified Recent Hurricanes." *Environmental Research: Climate* 3 (4): 045019. https://doi.org/10.1088/2752-5295/ad8d02.
80 Smith. *Billion-Dollar Disasters.*
81 Smith. *Billion-Dollar Disasters.*



This map depicts the total estimated cost borne by each state from billion-dollar weather and climate events from 1980-2024. Screenshot from NOAA NCEI Billion-dollar Disasters webpage.

Figure 5- Map of total costs from billion-dollar weather and climate disasters across the United States from 1980 to 2024 (CPI-adjusted). Darker shading indicates higher total damages, with the greatest costs concentrated in Gulf Coast and southeastern states.[82]

V. Global Average Temperatures are the Wrong Metric for Health Impacts[83,84]

Similarly, a focus on GMST and GSLR fails to account for the inequitably distributed health harms that stem from climate change, including extreme heat, increases in exposure to wildfire smoke, and changes to vector-borne and water-borne diseases. GMST and GSLR are spatially and temporally aggregated metrics that smooth over the regional and seasonal extremes and local variabilities where health impacts materialize. They reveal nothing about extreme events, differential exposure, vulnerability, or adaptive capacity – the factors that determine whether a temperature increase becomes a health crisis. An annual global average does not distinguish between an early season extreme heatwave or a community with air conditioning and green space versus one without; similarly, global sea level rise tells us little about which populations live near flood-prone hazardous sites. These metrics were designed to track planetary physics at an aggregated level, not human welfare, much less the welfare of Americans specifically.

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[82] Smith. *Billion-Dollar Disasters.*

[83] CDC. 2024. "About CDC's Climate and Health Program." February 9. https://www.cdc.gov/climate-health/php/about/index.html.

[84] Committee on Anthropogenic Greenhouse Gases and U.S. Climate: Evidence and Impacts, Climate Crossroads, Board on Atmospheric Sciences and Climate, et al. 2025. "Chapter 5 Impacts on Human Health." In *Effects of Human-Caused Greenhouse Gas Emissions on U.S. Climate, Health, and Welfare*. National Academies Press. https://doi.org/10.17226/29239.

GMST is the wrong indicator for health impacts because averages mask the reality of extreme heat and heatwaves or socioeconomic determinants of health, which are known to be major drivers of heat related deaths and illnesses globally and in the U.S. Climate change is already increasing the frequency, duration and intensity of heatwaves, including increases in night-time heat.[85]

Failing to consider how increases in GMST manifest on the ground in the U.S. within the U.S. obscures the extent of the human health and welfare implications. Extreme heat days are also associated with a significant increase in emergency room visits.[86] Research also shows that climate-driven extreme heat could lead to a loss of about 1.2% in U.S. GDP per degree Celsius increase in temperature, including labor costs, mortality costs and costs to major economic sectors.[87] Outdoor workers could experience an estimated $49.2 billion in annual earnings at risk by the end of the century.[88] Without action to curtail heat-trapping emissions, the incidence of extreme heat—and its impacts on people—will increase significantly in the U.S.[89] A focus solely on GMST fails to capture human health harms for Americans.

Extreme heat is the leading weather-related killer in the United States.[90] Driven by climate change, extreme heat and drought are becoming hotter, longer lasting, and more frequent.[91] The summer of 2024 was the hottest year on record for the world, however the global mean temperature reflected in that record does not capture the cascade of impacts that directly result from warmer temperatures globally and in the U.S. The long-term trend in the increase in frequency and intensity of heatwaves is a major challenge to human health, through heat exhaustion and heat stroke, and by exacerbating cardiovascular, respiratory, and kidney conditions.[92,93,94] Outdoor workers, elderly people, young

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85 Marvel, et al. *Climate Trends.*
86 Sun, Shengzhi, Kate R. Weinberger, Amruta Nori-Sarma, et al. 2021. "Ambient Heat and Risks of Emergency Department Visits among Adults in the United States: Time Stratified Case Crossover Study." *BMJ* 375 (November): e065653. https://doi.org/10.1136/bmj-2021-065653.
87 Hsiang, Solomon, Robert Kopp, Amir Jina, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science* 356 (6345): 1362–69. https://doi.org/10.1126/science.aal4369.
88 Licker, Rachel, Kristina Dahl, and John T. Abatzoglou. 2022. "Quantifying the Impact of Future Extreme Heat on the Outdoor Work Sector in the United States." *Elementa: Science of the Anthropocene* 10 (1): 00048. https://doi.org/10.1525/elementa.2021.00048.
89 Dahl, Kristina, Rachel Licker, John T. Abatzoglou, and Juan Declet-Barreto. 2019. "Increased Frequency of and Population Exposure to Extreme Heat Index Days in the United States during the 21st Century." *Environmental Research Communications* 1 (7): 075002. https://doi.org/10.1088/2515-7620/ab27cf.
90 NOAA National Weather Service. n.d. "National Weather Service." Severe Weather Awareness - Heat Waves. https://www.weather.gov/mkx/heatwaves.
91 Shindell, Drew, Yuqiang Zhang, Melissa Scott, Muye Ru, Krista Stark, and Kristie L. Ebi. 2020. "The Effects of Heat Exposure on Human Mortality Throughout the United States." *GeoHealth* 4 (4): e2019GH000234. https://doi.org/10.1029/2019GH000234.
92 Marino, et al. *Commonwealth Fund.*
93 National Academies of Sciences, Engineering, and Medicine. 2025. *Effects of Human-Caused Greenhouse Gas Emissions on U.S. Climate, Health, and Welfare.* Washington, DC: The National Academies Press.
94 Hayden, Mary H., Paul J. Schramm, Charles B. Beard, et al. 2023. *Chapter 15 : Human Health. Fifth National Climate Assessment.* Edited by Allison R. Crimmins, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Brooke C. Stewart, and Thomas K. Maycock. U.S. Global Change Research Program. https://doi.org/10.7930/NCA5.2023.CH15.

children, pregnant people, people who are unhoused, and people with pre-existing health conditions are most at risk.[95,96] The impacts of climate change compound and build on each other. Heatwaves, for example, exacerbate cardiovascular and respiratory conditions,[97,98] while compromised food and water security[99] due to extreme heat and drought increases risks of malnutrition and infectious diseases.[100] Drought also contributes to respiratory and cardiovascular-related health impacts - dry conditions increase airborne dust and particulate matter while simultaneously elevating wildfire risk, exposing populations to fine particles that penetrate deep into lungs and trigger systemic inflammation.[101,102]

A 2025 Commonwealth Fund report on climate and health highlighted that environmental hazards, many of which are exacerbated by climate change, are responsible for approximately 19% of deaths globally.[103] According to the 2025 Lancet Countdown report on Health and Climate Change, "*on average, 16 (84%) of the 19 life-threatening heatwave days that people were exposed to annually in 2020–24 would not have occurred without climate change.*"[104] In the U.S., the health care sector itself is vulnerable: nearly 15% of hospital beds in Florida are in high-hazard flood zones, and facilities across the country are ill-prepared for the increasing frequency of extreme weather.[105] The report found that states with higher environmental risks and weaker clean energy policies face greater health burdens.

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95 Romanello, Marina, Maria Walawender, Shih-Che Hsu, et al. 2024. "The 2024 Report of the Lancet Countdown on Health and Climate Change: Facing Record-Breaking Threats from Delayed Action." *The Lancet* 404 (10465): 1847–96. https://doi.org/10.1016/S0140-6736(24)01822-1.
96 Chersich, Matthew Francis, Minh Duc Pham, Ashtyn Areal, et al. 2020. "Associations between High Temperatures in Pregnancy and Risk of Preterm Birth, Low Birth Weight, and Stillbirths: Systematic Review and Meta-Analysis."
BMJ, November 4, m3811. https://doi.org/10.1136/bmj.m3811.
97 Silveira, Ismael H., Taísa Rodrigues Cortes, Michelle L. Bell, and Washington Leite Junger. 2023. "Effects of Heat Waves on Cardiovascular and Respiratory Mortality in Rio de Janeiro, Brazil." *PLOS ONE* 18 (3): e0283899. https://doi.org/10.1371/journal.pone.0283899.
98 Psistaki, Kyriaki, Panayiotis Kouis, Panayiotis K. Yiallouros, and Anastasia K. Paschalidou. 2025. "Heatwave Characteristics and Health Impacts: A Review of Epidemiological Evidence and Implications for Heatwave Response Plans." *Environmental Research: Health* 3 (4): 042003. https://doi.org/10.1088/2752-5309/ae1861.
99 Lawrence, Sarah. 2021. "Infectious Disease and Climate Change: Food & Water Scarcity." Infectious Disease and Climate Change: Food & Water Scarcity, American Security Project, November 22. https://www.americansecurityproject.org/infectious-disease-and-climate-change-food-water-scarcity/.
100 Romanello, et al. *2024 Report of the Lancet Countdown.*
101 Gwon, Yeongjin, Yuanyuan Ji, Jesse E. Bell, et al. 2023. "The Association between Drought Exposure and Respiratory-Related Mortality in the United States from 2000 to 2018." *International Journal of Environmental Research and Public Health* 20 (12): 6076. https://doi.org/10.3390/ijerph20126076.
102 Gwon, Yeongjin, Yuanyuan Ji, Azar M. Abadi, et al. 2024. "The Effect of Heterogeneous Severe Drought on All-Cause and Cardiovascular Mortality in the Northern Rockies and Plains of the United States." *Science of The Total Environment* 912 (February): 169033. https://doi.org/10.1016/j.scitotenv.2023.169033.
103 Marino, et al. *Commonwealth Fund.*
104 Romanello, Marina, Maria Walawender, Shih-Che Hsu, et al. 2025. "The 2025 Report of the Lancet Countdown on Health and Climate Change: Climate Change Action Offers a Lifeline." *The Lancet* 406 (10521): 2804–57. https://doi.org/10.1016/S0140-6736(25)01919-1.
105 Marino, et al. *Commonwealth Fund.*

The impacts of climate change are not borne equally. Scientific evidence overwhelmingly shows that marginalized communities—low-income populations, communities of color, and Indigenous groups—face disproportionate risks[106] from both sea-level rise[107] and extreme weather, a reality not captured by a focus on global average temperature and global mean sea level rise.

A *Nature Communications* study on sea-level rise and hazardous sites revealed a stark environmental justice crisis. Controlling for population density, neighborhoods with higher proportions of renters, non-voters, linguistically isolated households, and residents living in poverty are significantly more likely to be located near hazardous sites at risk of flooding They found that a one standard deviation increase in the proportion of renters is associated with an up to 41% higher likelihood of having a hazardous site within 1 kilometer.[108]

This inequity is the result of historical land-use decisions and systemic discrimination. When sea levels rise or floods occur, these communities are the first to suffer contaminant releases, displacement, and health impacts. The cumulative impact of all of these factors exacerbates the disproportionate adverse health and welfare impacts for these communities, which EPA has completely failed to account for.

The Commonwealth Fund scorecard further illustrates this inequity. States with higher environmental risks often have weaker health care infrastructure and fewer resources for adaptation.[109] For example, low-lying coastal states like Florida and Louisiana have a high percentage of health care facilities in flood zones.

A focus on GMST and GSLR fails to capture both the human health impacts of climate change and the unequal effects of these impacts across populations and communities. As such, this focus is insufficient for preparing for the risks associated with current and further climate change in the U.S.

VI. Summary

The characterization of climate change impacts based solely on global mean surface temperature and global mean sea level oversimplifies the complex challenges that arise from physical, societal, economic, and ecological impacts associated with these increases. While the global averages may appear "small" in isolation, they mask a reality of profound regional disparity and escalating risk. The U.S. East and Gulf Coasts are facing accelerated sea-level rise that inundates communities and threatens to flood hazardous sites within decades, not centuries. Alaska is warming at a rate that is destabilizing the very ground its communities stand on. Such regional differences highlight how

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[106] United States Environmental Protection Agency. 2021. "EPA Report Shows Disproportionate Impacts of Climate Change on Socially Vulnerable Populations in the United States." News Release. September 2. https://www.epa.gov/newsreleases/epa-report-shows-disproportionate-impacts-climate-change-socially-vulnerable.

[107] Cushing, Lara J., Yang Ju, Seigi Karasaki, et al. 2025. "Sea Level Rise and Flooding of Hazardous Sites in Marginalized Communities across the United States." *Nature Communications* 16 (1): 9711. https://doi.org/10.1038/s41467-025-65168-2.

[108] Cushing, et al. *Sea Level Rise.*

[109] Marino, et al. *Commonwealth Fund.*

GMST and GSLR alone are inadequate measures of the full impact of climate change on communities, ecosystems and economies across the United States. And across the nation, extreme weather events, supercharged by climate warming, are inflicting billions of dollars in damage and causing significant threats to public health, including loss of life.

Here we show how frameworks that rely on global averages to assess risk at regional and local levels can systematically underestimate the threat to American health and welfare. For many Americans, the climate crisis is not a distant future scenario defined by global averages, but a present-day emergency defined by rising waters, intensifying storms, and disproportionate harm to the most vulnerable.

APPENDIX C

Technical Memorandum on EPA's Final Rule Analysis of Variability and Measurability

Ellen Robo and Grace Hauser, Environmental Defense Fund

This technical memorandum supports the petition filed by Environmental Defense Fund, Natural Resources Defense Council, et al. seeking reconsideration of EPA's final rule "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards," 91 Fed. Reg. 7,686 (Feb. 18, 2026). This memorandum provides technical analysis demonstrating that EPA's methods for assessing temperature variability and measurability in the Final Rule were flawed and systematically biased toward overstating temperature variability and temperature and sea level measurement uncertainty.[1] Section 1 addresses temperature variability, identifying five independent errors in EPA's approach — including failure to correct for the underlying upward trend in global mean surface temperature (GMST), reliance on annual rather than multi-year averages, a potentially inaccurate use of sample rather than population standard deviation, use of an unjustified and historically anomalous reference window (2016–2025), and inadequate consideration of interval length effects— each of which inflates EPA's variability estimate. Taken together, these errors cause EPA to overstate temperature variability by as much as 85%. Section 2 addresses measurability, showing that EPA's cited source does not support its stated uncertainty value, and that multiple independent datasets report measurement uncertainties materially lower than the levels EPA deemed de minimis.

I. Temperature variability

As discussed in the body of the petition, EPA's use of "temperature variability" as a metric to determine futility is inherently arbitrary. Here we demonstrate that—even accepting EPA's fatally flawed methodology of comparing projected global mean surface temperature impacts from section 202(a) regulation to a global mean surface temperature variability metric—EPA's stated GMST variability metric is itself arbitrary and appears to be the result of an arbitrary and unjustifiable methodology. EPA's process for determining the temperature variability in the climate system was flawed for at least five reasons which materially change the final result: (1) EPA failed to correct for the underlying increasing trend in global mean surface temperature; (2) annual averages are an inappropriately short timeframe to assess whether an increase in temperature would be

[1] This memorandum accepts as the starting point EPA's basic methodology of comparing certain variability and measurability metrics to projected impacts of US vehicle GHGs in order to determine the futility of section 202(a) GHG regulation. However, as explained in the petition, the underlying methodology is fundamentally arbitrary, capricious, and contrary to law. The more discrete critiques articulated in this memorandum, including the technical methodologies and numerical figures we present, do not imply that we in any way agree with EPA's basic methodology for assessing futility.

inconsequential given the "variability" in the system; (3) EPA should have used population standard deviation and not sample standard deviation if the Agency meant to describe "variability" for 2016-2025; (4) the use of the selected time period, 2016-2025, was arbitrary and particularly unsupportable if intended to represent "variability" in 1950-2025; and (5) the use of a 10-year time interval to calculate variability was arbitrary. Each of these arbitrary and/or irrational choices operates in the direction of overstating variability and therefore overstating the degree to which the policy signal is obscured by background noise. Section 1 identifies and addresses these flaws and undermines EPA's central claim that US motor vehicle GHG regulation is futile because its temperature impact is insignificant.

A. EPA failed to correct for the underlying upward trend in global mean surface temperature (GMST).

Global mean surface temperature has risen dramatically over the past century due to increasing concentrations of GHGs, such as carbon dioxide (CO_2), in the atmosphere (Figure 2). The global mean surface temperature anomalies time series[2] referred to by EPA has a clear and well-documented upward trend (Figure 1). It is unclear precisely how EPA computed a variability statistic of 0.14°C used to support the Rescission of the Endangerment Finding[3] because the Agency's statistical methods are not documented, an arbitrary error. We were able to reconstruct EPA's result of 0.14°C by calculating the sample standard deviation of annual global mean surface temperature anomaly values for 2016-2025 from the dataset cited by EPA. In the remainder of this memorandum, we assume that EPA followed this methodology and critique it accordingly.

[2] NOAA National Centers for Environmental Information (NCEI). (2026, April). *Climate at a Glance: Global Time Series*. Published March 2026, retrieved on April 3, 2026. https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series

[3] Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards, 91 Fed. Reg. 7,686 (Feb. 18, 2026) ("Final Rule"). https://www.regulations.gov/document/EPA-HQ-OAR-2025-0194-31029

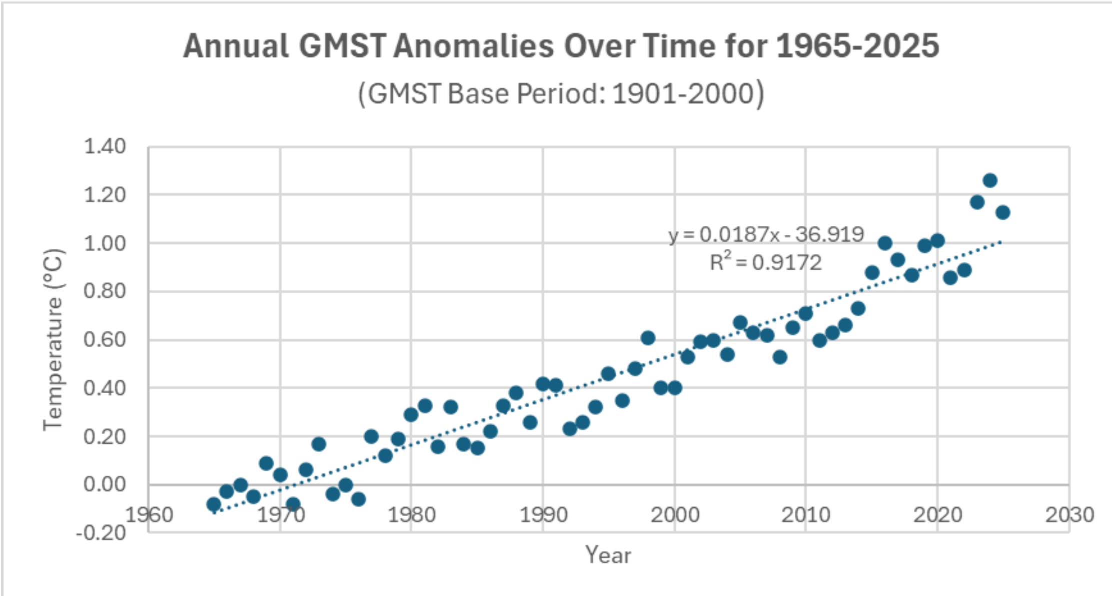

Figure 1. *Global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. time for 1965-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. Each dot represents the temperature anomaly for a given year. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.019°C/year.*

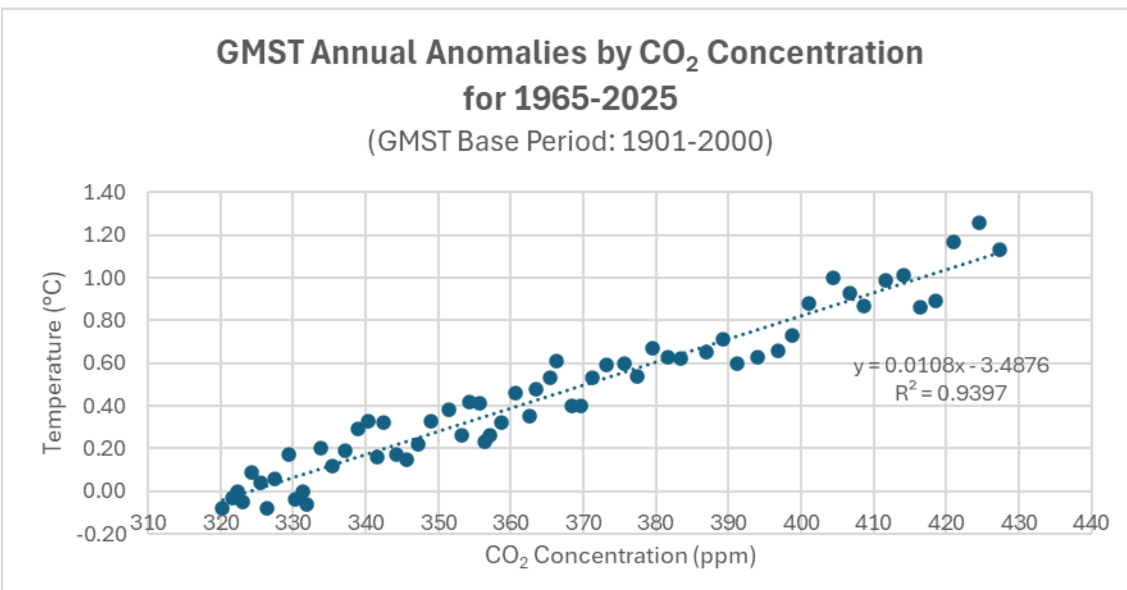

Figure 2. *Global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. Carbon dioxide (CO_2) concentration (ppm) for 1965-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. CO_2 data was sourced from NASA*[4] *for the years 1965-2011 (the most recent year*

[4] NASA Goddard Institute for Space Studies. (2012, February 6). *Global Mean CO_2 Mixing Ratios (ppm): Observations.* https://data.giss.nasa.gov/modelforce/ghgases/Fig1A.ext.txt

available) and from the NOAA Global Monitoring Lab[5] *for the years 2012-2025. Each dot represents the temperature anomaly and CO_2 concentration for a given year. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.011°C/ppm CO_2.*

Global mean surface temperature changes across multiple time scales — from day-to-day and seasonal fluctuations to longer-term changes driven by anthropogenic GHG emissions.[6] Standard deviation measures dispersion around a constant mean and is best suited for a symmetric, bell-curved distribution.[7] When a long-term trend is present in the data, as with the well-documented upward trajectory of temperature, the data are not symmetrically distributed, and standard deviation is not appropriate to apply directly.[8] Statistical best practice requires first fitting and subtracting the trend, for instance using a least squares regression — retaining only the residuals — before calculating standard deviation.[9] EPA's cited 0.14°C standard deviation over 2016–2025[10] does not appear to account for this step, meaning the estimate likely conflates the underlying warming trend with genuine temperature variability, overstating the relative magnitude of variability. This failure to follow well-established statistical practices is clearly erroneous.

To illustrate why using standard deviation as a statistical method to evaluate variability without first correcting for the underlying trend is incorrect, we created a sample data set of annual means plotted in Figure 3. The purple line represents data with a steady and unequivocal upward trend over time, such as global mean surface temperature, while the orange line displays noisy data that is varying around a constant mean of 4.5, such as the trend exhibited by internal climate variability. The purple

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[5] NOAA Global Monitoring Laboratory. (2021, February 10). *Mauna Loa CO_2 annual mean data (CSV)*. Carbon Cycle Greenhouse Gases: Trends in CO_2, CH_4, N_2O, SF_6. https://gml.noaa.gov/ccgg/trends/data.html

[6] Hawkins, E. & Sutton, R. (2009). The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society, 90*(8), 1095-1108. https://doi.org/10.1175/2009BAMS2607.1

[7] El Omda, S., & Sergent, S. R. (2024). *Standard Deviation*. PubMed; StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK574574/. "The main issue is in data sets where there are extreme values or severe skewness, as these results can influence the mean and SD by a significant amount. Consequently, in scenarios where the data set does not follow a normal (Gaussian) distribution, other measures of dispersion are often used. Most commonly, the interquartile range (IQR) is used alongside the median of the dataset."

[8] Harrell, F. (2024, March 23). *What Does a Statistical Method Assume? – Statistical Thinking*. Statistical Thinking; Department of Biostatistics, Vanderbilt University School of Medicine. https://www.fharrell.com/post/assume/. "The standard deviation assumes that Y has a symmetric distribution whose dispersion is well described by a root mean squared measure"; "When the Y distribution is not symmetric, the SD may not be representative of the overall dispersion of Y."

[9] Brockwell, P. J., & Davis, R. A. (2016). Introduction. In *Introduction to time series and forecasting*. Springer. "If the seasonal and noise fluctuations appear to increase with the level of the process, then a preliminary transformation of the data is often used to make the transformed data more compatible with the model."

[10] 91 Fed. Reg. 7691 (Feb. 18, 2026): "For context, variability in GMST measurement from 2016 to 2025 was 0.14 °C, which is almost four times greater than the modeled GMST impact by 2100 of eliminating all U.S. vehicle and engine GHG emissions."

and orange lines have the same exact population standard deviation, 2.87, but the "interannual" variability is clearly greater for the orange line than the purple line.

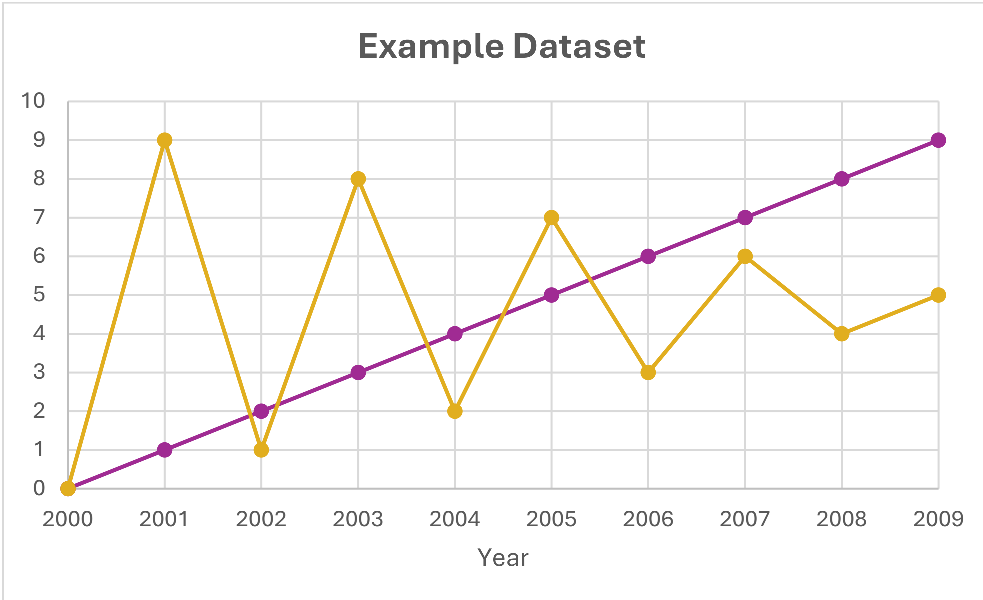

Figure 1. *Example dataset illustrating how standard deviation is not an appropriate way to measure variability. The purple line shows a steady and unequivocal upward trend while the orange line shows noisy data that is varying around a constant mean of 4.5. Though both datasets have a standard deviation of 2.87, the interannual variability of the datasets is different.*

Here we account for the underlying upward trend in global mean surface temperature over time. We use the same NCEI Climate at a Glance Global Time Series dataset[11] from which EPA sourced 1950-2025 global land and ocean average temperature anomalies data. We then plotted the 2016-2025 GMST anomalies data and calculated the line of best fit using linear least squares (Figure 4). We then calculated the residuals, or the difference between the observed data points and the line of best fit. Next, we calculated the sample standard deviation of the residuals. The result was a value of 0.1073°C, which is roughly 23% lower than EPA's calculated value of 0.14°C. Thus, EPA's choice to not correct for the trend before calculating the standard deviation was arbitrary and materially changed the outcome of the analysis.

[11] NOAA NCEI. *Climate at a Glance: Global Time Series*

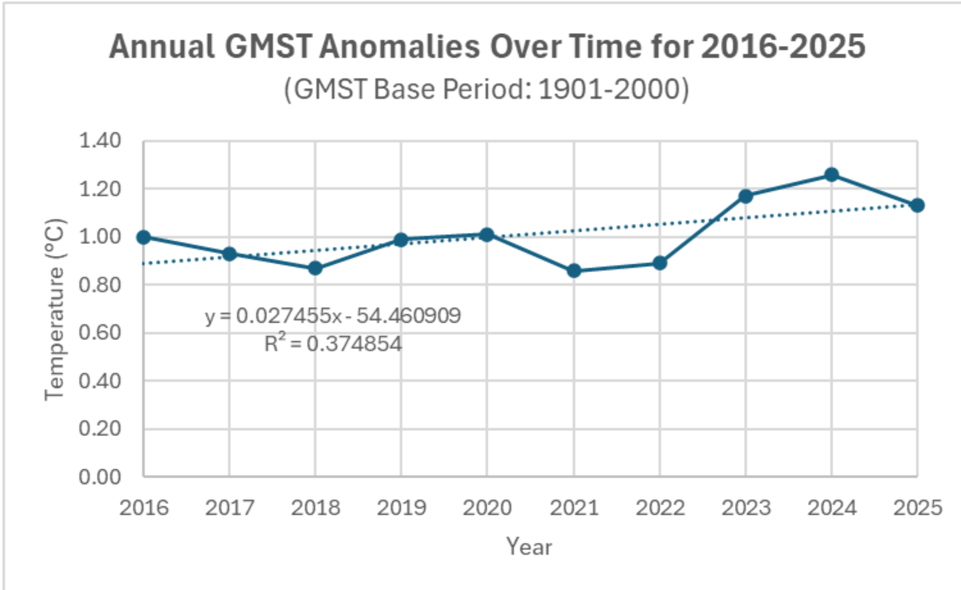

Figure 2. *Global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. time for 2016-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. Each dot represents the temperature anomaly for a given year. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.028°C/year.*

The underlying cause of the temperature trend is not time itself — time is just a proxy. The actual physical driver of the trend is increasing concentrations of atmospheric CO_2 and other GHGs. To be more precise, here we repeat the process above but treat CO_2 as the independent variable and global mean surface temperature anomalies as the dependent variable (Figure 5). We calculated the sample standard deviation of the residuals to be 0.1049°C, and 25% lower than EPA's calculated value of 0.14°C.

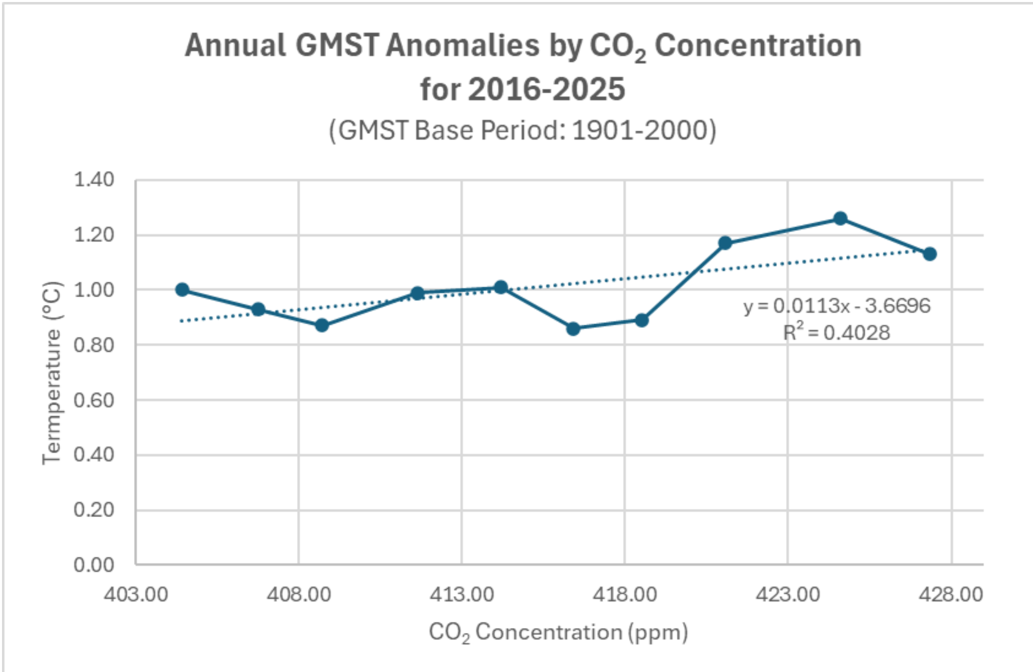

Figure 3. *Global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. carbon dioxide (CO_2) concentration (ppm) for 2016-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. CO_2 data was sourced from NASA for the years 1965-2011 (the most recent year available) and from the NOAA Global Monitoring Lab for the years 2012-2025. Each dot represents the temperature anomaly and CO_2 concentration for a given year. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.011°C/ppm CO_2.*

Finally, even this approach is likely to overestimate true variability because it considers only CO_2 as the only explanatory variable. Global mean surface temperature is driven by a combination of radiative forcings, including other well-mixed GHGs (such as methane and nitrous oxide), aerosols, and natural forcings such as volcanic and solar variability. Climate science literature consistently shows that incorporating the full set of radiative forcings further reduces unexplained variability in temperature time series, as a larger share of the observed temperature change is attributed to known physical drivers rather than treated as residual noise.[12] Thus, a more complete physically based model would be expected to yield an even lower standard deviation of residuals than the CO_2 analysis presented here, reinforcing that EPA's estimate substantially overstates true temperature variability.

[12] Eyring, V., N.P. Gillett, K.M. Achuta Rao, R. Barimalala, M. Barreiro Parrillo, N. Bellouin, C. Cassou, P.J. Durack, Y. Kosaka, S. McGregor, S. Min, O. Morgenstern, and Y. Sun, 2021: Human Influence on the Climate System. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 423–552, doi: 10.1017/9781009157896.005.

B. Annual averages are an inappropriately short timeframe to assess whether an increase in temperature would be inconsequential given the "variability" in the system

EPA's use of annual averages to consider sustained changes in temperature is inappropriate for a fundamental reason: annual temperature values contain a large amount of short-term noise driven by internal climate dynamics such as ENSO, which can shift global mean surface temperatures by several tenths of a degree from one year to the next. This short-term noise is not representative of the background climate change against which multi-decadal policy signals should be assessed. NOAA's NCEI explicitly recognizes this, noting that conventional climate normals are calculated as 30-year averages and serve as the standard benchmark for climate conditions. As NCEI states, these 30-year averages are used by meteorological organizations around the world precisely because they smooth out short-term fluctuations and provide a stable reference for assessing climate conditions.[13] Using annual values rather than multi-year averages conflates this short-term noise with any remaining background variability that EPA claims is relevant for its assessment, artificially inflating the variability estimate EPA then used to declare the policy signal de minimis.

This error is particularly glaring because time data is inherently always averaged in some way, whether it be daily, monthly, seasonally, annually, or multi-annually. As such, EPA is already using averaged data; the Agency cites 12-month average global mean surface temperature anomalies data. EPA could more accurately represent long-term temperature changes by averaging over a longer period, in accordance with best practices of climate science.

Furthermore, as discussed in Section 1.a., EPA did not correct for the well-documented upward trend in global mean surface temperature before calculating standard deviation. Because the trend was not removed, the standard deviation of the annual values not only represents both genuine year-to-year variability, but also the directional movement of the underlying trend, inflating the resulting figure. A standard approach in climate time series analysis, referred to as filtering out high frequency noise, is to separate long-term trends from higher-frequency noise prior to estimating variance.[14,15,16]

To illustrate the consequences of EPA's methodological choices, here we recalculate temperature variability using longer averages. To be clear, we are not suggesting that a correct approach would be to use a 10-year window as opposed to annual data, but to illustrate how the standard deviation is sensitive to the period the data is averaged over. We calculated 10-year average global mean surface

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[13] NOAA National Centers for Environmental Information (NCEI). (2019, August 2). *New type of U.S. Normals addresses influence of El Niño and La Niña.* Accounting for Variability in Our Changing Climate. https://www.ncei.noaa.gov/news/accounting-natural-variability-our-changing-climate
[14] Storch, H. V., & Zwiers, F. W. (1999). *Statistical analysis in climate research* (pp. 10–11, 197–215). Cambridge University Press
[15] Brockwell, P. J., & Davis, R. A.
[16] García-Carreras, B., & Reuman, D. C. (2013). Are Changes in the Mean or Variability of Climate Signals More Important for Long-Term Stochastic Growth Rate? *PLoS ONE*, *8*(5), e63974. https://doi.org/10.1371/journal.pone.0063974

temperature anomaly data from the same annually averaged NOAA NCEI Climate at a Glance data used by EPA;[17] fit a linear least squares regression to the data and subtracted the resulting trend line, retaining only the residuals; and then calculated the standard deviation of the residuals. This approach, described above, is well established in climate science and separates out the long-term trend from the short-term noise.

Using 10-year averages for temperature anomaly and time with the long-term trend removed via linear least square regression, the sample standard deviation is 0.0515°C, roughly 63% lower than EPA's reported "variability" statistic of 0.14°C (Figure 6). Using 10-year averages for temperature and CO_2 concentration with the long-term trend removed via linear least square regression, the sample standard deviation is 0.0208°C, roughly 85% lower than EPA's reported "variability" statistic of 0.14°C (Figure 7). These results demonstrate that EPA's choice of annual averages, combined with its failure to detrend, produced a statistically inappropriate estimate that overstates variability by as much as 85%.

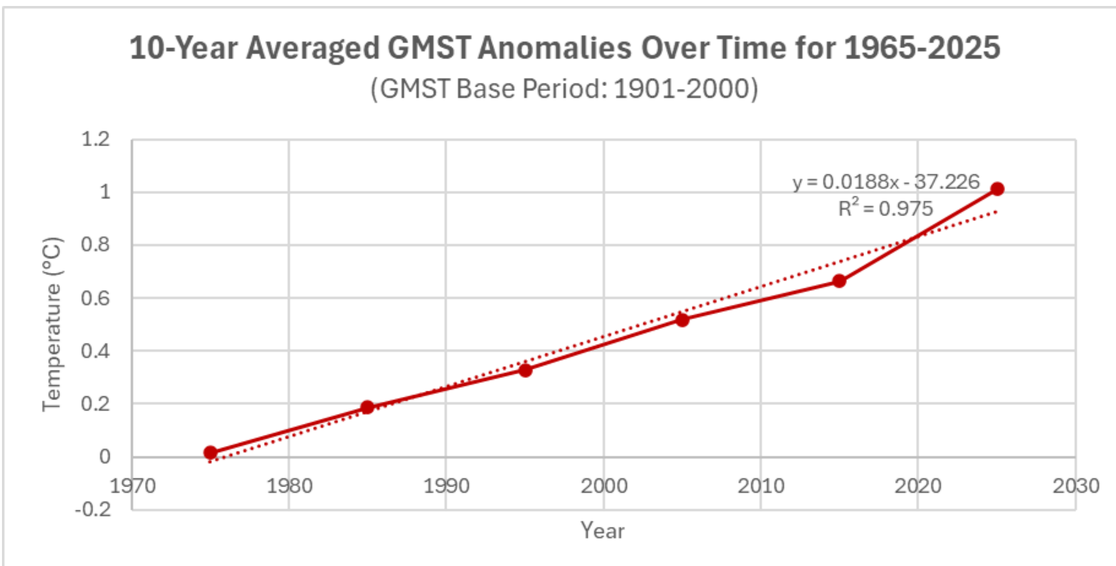

Figure 6. *10-year average global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. time for 1965-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. Each dot represents the average temperature anomaly for the previous 10-year period. For example, the dot at 1975 represents the mean temperature anomaly compared to the 1901-2000 average for the years 1966-1975. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.019°C/year.*

[17] NOAA NCEI. *Climate at a Glance: Global Time Series*

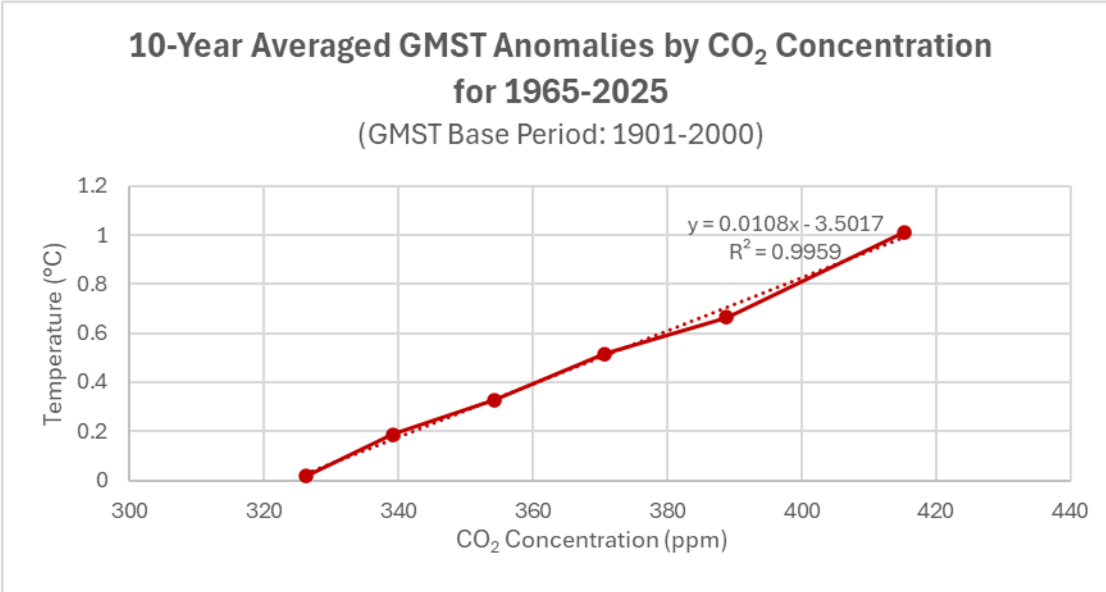

Figure 7. *10-year average global mean surface temperature (GMST) anomalies (°C) with respect to the 1901-2000 average vs. carbon dioxide (CO_2) concentration (ppm) for 1965-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. CO_2 data was sourced from NASA for the years 1965-2011 (the most recent year available) and from the NOAA Global Monitoring Lab for the years 2012-2025. Each dot represents the average temperature anomaly and average CO_2 concentration for the previous 10-year period. The dotted line is the line of best fit, which shows that GMST anomalies have increased during this period by a rate of roughly 0.011°C/ ppm CO_2.*

C. EPA should have used population standard deviation and not sample standard deviation if they meant to describe "variability" for 2016-2025

The premise of EPA's argument that natural climate variability is large relative to the projected temperature impact of U.S. motor vehicle GHG standards depends critically on how variability is measured. EPA calculated a 0.14°C "variability" figure for the 2016-2025 period. It is unclear if the Agency did so with the intent to measure standard deviation in this period alone (i.e., the population of data is restricted to the 2016-2025 data), or if they were using the 2016-2025 period to represent the entirety of data from 1950-2025 (i.e., the 2016-2025 data is only a sample). For the purposes of this section, our interpretation of EPA's inadequately short description is that the Agency intended to represent just the variability of 2016-2025.

The distinction between population and sample standard deviation relies on a fundamental question: are the data points in question a sample drawn from a larger population, or do they constitute the entire population of interest? The formula for calculating sample standard deviation divides by the number of observations minus one (n-1) to account for the bias introduced when a sample mean is used to estimate an unknown population mean.[18] This adjustment is appropriate when the observed values are a subset of a larger group that was not fully observed, as is often the case with climate

[18] El Omda, S., & Sergent, S. R.

data.[19] Conversely, population standard deviation divides by the number of observations (n) and is appropriate when the observed values constitute the complete population, such as a fully enumerated set of observations within a defined temporal window where all elements of interest are observed without sampling uncertainty (i.e., a closed set of annual GMST values over a specified period).

In the case of EPA's variability calculation, first we will assume that the Agency's intention was to calculate variability of the ten annual global mean surface temperature values from 2016-2025. As such, these data can be understood as fully observed measurements of a specific, completely enumerated set of years. There is one Earth, and its average global mean surface temperature for each of those years has been measured and recorded. There is no larger population of unobserved years from which these 10 values were drawn; they are the population. EPA therefore should have divided by n=10 rather than n-1=9 when calculating the standard deviation of these values. Here, we proceed as EPA should have to quantify the impacts of its error. Population standard deviation equals sample standard deviation multiplied by $\sqrt{(n-1/n)}$. With n=10, this adjustment factor is $\sqrt{(9/10)} \approx 0.9487$, meaning EPA's reported variability figure of 0.14°C should be reduced to approximately 0.133°C to adjust for this error alone, or a reduction of approximately 5.4%.

For the sake of consistency with EPA's methods, throughout this technical memorandum, we reported standard deviations as calculated using the sample standard deviation formula. Here we recalculate these using the population standard deviation formula (Table 1).

***Table 1**. Comparison of standard deviation estimates when calculating using the formula for sample standard deviation vs. population standard deviation.*

Data	Figure	Sample Standard Deviation of the Residuals (°C)	Population Standard Deviation of the Residuals (°C)
EPA's variability estimate	-	0.14	0.133
Recent GMST annual anomalies over time (2016-2025)	Figure 4	0.1073	0.1018
Recent GMST annual anomalies with CO_2 concentrations (2016-2025)	Figure 5	0.1049	0.0995
10-year averaged GMST anomalies with time (1965-2025)	Figure 6	0.0515	0.0477
10-year averaged GMST anomalies with CO_2 concentrations (1965-2025)	Figure 7	0.0208	0.0193

[19] Storch, H. V., & Zwiers, F. W. Chapter 4: Concepts in Statistical Inference.

D. The use of EPA's selected time period, 2016-2025, was inadequately considered, and is particularly unsupportable if intended to represent "variability" in 1950-2025

If, in fact, EPA was using the 2016-2025 period to represent the entirety of data from 1950-2025 (i.e., the 2016-2025 data is only a sample), EPA's decision was still arbitrary. The Agency provided no explanation for why the period from 2016-2025 was selected as the reference period, nor any sensitivity analysis showing how the results would change under alternative window choices. As we show here, a more representative reference window would produce a lower variability estimate.

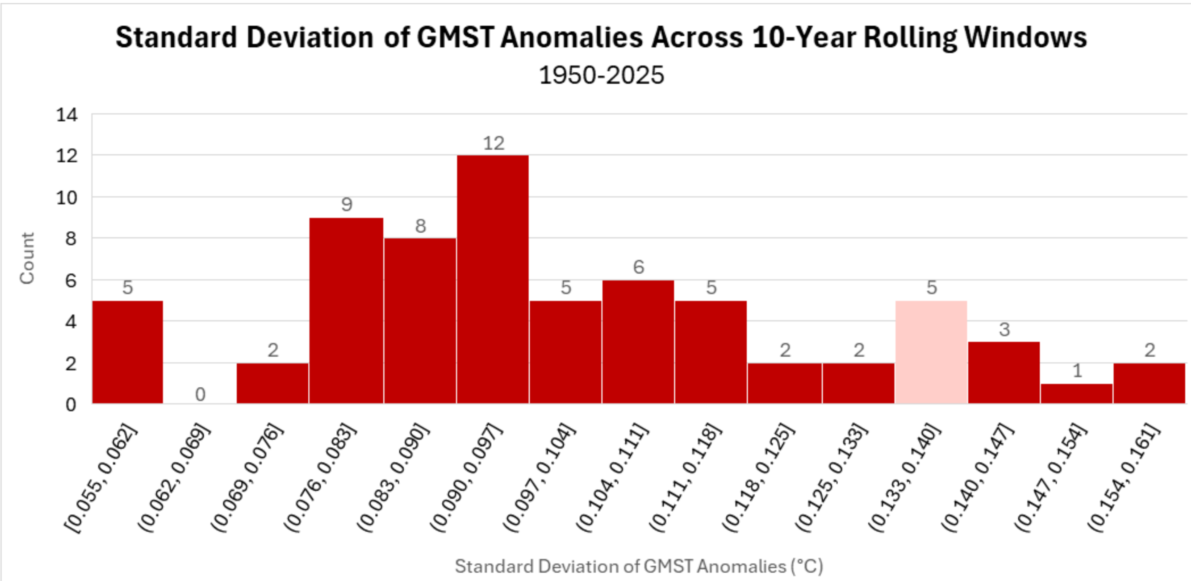

Figure 8. *Standard deviation of GMST anomalies (°C) across 10-year rolling windows from 1950-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. The lightest-hued bin contains the standard deviation for 2016-2025: 0.136°C. Only seven of the 67 windows have standard deviations above that of the 1950-2025 period.*

To evaluate how consequential this choice is, we calculated the standard deviation of GMST anomalies for each 10-year rolling period (i.e. 1950-1959, 1951-1960, etc.) from 1950-2025. This produced 67 distinct 10-year windows, each with its own standard deviation. We calculated the sample standard deviation for the anomalies in global mean surface temperature for the period 2016-2025 to be 0.136°C. As shown in Figure 8, the sample standard deviation for the 2016-2025 window is among the highest of all windows examined.[20] Of the 67 rolling 10-year windows calculated, only seven produced a higher sample standard deviation than the 2016-2025 period. In other words, EPA's chosen reference window falls in roughly the top 10% of all possible 10-year windows in terms of internal variability. By selecting, without justification, one of the most internally variable 10-year periods in the modern temperature record (Figure 8), EPA has systematically overstated the background variability against which the policy signal of 0.037°C is being compared. Had EPA

[20] We plotted the data with a range of bin sizes, which did not meaningfully impact the shape of figure or the conclusions drawn from Figure 8.

chosen a more typical window, the resulting standard deviation would have been meaningfully lower. For example, had EPA chosen a 10-year window containing the median year (1992), such as the 1987-1996 window, the resulting sample standard deviation would have been 0.0766°C, roughly 45% lower than EPA's calculated value of 0.14°C. If EPA had chosen the window with the median sample standard deviation in the 1950-2025 period, the Agency would have selected the 1981-1990 window, which has a sample standard deviation of 0.0962°C, roughly 31% lower than EPA's calculated value of 0.14°C.

EPA's choice of 2016-2025 as the reference window is not merely arbitrary; it is systematically biased toward a period of historically anomalous climate behavior. The IPCC Special Report on Global Warming of 1.5°C found that, "trends in the intensity and frequency of some climate and weather extremes have been detected over time spans during which about 0.5°C of global warming occurred."[21] This finding has direct implications for EPA's choice of reference window. The 2016-2025 period coincides with some of the highest recorded GHG concentrations in human history.[22] At these elevated GHG concentrations, the climate system is operating in a regime that is measurably different from earlier decades, with altered patterns of climate extremes that are themselves a consequence of the underlying warming trend. By selecting a reference window that falls within this altered climate regime, and without correcting for the underlying trend that produced it, EPA has compounded the error identified in Section 1.a.: not only did the Agency fail to detrend the temperature series, but it selected a window in which the residual variability is itself partially a product of the trend it failed to remove. In other words, the elevated variability of the 2016-2025 window relative to earlier periods is not purely a reflection of natural internal climate variability. It is at least partly a reflection of the altered climate state produced by the very GHG emissions whose regulation is under consideration. Using this window to argue that climate variability renders US motor vehicle GHG regulation futile is therefore circular: the elevated variability EPA cites as a reason not to regulate is itself a consequence of the kind of emissions that section 202(a) GHG regulation is meant to address.

[21] Hoegh-Guldberg, O., D. Jacob, M. Taylor, M. Bindi, S. Brown, I. Camilloni, A. Diedhiou, R. Djalante, K.L. Ebi, F. Engelbrecht, J. Guiot, Y. Hijioka, S. Mehrotra, A. Payne, S.I. Seneviratne, A. Thomas, R. Warren, and G. Zhou, 2018: Impacts of 1.5ºC Global Warming on Natural and Human Systems. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 175-312. https://doi.org/10.1017/9781009157940.005

[22] Rohde, R. (2026, January 14). *Global Temperature Report for 2025 - Berkeley Earth*. Berkeley Earth. https://berkeleyearth.org/global-temperature-report-for-2025/

E. EPA did not adequately consider the impacts of a 10-year time interval on variability.

EPA's decision to characterize climate variability using a 10-year time interval is a consequential methodological choice that was made without justification. As shown in Figure 9, the choice of window length materially affects the resulting standard deviation estimate. We are not suggesting that a 10-year window is an appropriate window length to use to characterize variability, but rather, as shown in Figure 9, to illustrate how the window length selected considerably affects the final variability estimate. This suggests that the basic methodological approach undertaken by EPA is arbitrary. This arbitrariness is compounded by the fact that EPA's specific 10-year window of 2016-2025 is itself an outlier within the distribution of all possible 10-year windows, as shown in Figure 8 and discussed in Section 1.d.

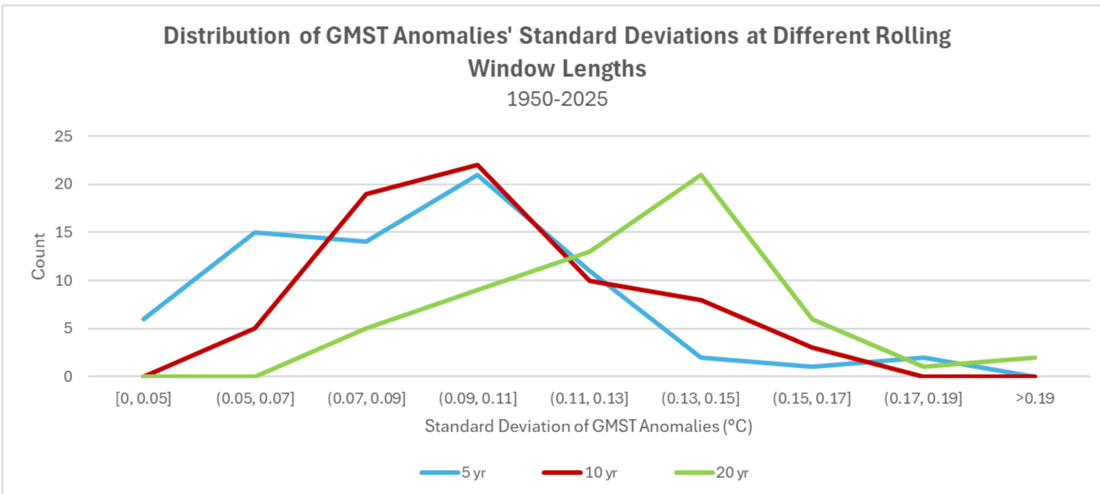

Figure 9. *Distribution of GMST anomalies' standard deviations (°C) at different rolling window lengths. Data is not detrended. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. The light blue line shows the distribution of standard deviation for rolling 5-year windows, while the red and green lines show the distributions for 10- and 20-years respectively. This shows how standard deviation is sensitive to window length.*

The same pattern holds for 5-year windows. Generally, the sample standard deviation for 5-year windows is smaller (Figure 9), but the most recent 5-year window of 2021-2025 has a sample standard deviation of 0.177°C, making it among the single most variable 5-year window in the 1950-2025 record (Figure 10). In other words, regardless of which interval length is used, EPA's choice of the most recent available window consistently produces one of the highest variability estimates in the historical record. The combination of an unjustified interval length and an unjustified window selection systematically biases EPA's variability estimate upward relative to what a different methodological choice would produce.

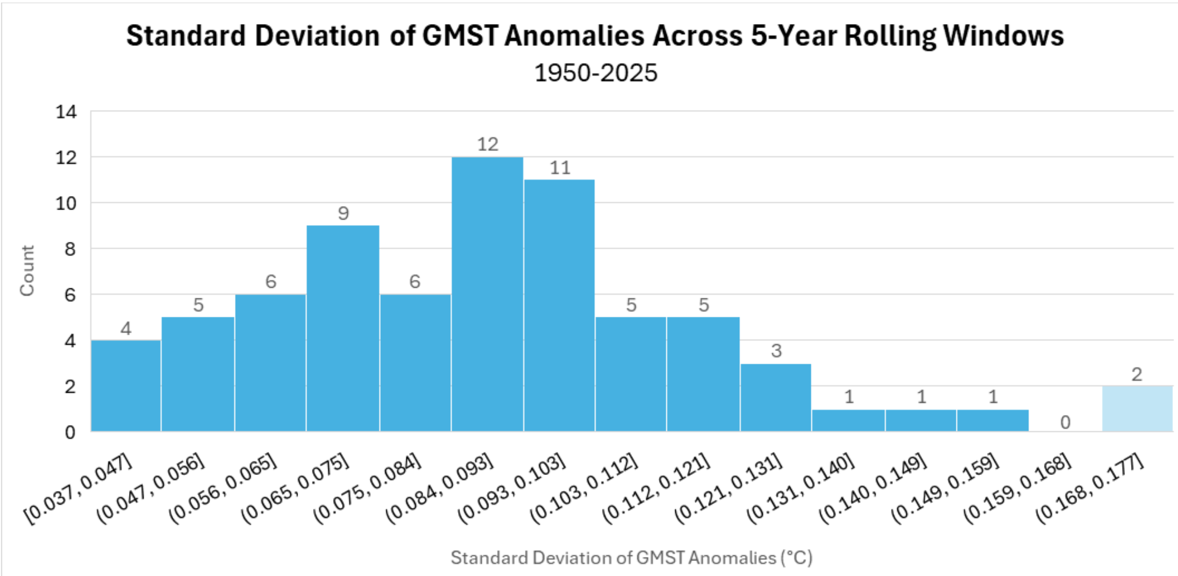

Figure 10. *Standard deviation of GMST anomalies (°C) across 5-year rolling windows from 1950-2025. GMST data was sourced from the NCEI Climate at a Glance: Global Time Series. The lightest-hued bin contains the standard deviation for 2021-2025: 0.177°C. The 2021-2025 window has the highest standard deviations in the 1950-2025 period.*

EPA provided no explanation for why a 10-year interval was selected, nor any sensitivity analysis demonstrating that the conclusions are robust to alternative interval lengths. Given that the choice of interval length shifts the center of the standard deviation distribution by as much as 0.04-0.05°C, this omission is significant.

II. Measurability

EPA's assertion that global mean surface temperature and global sea level rise ranges of measurability are larger than the EPA's projected impacts is completely unsupported and fundamentally arbitrary. For global mean surface temperature, the source EPA cites does not include the information they claim it does, the paper with similar numbers to EPA's has been updated to reduce the uncertainty, and there are at least six global annual temperature datasets with uncertainties below EPA's 0.037°C. For global sea level rise, EPA fails to provide any source or any number and available estimates of measurement uncertainty are below the 1.4 cm of global sea level rise EPA projects.

In the Final Rule, EPA says:

> [T]he predicted impacts through 2100 (0.013 °C[sic] as shown in Table 5) are below the range of measurability for GMST and likewise for GSLR (1.4 cm as shown in Table 7).[181]
>
> [181]See National Oceanic and Atmospheric Administration (NOAA), National Centers for Environmental Information, Global Surface Temperature Anomalies-Methodology and

Uncertainty, estimating uncertainty in annual global mean surface temperature of approximately ±0.05 °C since 1950, increasing to ±0.1–0.2 °C in the late 19th Century. Available at https:// www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies.[23]

A. EPA's use of measurement uncertainty as a metric for establishing futility is arbitrary.

EPA's choice to use "measurability" as a metric to determine futility is arbitrary. Measurement uncertainty for global mean surface temperature and global sea level rise arises from many components including instrument precision, data coverage, and statistical methods to fill in data globally.[24] In practice, this means that global temperature estimates must account for the uneven distribution of weather stations and ocean buoys across the planet, gaps in historical records, differences in measurement techniques over time, and the challenge of converting thousands of local temperature readings into a single planetary average.[25] For GMST specifically, uncertainty stems from multiple independent sources across both land and ocean records. On land, these include station uncertainty (e.g., measurement errors, transcription errors, and adjustments to station records), bias uncertainty (e.g., changes in instrumentation methodology over time and urban heat island effects), and sampling uncertainty (from incomplete spatial and temporal coverage).[26] Over the ocean, uncertainty is further broken down into parametric uncertainty and reconstruction uncertainty, the latter of which "averages out to nearly zero at global scales."[27]

Over time, these uncertainties have generally declined as instruments have gotten more precise, data coverage has improved, and statistical methods have progressed.[28] EPA fails to explain why this trend would not continue leading to smaller measurement uncertainties by 2100. This omission is particularly striking given EPA's own acknowledgement that GMST uncertainty has decreased by up to 75% since the "late 19th century," indicating that the measurability metric is contingent on a moving target rather than a fixed scientific constraint.

B. Global mean surface temperature measurability

i. EPA's source does not include any information about temperature measurement uncertainty.

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[23] 91 Fed. Reg. 7733 (Feb. 18, 2026):

[24] NASA. (2025, January 10). *This is How Scientists Measure Global Temperature*. Nasa.gov. https://science.nasa.gov/earth/measuring_global_temperature/

[25] *Ibid.*

[26] Lenssen, N. J. L., Schmidt, G. A., Hansen, J. E., Menne, M. J., Persin, A., Ruedy, R., & Zyss, D. (2019). Improvements in the GISTEMP uncertainty model. Journal of Geophysical Research: Atmospheres, 124, 6307–6326. https://doi.org/10.1029/2018JD029522

[27] Lenssen et al. 2019

[28] NASA. *This is How Scientists Measure Global Temperature.*

The source EPA provides in the Final Rule (quoted above) redirects to a different NCEI webpage: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/data-info. On this webpage, there is no discussion of measurement uncertainty, and the values EPA references are not included at any point in the cited webpage. EPA's failure to provide the actual source used to establish such a consequential number in the Rule is inexcusable and fundamentally arbitrary. EPA also fails to establish what the range in temperature provided, ±0.05°C and ±0.1-0.2°C, is describing. For example, whether it is describing uncertainty at the one standard deviation (1σ) level, at the 90% or 95% confidence interval, or in some other way. Given the utter lack of information provided by EPA, we were unable to reconstruct EPA's measurement uncertainty figures based on the reference EPA provided.

ii. The dataset referenced in EPA's citation includes materially lower uncertainties from the ones EPA states

One of the datasets referenced in footnote 181 is NOAAGlobalTemp (NGT).[29] We could not find information about the uncertainty in temperatures for version 6 of NGT, the most recent version which was released in February 2024. In the version 6 text datasets,[30] the uncertainty values are all marked as -999, a common way to mark data points as missing or unknown. It is possible that the maintainers of NGT have not yet finished calculating the uncertainty for version 6 of the data.

However, for version 5, which was released in June 2019, we identified a paper entitled "Uncertainty Estimates for Sea Surface Temperature and Land Surface Air Temperature in NOAAGlobalTemp Version 5" by Huang et al. published in January 2020.[31] In this paper, Huang et al. describe how they calculate the uncertainty for the NGT v5 and conclude that total uncertainty of globally averaged surface temperature is "0.05°–0.07°C for 1880–1900 and decreases gradually to approximately 0.02°C in the 2010s except for spikes during the two world wars." This is shown graphically in figure 10 of the paper, pasted below as Figure 11. The uncertainty values presented in this paper are reported as 1σ values, including the values stated above and shown in Figure 11.[32]

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[29] Huang, B., X. Yin, M. J. Menne, R. Vose, NOAA Global Surface Temperature Dataset (NOAAGlobalTemp), Version 6.1.0 Time Series. NOAA NCEI. https://doi.org/10.25921/vvaa-wq11.

[30] All files: https://www.ncei.noaa.gov/data/noaa-global-surface-temperature/v6.1/access/timeseries/; Example with -999s: https://www.ncei.noaa.gov/data/noaa-global-surface-temperature/v6.1/access/timeseries/aravg.ann.land.90S.20S.v6.1.0.202602.asc

[31] Huang, B., Menne, M. J., Boyer, T., Freeman, E., Gleason, B. E., Lawrimore, J. H., Liu, C., Rennie, J. J., Schreck, C. J., III, Sun, F., Vose, R., Williams, C. N., Yin, X., & Zhang, H. (2020). Uncertainty Estimates for Sea Surface Temperature and Land Surface Air Temperature in NOAAGlobalTemp Version 5. *Journal of Climate*, *33*(4), 1351-1379. https://doi.org/10.1175/JCLI-D-19-0395.1

[32] It is possible these values are actually the 95% confidence interval, or 2σ values. In Lenssen et al. 2024, discussed more below, they calculated the 95% CI for a number of different global temperature datasets including NGT. The values Lenssen et al. 2024 report as the 95% CI appear to match the values reported by Huang et al. 2020 as 1σ. This distinction is immaterial for the purposes

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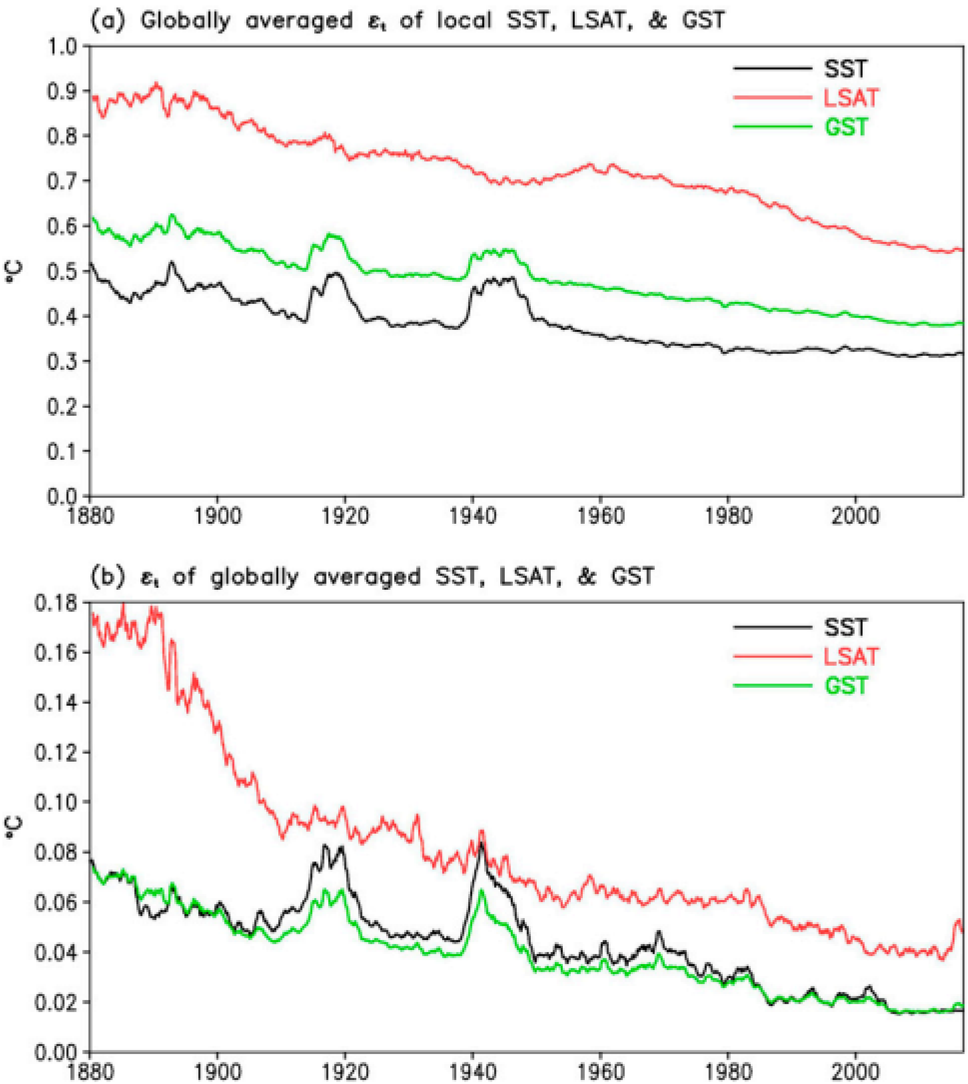

FIG. 10. (a) Globally averaged total uncertainty (1σ) of local SST (black), LSAT (red), and GST (green), and (b) total uncertainty (1σ) of globally averaged SST, LSAT, and GST. A 12-month running filter is applied in plotting.

Figure 11. *Figure copied from Huang et al. 2020. The green line in panel (b) displays the relevant uncertainty. ε_T represents the total uncertainty. SST: sea surface temperature, LSAT: land surface air temperature, GST: global surface temperature.*

It is important to note that 0.02°C is lower than EPA's projected global mean surface temperature impact from US vehicle GHGs in 2100 of 0.037°C. In other words, the dataset attached to the webpage EPA cites reports a global surface temperature uncertainty lower than EPA's projected

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of this memo since EPA fails to identify what confidence interval they believe should be used nor do they provide any justification.

GMST impact, directly contradicting EPA's conclusion that US vehicle GHG impacts are de minimis and that section 202(a) GHG regulation is futile.

iii. The paper with values that match EPA's stated range of measurability has been updated to have uncertainties below 0.037°C

While it is not clear what EPA meant to reference to get its "range of measurability" values given they do not match the data that is referenced in the Agency's citation, the values it states appear to match a statement from the abstract of Lenssen et al. 2019, "The resulting 95% uncertainties are near 0.05°C in the global annual mean for the last 50 years and increase going back further in time reaching 0.15°C in 1880."[33] This paper described the uncertainty values for NASA's GISTEMP dataset. However, since 2019, the uncertainty for GISTEMP has been updated as detailed in Lenssen et al. 2024.[34] The resulting uncertainties are significantly lower than the values from the 2019 paper (Figure 12). Between 1950 and 2020, the average global annual uncertainty was 0.055°C for Lenssen 2019 and 0.035°C for Lenssen 2024. Forty-one of the annual uncertainties in Lenssen 2024 are below 0.037°C while none of the uncertainties from Lenssen 2019 where lower than 0.04°C.

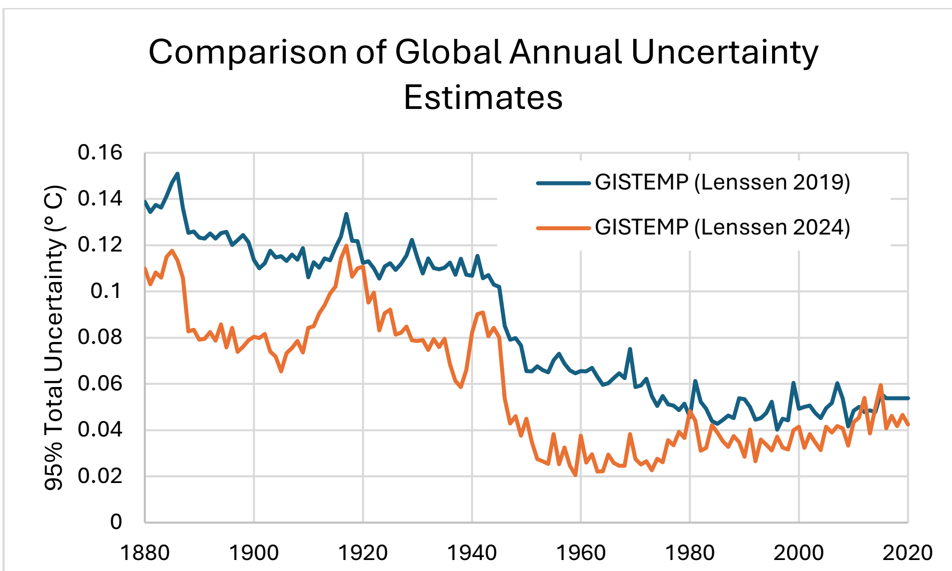

Figure 12. *Global annual uncertainty estimates for 1880 to 2020 from two versions of the GISTEMP data and two corresponding papers, Lenssen et al. 2019 and Lenssen et al. 2024.*

[33] Lenssen, N. et al. Improvements in the GISTEMP Uncertainty Model.
[34] Lenssen, N., Schmidt, G. A., Hendrickson, M., Jacobs, P., Menne, M. J., & Ruedy, R. (2024). A NASA GISTEMPv4 observational uncertainty ensemble. *Journal of Geophysical Research: Atmospheres*, 129, e2023JD040179. https://doi.org/10.1029/2023JD040179

iv. Additional datasets of global mean surface temperature have measurement uncertainty values materially lower than EPA's stated range of measurability

In addition to the datasets discussed above, there are many additional global annual temperature datasets that report uncertainties lower than EPA's 0.037°C for some or all of the last 75 years.[35] Figure 13 shows the number of years since 1950 and since 1970 that each dataset has had global annual uncertainties below 0.037°C. Figure 14 shows the average uncertainty of global annual mean temperature since 1950 and since 1970. For each of the datasets, one or both of the averages are below 0.037°C and for some of them, the average is substantially below 0.037°C, for instance the average since 1970 for DKRZ is 0.017°C (Figure 14).

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[35] The data for NOAA GlobalTemp, GISTEMP (Lenssen 2024) and DKRZ are from Lenssen et al. 2024 and correspondence with the authors for the underlying data for Figure 4 in the paper; Berkeley Earth data: Rohde, R. A. & Hausfather, Z. (2020). *The Berkeley Earth Land/Ocean Temperature Record*, Earth Syst. Sci. Data, 12, 3469ï¿½3479, https://doi.org/10.5194/essd-12-3469-2020. Retrievable at: https://berkeley-earth-temperature.s3.us-west-1.amazonaws.com/Global/Land_and_Ocean_summary.txt; HadCRUT5 data is "Global Annual Ensemble Means and Uncertainties" retrievable at: https://www.metoffice.gov.uk/hadobs/hadcrut5/data/HadCRUT.5.1.0.0/download.html; DCENT data is "Global Annual Time Series" retrievable at: https://dcent-i.github.io/#access; The uncertainty values for all of the datasets except DCENT are 95% CI. DCENT only provides a 1 standard deviation confidence interval. As discussed above in footnote 32, the NOAA GlobalTemp data was calculated from ensemble members for the Lenssen 2024 paper as 95% CI but visually matches the 1 standard deviation data in the Huang 2020 paper. The uncertainty values calculated by Lenssen 2024 are included in the figures in this section.

[35] Because of how Berkeley calculates their five-year uncertainty, they do not report 2023 or 2024 values.

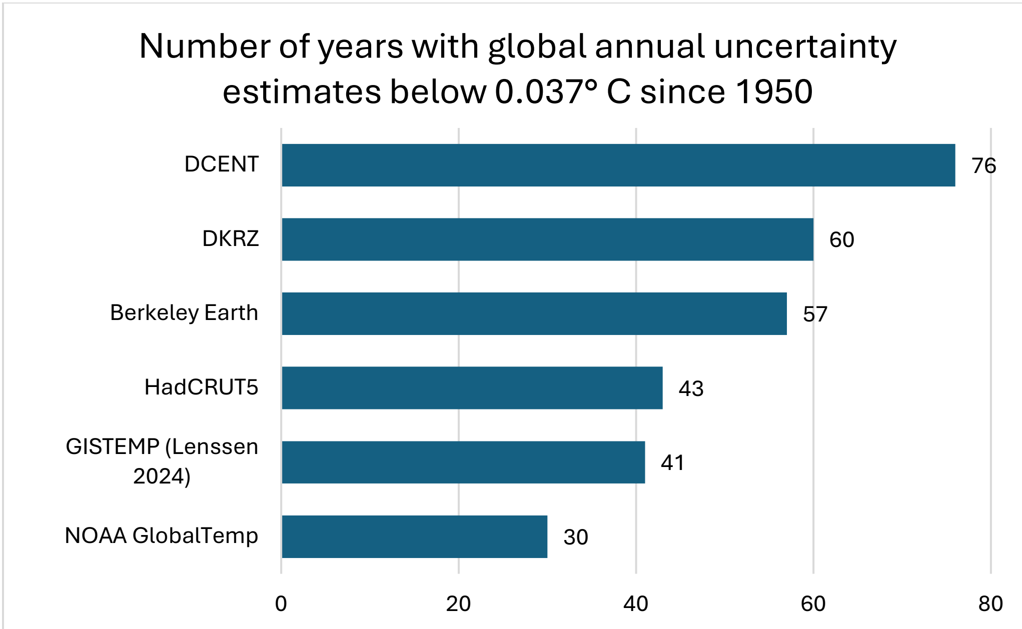

Figure 13. *Number of years with global annual uncertainties below 0.037° C since 1950 for six different datasets. Most of the uncertainties presented at 95% CI. DCENT only provides 1 standard deviation confidence intervals. See footnote 31 and 34 for more discussion about NOAA Global Temp.*

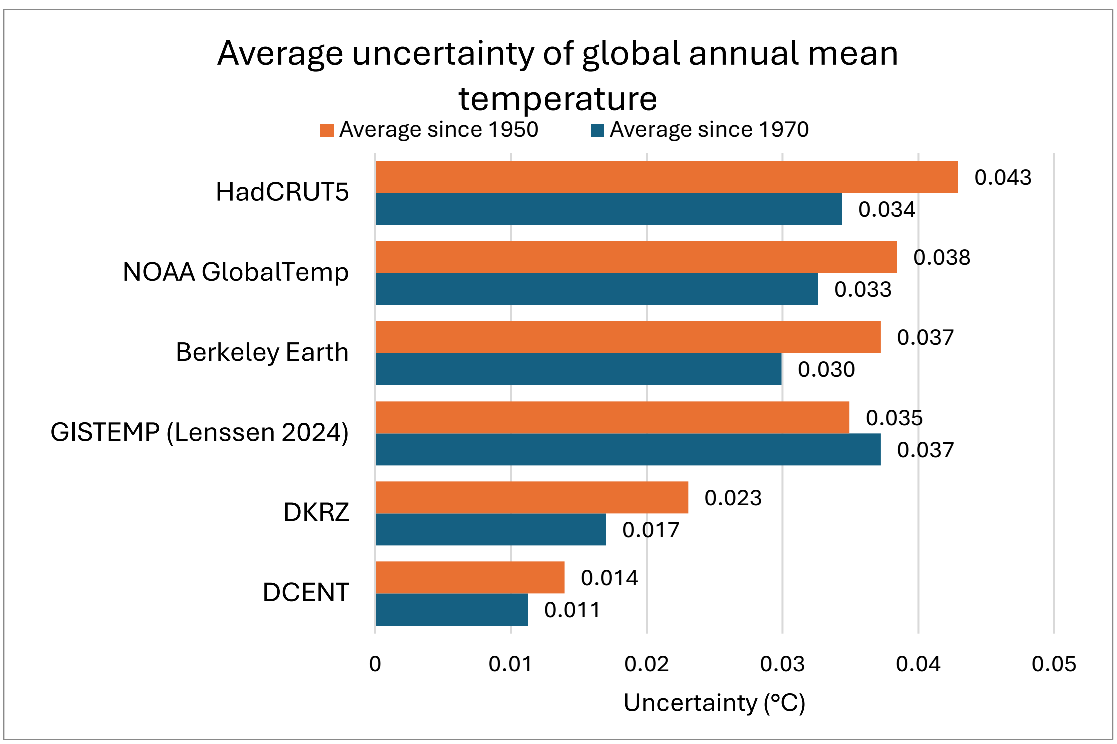

Figure 14. *Average uncertainty for global annual mean temperature for six different datasets. The averages are taken from 1950 to 2025 and from 1970 to 2025. Not all datasets have all of the recent years of data. Most of the uncertainties presented at 95% CI. DCENT only provides 1 standard deviation confidence intervals. See footnote 31 and 34 for more discussion about NOAA GlobalTemp.*

v. EPA should have considered the uncertainty for longer time frames

The signal represented by the warming from US onroad vehicle GHG emissions is long term, the temperature increase will not appear in 2100 and then suddenly disappear. As such, EPA should have considered the uncertainty for a longer time frame and not annual uncertainty. Since some of the uncertainty is uncorrelated and independent,[36] when the uncertainty over several years is calculated it is lower than the annual uncertainty. Berkeley Earth includes a five-year uncertainty that is, on average since 2000, 16% lower than their annual uncertainty and an average of 21% lower since 1975. Every year since 1966 has a five-year uncertainty lower than 0.037°C (Figure 15).[37]

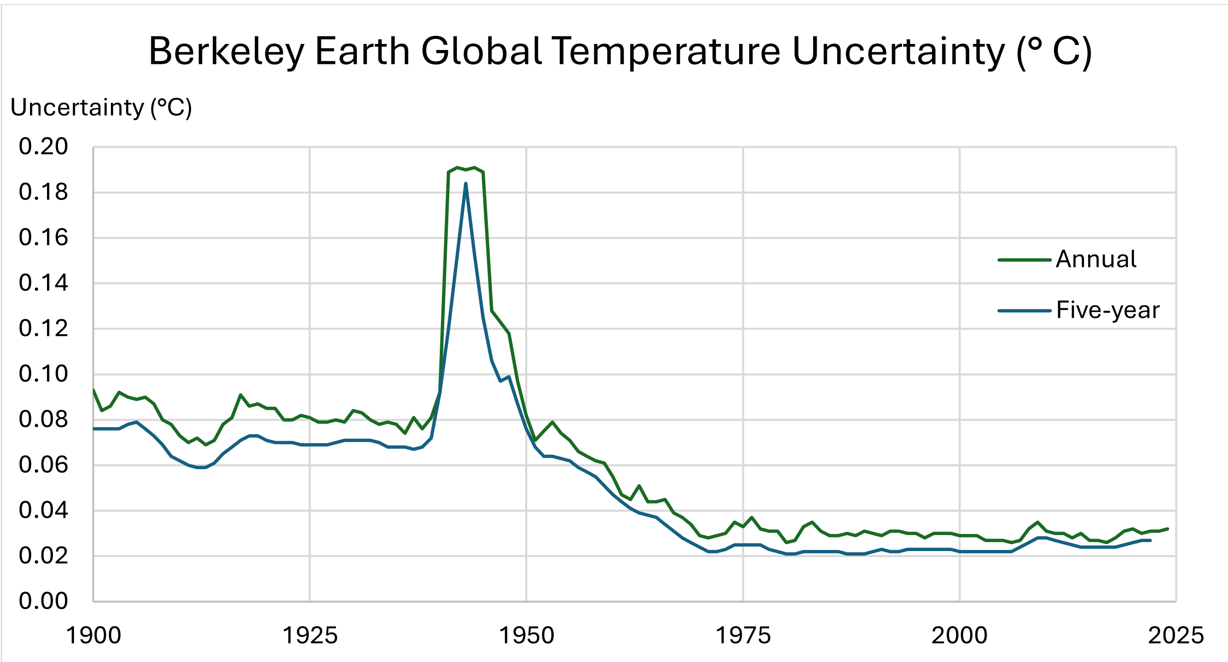

Figure 15. *Annual and five-year global temperature uncertainties from Berkeley Earth, 1900 to 2025.*

C. For sea level measurability, EPA fails to provide any value and the measurement uncertainty values we identified are much smaller than 1.4 cm

For sea level measurability, EPA did not provide an uncertainty value or any source for its claim that the measurability is larger than 1.4 cm. In fact, the sources we found state a much lower uncertainty for global average sea level measurements. For more than three decades, satellite altimeters have used radar to precisely measure sea surface height. The measurements have an uncertainty of around

[36] This is not true for all of the components of the uncertainty and so the reduction is not the square root of the number of values being averaged (root sum square) which would be the case if the uncertainty was purely independent.
[37] Rohde, R. A. & Hausfather, Z. *The Berkeley Earth Land/Ocean Temperature Record.*

4mm or 0.4cm, well below the 1.4cm EPA projected in 2100. This data represents uncertainty at the 90% confidence interval.[38]

III. Conclusion

This memorandum demonstrates that EPA's futility analysis is fundamentally flawed in both its assessment of temperature variability and its claims regarding measurability. In each case, EPA's methodological choices systematically biased the analysis toward overstating the barriers to regulatory significance.

With respect to temperature variability, EPA committed multiple methodological errors: (1) failure to correct for the underlying increasing trend in global mean surface temperature; (2) use of inappropriately short annual averages to assess whether an increase in temperature would be inconsequential given the "variability" in the system; (3) the potentially erroneous calculation of population standard deviation and not sample standard deviation; (4) the arbitrary use of the selected time period, 2016-2025, which is particularly unsupportable if intended to represent "variability" in 1950-2025; and (5) the arbitrary use of a 10-year time interval to calculate variability. Each of these errors inflates EPA's variability estimate. Taken together, they cause EPA to overstate temperature variability by as much as 85%.

With respect to measurability, EPA's analysis is also flawed. EPA cited a source that does not contain the uncertainty values it claims to rely upon. The dataset most plausibly associated with EPA's figures has since been updated, and under its revised uncertainty estimates, EPA's projected global mean surface temperature impact exceeds the average uncertainty for the global annual mean temperature for the past 75 years. Multiple independent global temperature datasets report annual measurement uncertainties that are, on average, below EPA's projected 0.037°C impact—and 5-year averaged uncertainties that are even lower. For global mean sea level, EPA provided no source for its 1.4cm measurability threshold. The best available satellite altimetry data reports uncertainties of 0.4cm, more than three times smaller.

In sum, EPA's conclusion that section 202(a) GHG regulation is futile rests on a variability metric that overstates background temperature noise by as much as 85% and a measurability metric that is unsupported by the scientific sources EPA cites. Even accepting EPA's basic framework for assessing futility, the Agency's own projected policy impact of 0.037°C is not de minimis when

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[38] NASA. (n.d.). *Key Indicators: Global Mean Sea Level*. NASA Sea Level Change Portal. https://sealevel.nasa.gov/understanding-sea-level/key-indicators/global-mean-sea-level/; Willis, J. K., S. Fournier, K. Marlis, and E. Killett. 2025. NASA-SSH Global Mean Sea Level from Simple Gridded Sea Surface Height. Ver. 1. PO.DAAC, CA, USA. at https://doi.org/10.5067/NSIND-GMSV1; Ablain, M., Meyssignac, B., Zawadzki, L., Jugier, R., Ribes, A., Spada, G., Benveniste, J., Cazenave, A., & Picot, N. (2019). Uncertainty in satellite estimates of global mean sea-level changes, trend and acceleration. *Earth System Science Data*, *11*(3), 1189–1202. https://doi.org/10.5194/essd-11-1189-2019

properly evaluated against adjusted variability and measurability estimates. The Final Rule's futility determination therefore is fatally flawed and should be reconsidered.

APPENDIX D

Modeling the Sea-Level Change from U.S. Vehicle Emissions

Modeling the Sea-Level Change from U.S. Vehicle Emissions

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Abstract

Recent U.S. Environmental Protection Agency (EPA) analyses have argued that greenhouse gas emissions from U.S. on-road vehicles contribute negligibly to global mean sea-level rise (GMSLR). Here, I replicate and extend the EPA's modeling framework using the FaIR climate model coupled with the BRICK sea-level model, incorporating a probabilistic weighting approach and a longer model timescale to better represent joint climate-sea-level uncertainty. In addition to the baseline SSP2-4.5 scenario and an EPA-consistent emissions reduction case, I examine alternative scenarios reflecting stalled technological progress and a counterfactual pre-regulation vehicle fleet. Results reproduce EPA estimates of approximately 1-2 cm of GMSLR reduction by 2100 under vehicle emissions mitigation but show that these differences grow substantially over multi-century timescales, exceeding 6 cm by 2200. Downscaling to U.S. coastlines reveals larger local effects, particularly along the Gulf of Mexico Coast. These findings highlight the long-term and regionally amplified benefits of emissions reductions from the transportation sector.

1 Introduction

In February 2026, the United States Environmental Protection Agency (EPA) repealed its 2009 Greenhouse Gas Endangerment Finding and along with it, its Motor Vehicle Greenhouse Gas Emissions Standards Under the Clean Air Act.[1] The justification for this relied partially on computational modeling to show that the consequent sea-level rise associated with greenhouse gas (GHG) emissions from U.S. on-road vehicles is *de minimis* - that is, too small to matter. Included in the final rule is a "Technical Memo on: Temperature, CO2 Concentration, and Sea Level Rise Impacts of Greenhouse Gas Emissions from U.S. Motor Vehicles for the "Rescission of the Greenhouse Gas Endangerment Finding and Motor Vehicle Greenhouse Gas Emission Standards Under the Clean Air Act" Final Rule[2] (henceforth referred to as "EPA Technical Memo"). The EPA Technical Memo provides details on the modeling done, including data tables giving their results. EPA's estimated reduction in global mean sea-level rise (GMSLR), assuming emissions associated with all U.S. on-road vehicles are removed beginning in 2027, is 1.4 cm over the 2027-2100 time period, with a 95% credible interval of 0.39-4.77 cm. The EPA modeling chain used the Building Blocks for Relevant Ice and Climate Knowledge (BRICK) sea-level model[3], of which I am one of the two original lead authors. I continue to manage the development of BRICK.

Here, I examine the baseline SSP2-4.5 GHG emissions scenario and several reduced emissions scenarios mirroring the cases in the EPA Technical Memo. I connect the temperature and ocean heat changes resulting from these scenarios to global mean sea-level rise, and subsequently to local mean sea-level rise (LMSLR) for the United States coastline. These projections can facilitate more targeted evaluations of the economic impacts to the United States associated with reduced GHG emissions from U.S. on-road vehicles. Further, there are a number of modeling choices in the EPA Technical Memo that I seek to clarify and make transparent in the work presented here.

- First: GMSLR and GMST were used instead of local hazards. As these are global means, they may differ from the actual hazards faced by the United States' coasts. Here, I downscale the GMSLR from BRICK to LMSLR for the U.S. coasts. I also aggregate over the U.S. Gulf of Mexico Coast to capture a region more geographically homogeneous.
- Second: It is not clear which version of the BRICK model was used. Given the timing of the EPA Final Rule and accompanying Technical Memo (February 2026), and an interest in reproducing the EPA's general methods for purposes of understanding the Agency's analysis, I employ a model version of BRICK that was released in February 2025; the next model version was released in December 2025.
- Third: It is not clear which version of calibrated BRICK model parameters were used. Again, given the timing of the EPA modeling work, I employ a set of BRICK model parameters that were released alongside the model version noted above. Other structural choices for the model version and calibrated parameters are possible, and reasonable. The choices I made here are in an effort to reproduce the EPA modeling chain as accurately as possible based on the details provided in the EPA Technical Memo. I note that the Technical Memo does not include any supplemental files such as the computer codes used to perform the analysis. This standard scientific practice of providing underlying data and code builds and maintains trust in the scientific enterprise.
- Fourth: The EPA Technical Memo treats the combined FaIR-BRICK simulations as equally likely (p. 4). The models were calibrated separately, then combined, so the simulations constitute samples from a probability distribution that is distinct from the true FaIR-BRICK joint posterior distribution. Specifically, the FaIR parameters are sampled from their marginal posterior distribution, as are the BRICK parameters. I use a model weighting approach to reweight the FaIR-BRICK simulations according to how well they match observational data and account for the differences in sampling distributions.
- Fifth: Due to the multi-century scale of the sea-level response to GHG emissions and consequent global warming[4–7] , a longer simulation period than through the year 2100 is warranted. Here, I use a simulation period through the year 2200 to more fully capture the sea-level response to reduced GHG emissions from U.S. on-road vehicles.

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2 Modeling Workflow

2.1 Sea Level Modeling

I use the MImiBRICK[8] v1.2.0 implementation of BRICK, along with associated sets of calibrated parameters for BRICK[9]. MimiBRICK is an implementation of the BRICK sea-level model in Julia, in the Mimi integrated modeling framework[10]. MimiBRICK v1.2.0 is a model tag released in February 2025, while the following tag (v1.2.1) was released in December 2025. The MimiBRICK Zenodo repository contains several calibrated parameter sets, corresponding to multiple model configurations. The specific parameters file used in this work is "parameters_subsample_brick.csv", which was generated by calibrating BRICK in a "standalone" format, forced by a single trajectory of global mean surface temperature (GMST) and ocean heat uptake. Based on the modeling details provided in the EPA Technical Memo, this is my best guess at the BRICK configuration used by EPA.

In order to replicate the modeling workflow as closely as possible, based on the details provided in the EPA Technical Memo, I use input for GMST and ocean heat uptake from the Finite Amplitude Impulse Response climate model[11,12] (FaIR; version v2.2.0), using SSP2-4.5 radiative forcing and GHG emissions and a set of 841 calibrated parameters (v1.4.1)[13]. FaIR is an open-source, reduced-complexity climate model, designed for probabilistic projections of global temperature and atmospheric GHG concentrations from emissions.

In addition to the baseline SSP2-4.5 scenario, which mirrors scenario #1 in the EPA Technical Memo, three additional scenarios are produced. Scenario A here reconstructs scenario #2 in the EPA modeling and captures EPA's projected level of on-road vehicle emissions in the United States, absent GHG regulations. Emissions trajectories under scenario A interpolate the sparse data points provided in the EPA Technical Memo (2027, 2050, and 2100) and hold emissions constant after the year 2055. Scenario B here represents a case in which U.S. vehicle technology stays at model year 2025 levels (the most recent year with reported data) and rates of adoption of electric vehicles remain constant, but total vehicle emissions evolve through changes in vehicle miles traveled. Scenario C here represents a counterfactual scenario without modern vehicle GHG regulations, fixing emissions rates at circa 2009 levels with no electric vehicle adoption and allowing total emissions to grow with increasing vehicle use.

In this way, scenarios B and C represent "today's fleet" and a "pre-GHG protection fleet", respectively, while scenario A mirrors the EPA Technical Memo scenario #2. Echoing the EPA Technical Memo and Final Rule, I note that this approach models removing all emissions associated with U.S. on-road vehicles, such that the projections presented in the EPA Technical Memo and here constitute in some sense an upper bound on the reductions in sea-level rise as a result of any specific set of GHG standards. However, the assumption of SSP2-4.5 as the baseline scenario neglects the fact that this "middle of the road" or "maintain current policy" scenario relies on actually maintaining the decarbonization efforts that were underway a decade ago when the Shared Socioeconomic Pathways were developed[14,15]. These factors will have compensatory effects.

For each of the 841 emissions trajectories, the global mean surface temperature and ocean heat uptake model output from FaIR serves as input to BRICK. Output from BRICK includes global mean sea-level rise, and the contributions to GMSLR from the Greenland and Antarctic ice sheets, glaciers, thermal expansion, and land water storage. To facilitate reproducibility, I set random number seeds and save the indices of the BRICK ensemble members sampled from the larger dataset of 10,000 calibrated parameter sets. However, due to insufficient details provided to exactly replicate the experimental set-up from the EPA Technical Memo, it is not expected that emissions trajectories or the resulting projections of global temperatures or sea levels will precisely match those presented in the Technical Memo.

2.2 Model Calibration

The BRICK model parameters in the dataset noted above were calibrated based on the model-data match to observational datasets for the major components of global mean sea-level change: the Greenland and Antarctic ice sheets, glaciers, thermal expansion, and land water storage. The Bayesian model calibration algorithm used is described in detail elsewhere[3,16,17], and the resulting distributions for sea-level projections are consistent with the Intergovernmental Panel on Climate Change's Sixth Assessment Report (IPCC AR6)[18]. Importantly, BRICK contains a simple module to account for potential "low confidence" but high-impact Antarctic ice sheet processes that can contribute substantially to sea-level change in the coming centuries[16]. Thus, projections using BRICK are expected to fall on the higher side of probable ranges for sea-level rise for the latter half of the 21st century and beyond, particularly for higher GHG emissions scenarios. In SSP2-4.5, these fast dynamical contributions to sea level from the Antarctic ice sheet can occur by the year 2100[16].

The parameter datasets that EPA used for FaIR and BRICK were calibrated independently of one another, then combined to form paired (concomitant) parameter sets for a coupled FaIR-BRICK model, wherein temperatures and ocean heat uptake output from FaIR serves as input to BRICK. The EPA Technical Memo asserts that all parameter sets and resulting simulations are equally likely. From a model calibration and statistical modeling standpoint, this is not the case because the BRICK simulations were calibrated using different temperature and ocean heat input than that from FaIR. On the other hand, the simulations in the ensemble constructed here are intended to be samples produced from the joint distribution of FaIR-BRICK parameters.

As an example, a set of FaIR parameters that yields a warm simulation for temperature could be paired with a set of BRICK parameters that yields a low simulation for sea-level rise. This should be treated as having relatively lower probability than more compatible sets of FaIR and BRICK parameters. To account for the variation in the goodness-of-fit of the combined FaIR-BRICK parameters, I compute weights for each concomitant parameter set and resulting simulation and use these weights to compute weighted percentiles for resulting ensemble statistics (e.g., for global mean sea-level change).

$$log(w_i) = c \cdot (l(\theta_{i,FB}) - l(\theta_{i,B})) \tag{1}$$

In Equation 1, $\theta_{i,B}$ refers to the i-th set of BRICK model parameters and $\theta_{i,FB}$ refers to the i-th set of FaIR-BRICK parameters (so the BRICK parameters are the same for both). In turn, $l(\theta_{i,B})$ refers to the value of the log-likelihood function when the BRICK model is run using its original temperature and ocean heat forcing and the i-th set of BRICK model parameters, and $l(\theta_{i,FB})$ refers to the log-likelihood value when the combined FaIR-BRICK model is run using the combined i-th set of FaIR-BRICK parameters. In Equation 1, c is a constant that is tuned to balance the influence of the best-fitting simulations against sampling from the full breadth of the approximate joint distribution of FaIR-BRICK simulations. The computed weights use a value for this “annealing” constant of c=0.000128. This yields an effective sample size of about 420, or roughly 50% of the original sample size. This is in line with guidelines and typical practice for importance sampling methods[19,20], where samples from one distribution are desired (e.g., the distribution of FaIR-BRICK parameters) but inaccessible, so they are approximated using samples from an easier-to-sample distribution (e.g., the marginal distributions of FaIR and BRICK parameters). Only the sea-level portion of the likelihood function is used because all 841 sets of FaIR parameters are known *a priori* to be well-calibrated to climate data; the BRICK parameters were calibrated to sea-level data, but the quality of the simulation is affected by changing the underlying temperature and ocean heat forcing data.

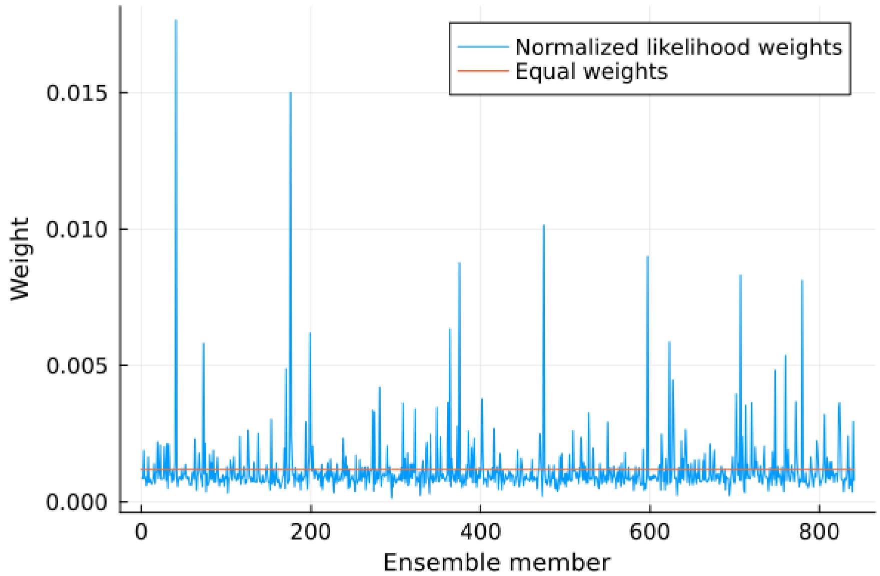
The log-weights from Equation 1 are then shifted by subtracting the maximum weight (to center them closer to 0 and avoid undue influence from the best-fitting simulations) and exponentiated to compute the unnormalized simulation weights, as shown in Equation 2.

$$W_i = exp[log(w_i) - max(log(w_i))] \tag{2}$$

Normalized weights are obtained by dividing by the sum, as shown in Equation 3.

$$W_{i,norm} = W_i / \sum_{i=1}^{841} W_i \tag{3}$$

Figure 1: Computed weights for each FaIR-BRICK simulation, based on the BRICK log-likelihood function. The dashed red line corresponds to equal weights of 1/841 ≈ 0.0012.



2.3 Local Hazards

The EPA Final Rule and Technical Memo use changes in GMST and GMSL as the measure of the impact of rescinding the vehicle emissions standards in the Clean Air Act. I use the BRICK sea-level output to estimate the associated local sea-level changes for the United States, which is better connected to the actual consequences to the U.S. of the policy change. In the case of sea-level rise, this is because local mean sea-level change can differ from global mean sea-level change due to differences in vertical land motion, ocean dynamics, and gravity effects from redistributing large amounts of ice/water[21].

I select two model simulations to downscale to local mean sea level. The first model simulation is the one with the highest normalized weight (Equation 3). I refer to this simulation the “MLE” simulation, as a maximum likelihood estimator is an approximate interpretation of how it was selected. I caution however that other simulations among the FaIR-BRICK ensemble also provide high-quality fits to the BRICK sea level calibration data, based on the model weights (Figure 1). The second model simulation that I downscale to local sea-level rise is the one that yields the median GMSLR in the year 2100 under the baseline scenario. These two simulations provide a reasonable representation of likely future local sea level rise for the United States coastline.

To compute the local mean sea-level rise (LMSLR) in the four scenarios described above, for each of the two model simulations chosen, I downscale the components of global mean sea-level change in each case to their effects on local mean sea level on a 1-degree latitude-longitude grid, using a set of well-established sea level fingerprints[22]. I compute the LMSLR for each of the 1,077 United States coastal segments from a common coastal database[23], over the 2010-2200 time horizon. To examine a specific geographic region with more similar properties, I also aggregate the localized sea-level rise over the 178 coastal segments of the United States Gulf of Mexico Coast.

3 Results

Where parenthetical uncertainty ranges are reported in the results, they are 95% credible intervals.

3.1 Global mean sea level

Results for global mean sea-level change relative to pre-industrial mean (1850-1900) are broadly consistent with those reported in the EPA Technical Memo in the baseline case (Table 1). In 2050, I find GMSLR of about 27.2 (18.4-53.6) cm, as compared to 38.9 cm reported in the EPA Technical Memo (relative to 1850-1900 mean). By 2100, GMSLR in the baseline case yields about 91.3 (42.5-179.4) cm, as compared to 94.3 (59.9-157.9) cm by the EPA's modeling. As expected, scenarios A, B, and C all match the baseline scenario in 2009, and scenarios A and B match the baseline case in 2027.

Table 1: Global mean sea-level rise relative to pre-industrial mean (1850-1900), by scenario. Shown are the ensemble projected median and 95% credible interval (cm), weighted as described in Sec. 2.2.

	Baseline	**Scenario A**	**Scenario B**	**Scenario C**
2009	10.1 (6.0-15.3)	10.1 (6.0-15.3)	10.1 (6.0-15.3)	10.1 (6.0-15.3)
2027	15.6 (10.6-22.5)	15.6 (10.6-22.5)	15.6 (10.6-22.5)	15.5 (10.5-22.5)
2050	27.2 (18.4-53.6)	27.0 (18.4-53.5)	27.0 (18.4-53.5)	26.8 (18.3-52.2)
2100	91.3 (42.5-179.4)	89.7 (42.0-176.5)	89.5 (41.9-176.3)	87.5 (41.4-174.2)
2150	177.9 (68.6-330.0)	174.7 (67.2-324.9)	174.3 (66.9-323.8)	170.5 (65.7-318.5)
2200	268.5 (95.6-475.1)	260.4 (90.5-467.6)	259.1 (89.8-464.9)	252.6 (87.5-456.1)

Results for global mean sea-level change relative to 2027 (the first year of assumed emissions reductions) also agree well in the baseline scenario and scenario A, relative to the EPA Technical Memo (Table 2). By 2050, I find 11.4 (6.0-32.7) cm of GMSLR in the baseline case, as compared to 12.4 (9.4-20.3) cm in the EPA Technical Memo. By 2100, this GMSLR reaches 76.1 (29.9-160.7) in this work, and 69.5 (35.2-132.7) cm in the EPA modeling. The reduction in GMSLR in scenario A relative to the baseline case is 0.07 (0.04-1.04) cm in 2050 and 1.45 (0.40-5.16) cm in 2100, compared to the reductions of 0.09 (0.06-1.06) cm in 2050 and 1.40 (0.39-4.77) cm in 2100. Over the 22nd century, these benefits in terms of reduced GMSLR increase to 3.61 (1.16-12.73) cm and 6.39 (2.35-21.18) cm in 2150 and 2200, respectively, in scenario A, and 4.28 (1.43-17.32) cm and 8.32 (3.12-29.34) cm in 2150 and 2200 in scenario B.

Table 2: Global mean sea-level rise relative to 2027, by scenario. Shown are the ensemble projected median and 95% credible interval (cm), weighted as described in Sec. 2.2.

	2027 Baseline	**Scenario A**	**Scenario B**
2050	11.4 (6.0-32.7)	0.07 (0.04-1.04)	0.07 (0.04-1.03)
2100	76.1 (29.9-160.7)	1.45 (0.40-5.16)	1.61 (0.44-5.82)
2150	163.6 (55.4-309.3)	3.61 (1.16-12.73)	4.28 (1.43-17.32)
2200	253.8 (82.1-454.1)	6.39 (2.35-21.18)	8.32 (3.12-29.34)

In (counterfactual) scenario C, reductions in GMSLR relative to baseline would reach 0.04 (0.03-0.08) cm by 2027, 0.29 (0.15-2.23) cm by 2050, 3.57 (0.91-9.65) cm by 2100, and 14.4 (5.17-60.3) cm by 2200 (Table 3).

Table 3: Global mean sea-level rise relative to 2009, for the baseline scenario and scenario C. Shown are the ensemble projected median and 95% credible interval (cm), weighted as described in Sec. 2.2.

	2009 Baseline	**Scenario C**
2027	5.5 (2.5-9.3)	0.04 (0.03-0.08)
2050	17.0 (9.6-41.0)	0.29 (0.15-2.23)
2100	81.0 (33.3-169.0)	3.57 (0.91-9.65)
2150	167.8 (59.0-317.4)	8.25 (2.58-30.40)
2200	260.5 (85.6-463.4)	14.37 (5.17-60.30)

3.2 Local mean sea level

I compute the local mean sea-level rise for all U.S. coastal segments within the DIVA database[23]. This dataset divides the global coastline into 12,148 segments with a median length of about 17 km. Since the coastlines of the United States show variation in major drivers of risk (e.g., east versus west coasts of the continental U.S., also, Alaska, Hawai'i, and various U.S. outlying territories), I specifically examine the mean local sea-level change along the U.S. Gulf of Mexico Coast ("Gulf Coast"). For ease of visualization and interpretation, I only downscale the FaIR-BRICK ensemble members yielding the maximum likelihood weight ("MLE") and the median GMSLR in the baseline case in the year 2100 ("Med2100"). These two simulations both are reasonable structural choices for a single "best-fitting" representative model simulation and well-represent a likely range of anticipated uncertainty around the ensemble centers. I note that GMSLR was downscaled to local sea-level rise on a 10-year time step to match the dataset used to account for non-climatic factors affecting local sea levels[24–26]. Consequently, results in Table 4 are shown relative to the year 2030 instead of 2027 as in the EPA Technical Memo and Table 2.

Table 4: Baseline GMSLR and LMSLR for the U.S. Gulf of Mexico Coast (cm), shown relative to 2030 for consistency with how downscaling was done, which used a 10-year timestep. Gulf Coast baseline is the mean local mean sea level for all 178 US Gulf of Mexico coastal segments, relative to 2030, in each of the two downscaled simulations, MLE and Med2100. Scenarios A, B, and C are given as the reduction in LMSLR relative to the Gulf Coast baseline scenario.

	GMSLR relative to 2030		**Gulf Coast baseline**		**Scenario A**		**Scenario B**		**Scenario C**	
	MLE	Med2100	MLE	Med2100	MLE	Med2100	MLE	Med2100	MLE	Med2100
2050	11.2	8.76	12	12	0.1	0.1	0	0.1	0.2	0.2
2100	47.4	78.3	53	92	2.8	3.7	2.8	3.8	3.4	6.5
2150	106.2	164.3	121	190	12.5	4.8	15.1	5.1	20.9	8.7
2200	181.7	249.7	205	286	20.1	6.2	26.5	7.3	55.5	12.1

The tendency of the Gulf of Mexico to experience higher LMSLR than GMSLR is evidenced by both the MLE and Med2100 simulations (Table 4, first 4 columns). The MLE simulation has slightly higher LMSLR than GMSLR in 2050 relative to 2030 (12 cm locally versus 11.2 globally). This difference grows to over 5 cm by 2100 and more than 20 cm by 2200. The Med2100 simulation displays an even higher rate of local sea-level rise compared to GMSLR. In the Med2100 simulation, by 2050, the Gulf Coast experiences more than 3 cm higher sea-level rise than global mean. By 2100, this difference increases to more than 13 cm and by 2200, more than 30 cm higher LMSLR than GMSLR in the Med2100 simulation. While land subsidence is responsible for much of the comparatively higher LMSLR for the Gulf Coast, the relative contributions from the major ice sheets, Greenland and Antarctica, also play a key role. Specifically, due to gravitational effects from melting large amounts of ice, contributions to GMSLR from the Greenland ice sheet serve to lower local mean sea level along the Gulf Coast, whereas contributions from the Antarctic ice sheet raise local mean sea level there. Since the Med2100 simulation sees a much higher sea level contribution from the Antarctic ice sheet, LMSLR is also relatively higher compared to the MLE simulation.

Also owing to the relatively larger sea level contribution from the Antarctic ice sheet, the Med2100 simulation shows lower reductions in LMSLR in the three reduced emissions scenarios when compared to the MLE simulation (Table 4, right 6 columns). Reductions in LMSLR for the Gulf Coast in scenario A for the two simulations considered here span 2.8-3.7 cm in 2100 to 6.2-20.1 cm by 2200. This exceeds the median reduction in GMSLR of 1.4 cm by 2100 reported in the EPA Technical Memo, indicating that local benefits for the U.S. Gulf Coast can be substantially larger than those suggested by global mean values alone. Scenario B yields similar reductions in 2100 (2.8-3.8 cm of reduced LMSLR) but larger benefits by 2200 (7.3-26.5 cm). Scenario C shows even greater and earlier reductions in LMSLR, with 0.2 cm in 2050, 3.4-6.5 cm by 2100, and 12.1-55.5 cm by 2200.

4 Discussion

I have implemented a modeling workflow that mirrors the sea-level projections workflow presented in the EPA Technical Memo as closely as possible given the details provided, while also improving the modeling workflow by taking into account variation in the quality of ensemble members through a weighting approach. I find projections of GMSLR that are broadly consistent with the projections as presented in the EPA Technical Memo, particularly for GMSLR by 2100 in the baseline scenario and in the reduced emissions scenario A. By downscaling the GMSLR projections to LMSLR for the entire U.S. coastline and the U.S. Gulf of Mexico Coast, I connect these sea-level projections to local coastal hazards more specific to the United States. These LMSLR projections, particularly for scenario A relative to the baseline scenario, demonstrate that vehicle emissions reductions via the Clean Air Act disproportionately benefit the U.S. Gulf Coast (Table 4).

For global mean sea level, the difference between the baseline SSP2-4.5 scenario and scenario A (EPA's scenario #2) is modest in the near-term, but grows over time, reflecting the long timescale of the sea-level response to changing emissions and temperature. By 2100, removing U.S. on-road vehicle emissions yields a median reduction of about 1.45 cm of GMSLR, but this effect more than quadruples to over 6 cm by 2200 (Table 2). Scenarios B and C also produce greater GMSLR reductions by 2100, and by the year 2200, these benefits grow to over 8 cm in scenario B and over 14 cm in scenario C (Tables 2 and 3). These results highlight the importance of considering the long-term consequences of continued emissions, even at marginal GHG levels that may seem too low to matter.

In the downscaling to local coastal hazards, for ease of interpretation, I use just two model simulations among the 841-member ensemble to characterize uncertainty. These are the simulation with the maximum likelihood weight among the ensemble (MLE) and the simulation yielding the median GMSLR in the year 2100 in the baseline scenario (Med2100). Both simulations were chosen based on their match to central tendency in the ensemble. Consequently, they may well underestimate the true breadth of potential future LMSLR for the U.S. Gulf Coast, even though the uncertainty ranges in Table 4 are substantial (represented by the range between the MLE and Med2100 simulations). Indeed, the sizable uncertainties associated with human decision-making, climate mitigation, and adaptation are given as reasons for the EPA Final Rule to avoid estimating actual economic benefits or on-the-ground impacts from reduced greenhouse gas emissions. However, previous work has demonstrated, for example in the case of managing coastal risk in New Orleans, Louisiana, that in the face of climate change, the most expensive strategy we can pursue is to do nothing[27].

5 Code and Data Availability

All model and analysis code, input, and output files are available at https://zenodo.org/records/19577321. Figures and tables from this work may be reused or adapted with permission from the author.

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