Journal of Research High School

Vol. 2026 (9) 689 – 694
ISSN 2688-3651 [online]

Comparison of the Contribution of Greenhouse Gases to Global Temperature and Sea Level Rise

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Received November 17, 2025; Revised May 22, 2026; Accepted June 24, 2026

Abstract

Greenhouse gases such as carbon dioxide, nitrous oxide, and methane are major contributors to climate change. This study examines how the atmospheric concentrations of these gases are associated with global mean sea level and global surface temperature anomaly from 2001 to 2020. Multiple linear regression was used to compare the relationships between the three greenhouse gases and the two climate indicators. The results suggest that nitrous oxide showed the strongest positive association with global mean sea level, while methane showed the strongest positive association with temperature anomaly in the examined models. However, because the greenhouse gas predictors were highly correlated and the dataset included only 20 annual observations, the findings should be interpreted as descriptive associations rather than causal estimates. Future studies using longer datasets, radiative forcing-based variables, and time-series methods would allow a more reliable evaluation of the relative associations of individual greenhouse gases with climate indicators.

Keywords: Greenhouse Gases, Global Mean Sea Level, Surface Temperature Anomaly, Multiple Linear Regression

1. Introduction

Global mean sea level (GMSL) rise is one of the major consequences of anthropogenic climate change. It threatens coastal ecosystems and human populations by increasing the risks of coastal flooding, erosion, saltwater intrusion, and habitat loss (Intergovernmental Panel on Climate Change, 2021; National Centers for Environmental Information, 2021). Modern sea-level rise is primarily driven by two processes: thermal expansion of warming seawater and the addition of meltwater from glaciers and ice sheets (Intergovernmental Panel on Climate Change, 2021; National Centers for Environmental Information, 2021). Both processes are closely connected to increases in global temperature.

Rising atmospheric concentrations of greenhouse gases, including carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4), increase radiative forcing and contribute to global warming (Myhre et al., 2013; Intergovernmental Panel on Climate Change, 2021). Radiative forcing refers to a change in Earth's energy balance caused by external factors, such as changes in atmospheric greenhouse gas concentrations. Because temperature and sea level respond to greenhouse gas-driven climate change in different ways, comparing their statistical relationships with major greenhouse gases can help clarify how these variables are associated in recent observational data.

This study examines the associations between atmospheric concentrations of CO_2, N_2O, and CH_4 and two climate response variables, GMSL and the NASA GISS Land-Ocean Temperature Index (L-OTI), using annual global data from 2001 to 2020. In addition, this study evaluates regression diagnostics and statistical limitations, including multicollinearity and sample size, to assess how reliably the regression results can be interpreted.

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2. Methods

Two analysis files containing annual datasets for 2001-2020 were prepared and used throughout this study: climate.csv (greenhouse gas (GHG) v. sea level) and climate2.csv (GHG v. temperature). GMSL rise is measured in millimeters (mm) relative to the 1993-2008 average. The GMSL dataset used in climate.csv was assembled from the climate.gov dashboard and represents the average of the Church and White series and the University of Hawaii Sea Level Center (UHSLC) series; the original dashboard file is available from the climate.gov dataset cited in the References (National Centers for Environmental Information, 2021). The original sea-level dataset reports values in January, April, July, and October; those quarterly values were averaged to produce a single annual GMSL value for each year. The global temperature series used in climate2.csv is the NASA GISS L-OTI, without smoothing, which reports annual temperature anomalies relative to a 30-year baseline; the L-OTI anomaly combines land observations from weather stations with ocean observations from ships and buoys and is available from the NASA GISS data repository (NASA Goddard Institute for Space Studies, n.d.). Greenhouse gas (GHG) predictors are the long-run Our World in Data concentration series: carbon dioxide (CO_2) in parts per million (ppm), nitrous oxide (N_2O) in parts per billion (ppb), and methane (CH_4) in parts per billion (ppb) (Ritchie et al., 2025a; Ritchie et al., 2025b; Ritchie et al., 2025c). The CO_2, N_2O, and CH_4 series are incorporated without additional smoothing.

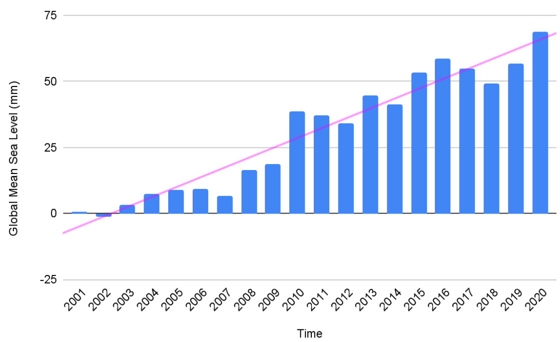

Figure 1. Annual GMSL rise from 2001-2020.

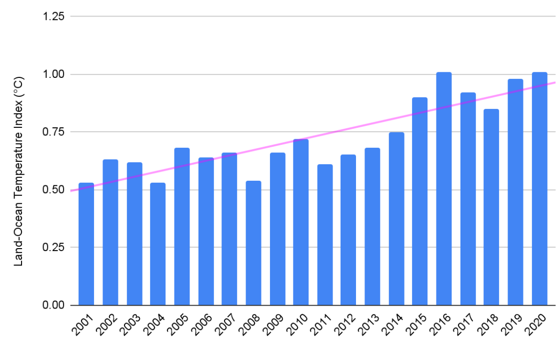

Figure 2. Annual L-OTI from 2001-2020.

Ordinary least squares (OLS) regressions were estimated in R. OLS regression was selected as a simple and interpretable first-step model for examining conditional associations between greenhouse gas concentrations and climate indicators. This approach allowed the direction, relative magnitude, and statistical significance of each greenhouse gas predictor to be compared while holding the other predictors constant. However, because the data consist of annual time-series observations and the greenhouse gas concentrations increase together over time, the OLS models were used only for descriptive association analysis, not for causal attribution.

In this study, p-values were used to evaluate whether each regression coefficient was statistically significant. A p-value represents the probability of observing a result as extreme as the one obtained if the true coefficient were zero. The statistical significance threshold was set at alpha = 0.05. Therefore, regression coefficients with p-values less than 0.05 were considered statistically significant, while coefficients with p-values greater than 0.05 were not considered statistically significant. The limitations related to temporal trends, high multicollinearity, and the small sample size are discussed further in the Discussion section. The first model regresses annual GMSL (Sea.Level.Rise) on N_2O, CO_2, and CH_4 (Sea.Level.Rise ~ CO_2 + N_2O + CH_4) using climate.csv. The second model regresses the L-OTI temperature anomaly (No_Smoothing) on the same three predictors (No_Smoothing ~ CO_2 + N_2O + CH_4) using climate2.csv. For each model, coefficients, standard errors, and adjusted R^2 were recorded, and diagnostic plots were examined. Diagnostic plots generated from R include the histogram of residuals, the normal Q-Q plot with reference line, and fitted values versus residuals; these were analyzed visually to assess normality, skew, tail behavior, and heteroskedasticity.

In Figures 3 and 7, the greenhouse gas concentrations are shown using natural logarithms only for visualization purposes. This transformation was used because CO_2, N_2O, and CH_4 are measured in different units and have different numerical ranges, making them difficult to compare visually on the same axis. The OLS regression models, however,

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were fitted using the original concentration values rather than the logarithm-transformed values.

3. Results

The sea level model yields an intercept of – 2502.5643 (SE 831.9637, p = 0.0083) and coefficients of 12.0717 for N_2O (SE 5.3802, p = 0.039), – 2.8354 for CO_2 (SE 2.0350, p = 0.183), and – 0.1497 for CH_4 (SE 0.1920, p = 0.447). Among the three greenhouse gas predictors, only the N_2O coefficient met the statistical significance threshold of $p < 0.05$ in the sea-level model. The model had an adjusted R^2 of 0.9377, indicating that the three-predictor model accounted for 93.77% of the variance in sea-level rise within the 2001–2020 dataset. The diagnostic plots for the sea-level model show residuals that are approximately symmetric but with a slight right-heavy tail and one large positive residual, as shown in Figure 4. The normal Q-Q plot places most points close to the reference line, with some deviation at the positive extreme, as shown in Figure 5. The fitted-versus-residuals plot does not show a systematic increase or decrease in residual spread across fitted values, as shown in Figure 6. The model's residual standard error is 5.677 mm, and the sample standard deviation of residuals is 5.2095 mm.

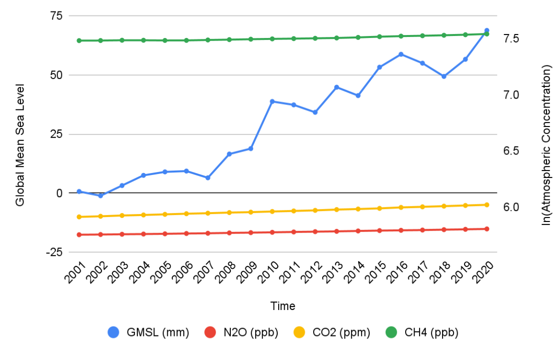

Figure 3. GMSL and natural logarithm-transformed atmospheric concentrations of N_2O, CO_2, and CH_4 from 2001 to 2020.

Multiple Linear Regression Equation of Sea Level

$$\text{Sea Level Rise (mm)} = -\,2502.5643 + 12.0717\ N_2O\ (\text{ppb}) - 2.8354\ CO_2\ (\text{ppm}) - 0.1497\ CH_4\ (\text{ppb}).$$

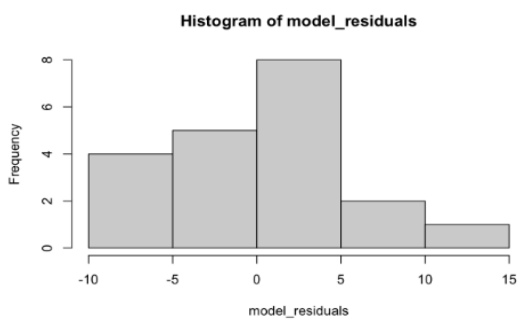

Figure 4. Histogram of Residuals.

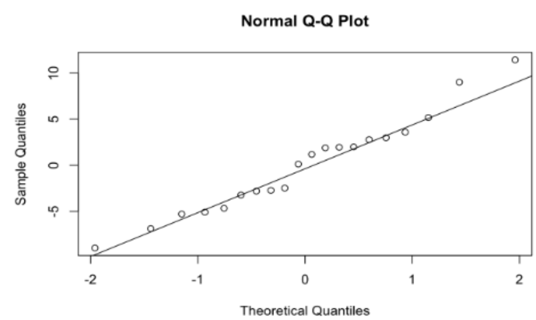

Figure 5. Normal Q-Q Plot of Residuals.

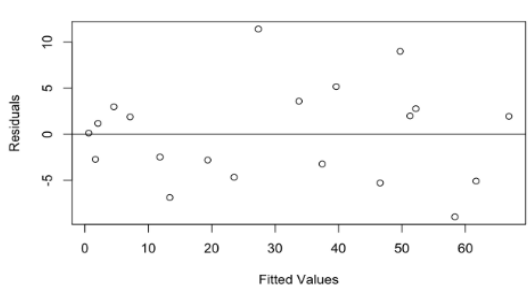

Figure 6. Fitted Values v. Residuals Plot.

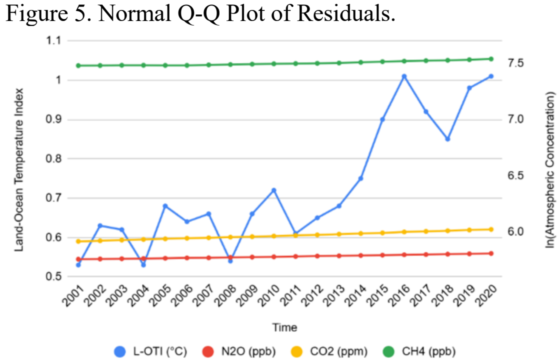

Figure 7. L-OTI and natural logarithm-transformed atmospheric concentrations of N_2O, CO_2, and CH_4 from 2001 to 2020.

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Multiple Linear Regression Equation of Temperature

$$\text{L-OTI (°C)} = 6.222848 - 0.089726\ N_2O\ (\text{ppb}) + 0.030510\ CO_2\ (\text{ppm}) + 0.006445\ CH_4\ (\text{ppb}).$$

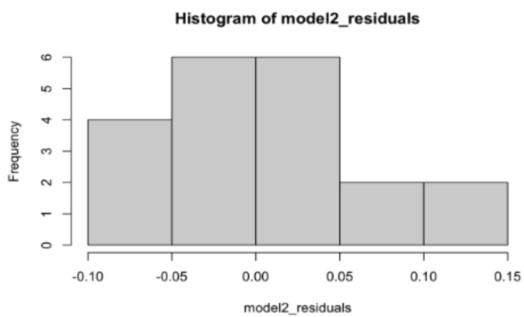

Figure 8. Histogram of Residuals.

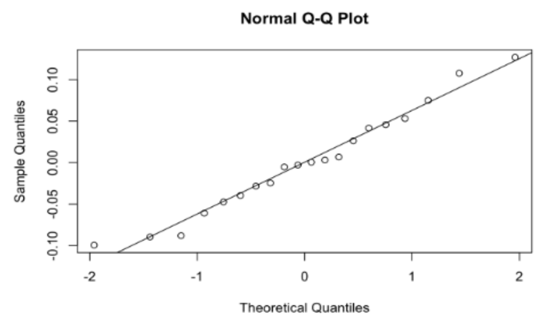

Figure 9. Normal Q-Q Plot of Residuals.

The temperature model yields coefficients of –0.08973 for N_2O ($p = 0.187$), 0.03051 for CO_2 ($p = 0.233$), and 0.006445 for CH_4 ($p = 0.0134$). Among the three greenhouse gas predictors, only the CH_4 coefficient met the statistical significance threshold of $p < 0.05$ in the temperature model. The model had an adjusted R^2 of 0.8142, indicating that the three-predictor model accounted for 81.42% of the variation in temperature anomaly within the 2001–2020 dataset. The diagnostic plots for the temperature model show residuals of very small magnitude, an approximately symmetric histogram, and Q-Q points that lie close to the theoretical line with only minor tail scatter, as shown in Figures 8 and 9. The fitted-versus-residuals plot does not show a clear heteroskedastic pattern, as shown in Figure 10.

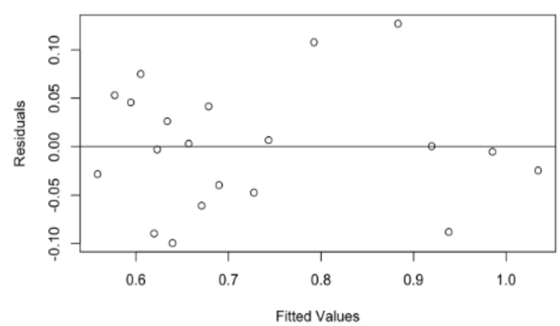

Figure 10. Fitted Values v. Residuals Plot.

4. Discussion

Table 1. Summary of regression coefficients for the sea-level and temperature models.

Summary of Regression Coefficients (GHG vs. Sea Level)				
	Coefficient	Standard Error	t-stat	p-value
Intercept	-2502.5643	831.9637	-3.008	0.00834
N_2O	12.0717	5.3802	2.244	0.03935
CO_2	-2.8354	2.0350	-1.393	0.18258
CH_4	-0.1497	0.1920	-0.780	0.44692

Summary of Regression Coefficients (GHG vs. Temperature)				
	Coefficient	Standard Error	t-stat	p-value
Intercept	6.222848	10.052629	0.619	0.5446
N_2O	-0.089726	0.065009	-1.380	0.1865
CO_2	0.030510	0.024589	1.241	0.2326
CH_4	0.006445	0.002320	2.778	0.0134

The two multivariate regressions give different signals about which greenhouse gas is most strongly associated with each response variable within the selected OLS models. In the sea-level model, N_2O was the only greenhouse gas predictor with a statistically significant positive coefficient, while in the temperature model, CH4 was the only greenhouse gas predictor with a statistically significant positive coefficient. These results indicate that, within the selected OLS models and the 2001–2020 dataset, N_2O was most strongly associated with GMSL and CH_4 was most strongly associated with L-OTI. However, these findings should be interpreted as conditional associations rather than

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causal estimates.

Research suggests that N2O, though less frequently emphasized in public discussion than other greenhouse gases, contributes to global warming and has a long atmospheric lifetime, which makes it persistently influential (Stell et al., 2022; United Nations Environment Programme, 2024). Furthermore, CH_4 is widely recognized as a potent near-term warming greenhouse gas (Ocko et al., 2018). For example, the IEA reports that CH_4 is responsible for around 30% of current global temperature rise (International Energy Agency, 2022). Harvard SEAS also notes that CH_4 has a much higher short-term warming potential than CO_2 and contributes substantially to modern warming (Schoos, 2023). These previous studies are consistent with the regression patterns observed in this study, but they do not remove the statistical limitations of the OLS models.

The difference in adjusted R^2 values between the sea-level model and the temperature model can be understood in terms of how each response variable integrates the effects of greenhouse gas forcing. Sea-level rise is driven largely by cumulative and long-term processes, primarily ocean thermal expansion and land-ice mass loss, which are directly linked to sustained greenhouse gas-induced radiative forcing. Because these processes respond slowly and persistently, sea level exhibits a smoother upward trend with relatively little year-to-year variability. This produces a stronger linear co-movement with atmospheric greenhouse gas concentrations and therefore a higher adjusted R^2. In contrast, global mean temperature reflects not only external forcing from greenhouse gases but also short-term internal climate variability, such as ENSO cycles, volcanic aerosols, and ocean heat redistribution. These fluctuations reduce the proportion of total variance that can be explained by greenhouse gas concentrations alone, resulting in the lower adjusted R^2 value observed in the temperature model.

The coefficients in a multiple regression model represent the association between each predictor and the response variable after holding the other predictors constant. Because CO_2, N_2O, and CH_4 all increase over time and are highly correlated with one another, the individual coefficients may be unstable and sensitive to the selected time period or model specification. Therefore, the statistically significant N_2O and CH_4 coefficients should not be interpreted as evidence that these gases independently caused the observed changes in sea level or temperature. The negative coefficient of CO_2 in the sea-level model is an example of this instability and must not be interpreted as CO_2 causing sea-level decline. The high R^2 values may reflect shared upward trends among atmospheric greenhouse gas concentrations, temperature, and sea level over time rather than direct causal attribution of individual greenhouse gases.

The residual diagnostics did not indicate severe violations of the basic OLS assumptions. However, acceptable residual plots do not eliminate the larger limitations of the analysis, including the small sample size, high multicollinearity among greenhouse gas predictors, and the time-series nature of the data. Because the statistical properties of time-series data may change over time, temporal trends can also introduce serial correlation or nonstationarity that is not fully addressed by simple OLS regression. For this reason, the OLS results are best understood as descriptive associations rather than definitive causal estimates of the relative contributions of individual greenhouse gases.

Future research should convert greenhouse gas concentrations into radiative forcing units, for example by using established radiative forcing equations and IPCC radiative efficiencies for CO_2, CH_4, and N_2O. Future studies should also use longer datasets and time-series methods that can address temporal trends, cointegration, and lagged climate responses. These improvements would allow a more reliable evaluation of the relative roles of individual greenhouse gases in climate change.

5. Conclusion

This study examined the associations between three greenhouse gases, CO_2, N_2O, and CH_4, and two climate indicators, GMSL and L-OTI, using annual data from 2001 to 2020. In the OLS models, N_2O showed the clearest positive association with sea-level rise, while CH_4 showed the clearest positive association with temperature anomaly. However, these findings should be interpreted cautiously. The dataset included only 20 annual observations, and the three greenhouse gas predictors were highly correlated with one another. Therefore, the regression results describe conditional associations within the selected models rather than definitive causal contributions of individual greenhouse gases. Future research should use longer datasets, radiative forcing-based variables, and time-series methods that can better address temporal trends, lagged climate responses, and multicollinearity. These improvements would allow a more reliable evaluation of the relative roles of different greenhouse gases in climate change.

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