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# *Contrasting Global Consensus and Regional Evidence: Short-Term $CO_2$–Temperature Relationships in China (2020–2024)*

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***Abstract.*** The positive relationship between carbon dioxide ($CO_2$) emissions and global warming has long been established, forming a cornerstone of the IPCC scientific consensus. However, most studies focus on global and long-term perspectives, while short-term and regional variations remain underexplored. This paper analyzes daily $CO_2$ emission data from Carbon Monitor and high-resolution monthly temperature data from the National Tibetan Plateau Data Center for China between 2020 and 2024. Using Pearson correlation, OLS regression with HAC errors, and seasonal adjustment (X-13-ARIMA-SEATS), we evaluate the $CO_2$–temperature relationship at multiple time scales. Results show a weak and statistically insignificant negative correlation at the monthly level ($r = -0.175$, slope = -0.637°C per Mt/day, $p = 0.340$). After deseasonalization and detrending, however, anomalies exhibit a stronger and statistically significant negative correlation ($r = -0.463$, slope = -0.180°C per Mt/day, $p < 0.001$). These findings suggest that short-term negative correlations are driven by socio-economic adaptive behaviors such as heating and cooling demand, rather than contradicting the greenhouse effect. By contrasting the global long-term consensus with short-term Chinese evidence, this study highlights the scale dependence of $CO_2$–temperature correlations and warns against the misinterpretation of short-term results.

***Keywords:*** $CO_2$ Emissions, Surface Temperature, Climate variability, Scale Effect, Correlation Heterogeneity

## 1. Introduction

The causal link between atmospheric carbon dioxide ($CO_2$) and global warming is one of the most firmly established findings in climate science. The IPCC Sixth Assessment Report (AR6) concludes that $CO_2$ concentrations have increased by nearly 50% since the pre-industrial era, contributing to a global mean surface temperature rise of approximately 1.1°C [1]. This forms the basis of the global consensus that $CO_2$ is the dominant driver of anthropogenic climate change.

Despite this consensus, short-term and regional analyses often reveal weaker or even opposite relationships. In China, emerging evidence suggests that extreme heat events may reduce carbon emission efficiency, implying that the short-term $CO_2$–temperature relationship can be negative under specific conditions [2]. These findings raise important questions about the interpretation of short-term correlations, particularly in regions with strong seasonal energy demand.

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This study focuses specifically on China between 2020 and 2024, not only because it is the world's largest emitter of $CO_2$ and therefore central to global mitigation efforts, but also because it experienced distinct short-term disruptions during this period. The COVID-19 pandemic and subsequent lockdowns led to unprecedented reductions in industrial activity and transport emissions, followed by a rapid recovery in 2021 that produced sharp emission rebounds. In addition, China endured the record-breaking 2022 heatwave, which altered electricity demand patterns and highlighted the complex role of heating and cooling sectors in shaping emissions [3]. These unique events provide an ideal opportunity to investigate how short-term socio-economic shocks interact with climate variability. Unlike most existing research that emphasizes long-term global averages, this study adopts a short-term, high-frequency perspective at the national scale.

By combining daily $CO_2$ emissions from Carbon Monitor with 1 km resolution monthly mean temperature data from the National Tibetan Plateau Data Center [4], this study systematically examines both the raw and deseasonalized relationships. The methodological framework applies correlation analysis, OLS regression with HAC errors, and seasonal adjustment to ensure statistical rigor. Overall, the literature demonstrates that while long-term global datasets confirm $CO_2$–temperature positive coupling, short-term and regional studies often yield weak or even negative correlations. This motivates the present study to re-examine the short-term emission–temperature relationship in China (2020–2024) using high-frequency and high-resolution datasets, coupled with rigorous statistical processing.

## 2. Literature review

Research on the $CO_2$–temperature relationship has developed across different spatial and temporal scales. At the global and long-term level, the IPCC Sixth Assessment Report (2021) firmly established that anthropogenic $CO_2$ emissions are the dominant driver of observed warming, with concentrations rising nearly 50% since pre-industrial times [1]. High-frequency monitoring systems such as Carbon Monitor have further confirmed the utility of near–real-time emission datasets for tracking global $CO_2$ emission changes [4]. Complementary efforts using machine learning have reconstructed global daily $CO_2$ emissions, revealing that emission–temperature correlations may shift depending on threshold values, but still remain positive over multi-decadal horizons [5].

At the regional scale, evidence from China demonstrates more complex patterns. For example, studies show that extreme heat events can reduce carbon emission intensity, weakening the expected correlation between higher temperatures and higher emissions [2]. High-resolution gridded $CO_2$ concentration datasets provide full spatial coverage, shedding light on the heterogeneity of China's carbon cycle [6]. In addition, analyses of intraseasonal variability reveal that atmospheric circulation anomalies in Eastern China during early 2022 produced temperature reversals that were not aligned with emission patterns [7]. Broader assessments of human influence on Chinese climate further confirm that short-term emission signals often reflect socio-economic activity rather than radiative forcing [8].

At the short-term scale, specific shocks illustrate how emissions and temperature may decouple. Studies of COVID-19 lockdowns demonstrated temporary emission reductions without corresponding climatic responses [9]. Analyses of the record-breaking 2022 heatwave in China further show how weather anomalies and energy demand adaptation can invert the expected $CO_2$–temperature relationship [3]. These findings suggest that while long-term forcing remains clear, short-term regional datasets may yield weak or negative associations.

Despite these advances, significant methodological gaps remain. Few studies have explicitly applied seasonal adjustment techniques such as X-13-ARIMA-SEATS, a method capable of

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decomposing time series into trend, seasonal, and irregular components [10]. This approach is essential for distinguishing recurring seasonal cycles from genuine anomalies, thereby providing a clearer perspective for interpreting short-term climate–carbon linkages.

## 3. Data and methods

### 3.1. Data sources

This study employs two datasets. Daily national $CO_2$ emissions for China were obtained from Carbon Monitor, covering January 2020 to December 2024 [4]. Data were aggregated into monthly averages (Mt/day). Monthly mean surface air temperature was obtained from the National Tibetan Plateau Data Center, a gridded dataset with a 1 km resolution [6]. National monthly means (°C) were calculated using area-weighted averages.

### 3.2. Data processing

The workflow ensured comparability between the datasets. Daily $CO_2$ data were first aggregated into monthly means and aligned with temperature data, resulting in 60 paired observations. Both series were standardized (z-scores) to avoid scale bias. Seasonal adjustment was then performed using X-13-ARIMA-SEATS [10], which decomposed the time series into trend, seasonal, and irregular components. The irregular component (deseasonalized anomalies) was retained for short-term analysis.

To handle extreme values, such as abnormally low emissions during COVID-19 lockdowns, a two-step procedure was adopted. First, outliers were flagged using a ±3 standard deviation threshold relative to the monthly mean. Second, flagged observations were cross-validated against documented policy or climate events (e.g., national lockdowns, extreme weather). When confirmed as event-driven rather than data errors, these values were retained in the dataset but separately tested in robustness checks. This ensured that genuine socio-economic shocks were not discarded as statistical noise while preventing spurious bias caused by true measurement errors.

Anomalies were then calculated as deviations from the 2020–2024 climatological mean for each month (e.g., July 2022 anomaly = July 2022 observed - July 2020–2024 mean). Finally, lag tests were conducted, examining 1-2 month offsets. Results showed no improvement over contemporaneous correlations, suggesting synchronous short-term dynamics.

### 3.3. Statistical methods

Three techniques were employed. First, Pearson correlation coefficients quantified the linear association between $CO_2$ emissions and temperature, both for raw monthly data and deseasonalized anomalies. Significance was assessed at the 95% confidence level (two-tailed). Second, Ordinary Least Squares (OLS) regression was used to estimate the slope of temperature change per unit of $CO_2$ emissions. To address heteroscedasticity and autocorrelation inherent in time-series data, HAC (Newey–West) robust standard errors were applied. Model outputs included regression slope, standard error, p-value, and coefficient of determination ($R^2$). Third, robustness checks were performed to validate model stability. Variance Inflation Factor (VIF) tests confirmed no multicollinearity among predictors. Durbin–Watson statistics suggested low serial correlation in residuals. Sensitivity analyses were also conducted by excluding flagged extreme observations (e.g., COVID-19 lockdown anomalies) to evaluate their influence on the overall results. Furthermore, alternative detrending methods, such as centered moving averages, were applied and produced

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results consistent with those from the X-13 approach. These additional steps enhanced the credibility and reliability of the findings.

## 4. Results

### 4.1. Temporal patterns

Figure 1 shows monthly $CO_2$ emissions and temperature (2020–2024). Both series exhibit strong seasonality. Emissions peak in winter and summer (heating/cooling), while temperature follows a sinusoidal pattern. Irregular spikes appear in early 2021 (post-COVID rebound) and summers 2022-2023 (heatwaves).

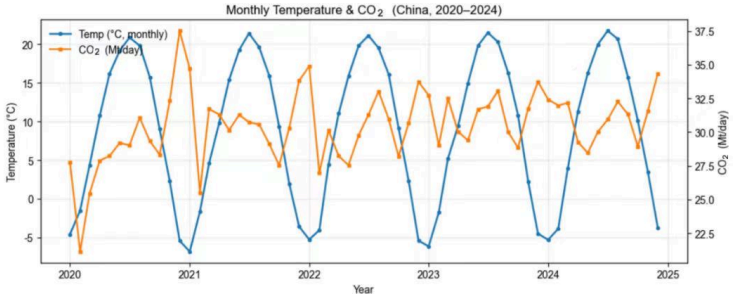


Figure 1. Monthly $CO_2$ emissions and temperature (2020-2024)

### 4.2. Monthly correlation

Figure 2 plots emissions against temperature. The OLS slope is -0.637°C per Mt/day, correlation r = -0.175, and p = 0.340. $R^2$ = 0.031 shows weak explanatory power. Extreme cold winters and hot summers coincide with high emissions, flattening the regression line. Monthly data thus provide weak evidence for a stable relationship.

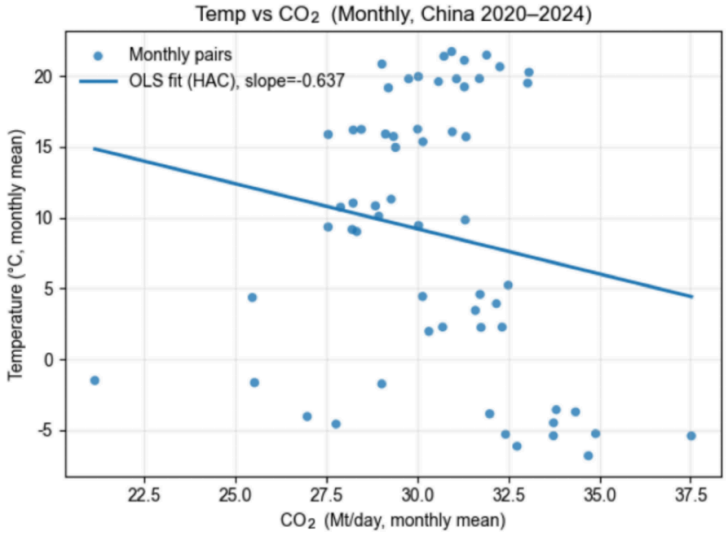


Figure 2. Monthly $CO_2$ emissions against temperature

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### 4.3. Deseasonalized anomalies

Figure 3 shows anomalies. The slope is -0.180°C per Mt/day, the correlation r = -0.463, and p < 0.001. $R^2$= 0.214 indicates anomalies explain ~21% of variance. When emissions exceed seasonal expectations, temperatures fall below expected values, and vice versa. Seasonal adjustment uncovers a statistically significant negative correlation that is hidden in raw monthly data.

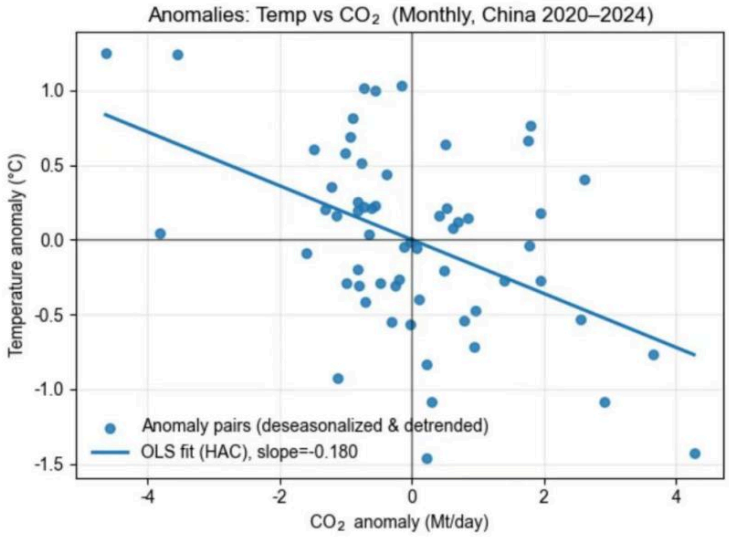


Figure 3. Monthly $CO_2$ the anomalies of emissions and temperature

## 5. Discussion

The results—weak monthly correlation but significant negative anomaly correlation—require nuanced interpretation. They do not undermine greenhouse theory but instead reflect short-term behavioral, sectoral, and policy-driven mechanisms.

Adaptive energy demand creates a U-shaped relation. In cold months, heating raises emissions as temperature falls. In hot anomalies, cooling surges, yet two effects dampen positive correlation: (i) efficiency/intensity—carbon per unit of energy may fall during peak demand periods due to cleaner or more efficient energy sources; (ii) industrial substitution—heatwaves trigger load shedding, offsetting residential cooling gains. These dynamics are consistent with global studies that identify threshold effects in $CO_2$–temperature interactions [5]. When temperatures fall below commonly cited comfort thresholds, typically around 18–20°C, energy demand for heating rises sharply, causing $CO_2$ emissions to increase even as surface temperatures decline. This threshold-driven mechanism explains why negative short-term correlations can emerge under colder-than-average conditions.

Policy and supply shocks also disrupt alignment. COVID-19 lockdowns and recovery caused emission fluctuations unrelated to weather [9]. Early 2022 in Eastern China saw intraseasonal reversal of temperature anomalies, while industrial activity followed policy cycles [7]. Such decoupling demonstrates how emissions are influenced by regulation, industry, and supply, not only climate.

Scale mismatch explains further. Radiative forcing acts over decades; short-term datasets are dominated by weather and behavior. Raw monthly data mix cycles, obscuring relationships. Only X-13 seasonal adjustment isolates anomalies, uncovering negative correlations [10]. Lag tests confirmed synchronous rather than causal short-run links.

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These findings emphasize scale dependence: positive $CO_2$–temperature coupling at global, long-term scales, but variable or negative short-term associations [1]. Scientifically, this warns against misinterpreting short-term statistics as evidence against climate change. For policy, it highlights the need to manage short-term adaptive demand, particularly in heating and cooling. Efficiency upgrades, flexible power systems, and demand management strategies are key to reducing emissions during extreme weather events.

## 6. Conclusion

This study examined the short-term $CO_2$–temperature relationship in China (2020-2024) using Carbon Monitor emissions and temperature data. Raw monthly data showed a weak, insignificant correlation, but deseasonalized anomalies revealed a significant negative relationship. These results underscore the scale dependence of $CO_2$–temperature linkages. While long-term global consensus confirms a strong positive correlation, short-term Chinese evidence reflects adaptive demand, sectoral heterogeneity, and policy shocks. Limitations include the short five-year window, reliance on national averages, and exclusion of other greenhouse gases. Future research should extend time frames, use regional sub-samples, and apply multivariate models. Short-term negative results should not be misinterpreted as contradicting the greenhouse effect. Instead, they highlight the intertwined nature of climate physics and human responses. Scientifically, they enrich understanding of carbon–climate dynamics; politically, they emphasize the need for addressing adaptive energy demand.

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