Matters Arising: Critical Methodological Flaws in Qin et al. (2025) "Mangrove sediment carbon burial offset by methane emissions from mangrove tree stems"

Maher, D.T[1], Jeffrey, L.C[2], Rosentreter, J.A[3], Johnston, S.G[4], Gauci, V.[5], Pangala, S.R.[6]

This article is a non-peer reviewed preprint submitted to EarthArXiv. of a "Matters Arising" article submitted to Nature Geoscience. The Maters Arising article refers to the paper "Mangrove sediment carbon burial offset by methane emissions from mangrove tree stems" by Qin et al. 2025 https://doi.org/10.1038/s41561-025-01848-4 In this letter we raise concerns around statistical methods, and upscaling in the published paper by Qin et al. 2025, and provide revised, statistically robust recalculations.

[1]Professor Damien Maher
Professor of Earth Science
Southern Cross University
damien.maher@scu.edu.au

[2]Dr Luke Jeffrey
Senior Lecturer
Southern Cross University
luke.jeffrey@scu.edu.au

[3]Assoc. Prof. Judith Rosentreter
Associate Professor of Biogeochemistry
Southern Cross University
judith.rosentreter@scu.edu.au

[4]Professor Scott Johnston
Professor of Biogeochemistry
Southern Cross University
scott.johnston@scu.edu.au

[5]Professor Vincent Gauci
Birmingham Professorial Fellow
University of Birmingham
v.gauci@bham.ac.uk

[6]Dr Sunitha Pangala
Royal Society Research Fellow
Imperial College London
s.pangala@imperial.ac.uk

Matters Arising: Critical Methodological Flaws in Qin et al. (2025) "Mangrove sediment carbon burial offset by methane emissions from mangrove tree stems"

SUMMARY OF CONCERNS

The authors report global mangrove stem CH_4 emissions of 730.60 Gg yr^{-1}, offsetting 16.9% of carbon burial. However, their analysis suffers from critical methodological flaws involving the failure to remove extreme statistical outliers, with 14.2% of chamber measurements and 15.5% of site observations identified as outliers by standard criteria. The analysis demonstrates inappropriate handling of severely skewed data, where the mean is 13.3 times the median for chamber data, and training of machine learning models on outlier-contaminated data without quality control. The machine learning model is then applied globally, which results in an overestimation of global mangrove stem CH_4 emission estimates. The study lacks sensitivity analysis to assess robustness of estimates and relies on inflated R^2 metrics that reward overfitting to measurement errors.

Our reanalysis using standard statistical methods and proper data quality control yields global emissions of 22.6 – 205.8 Gg yr^{-1}, representing a 3.5 to 32.4 fold overestimation in the published study. This range of estimates is more representative of previously published estimates of site-specific emission rates. The carbon burial offset should therefore be 0.5 to 4.7%, not 16.9% as claimed.

---

1. EVIDENCE OF EXTREME OUTLIERS

Analysis of the paper's published dataset reveals outlier contamination across both chamber measurements and site-level data. The chamber flux measurements (n=1,758) show a median of 0.152 mmol m^{-2} d^{-1} but a mean of 2.02 mmol m^{-2} d^{-1}, yielding a mean-to-median ratio of 13.3. The maximum value reaches 102.4 mmol m^{-2} d^{-1}, which is 672 times the median. This extreme right skew is the hallmark of outlier contamination which should initiate further scrutiny of the dataset. Using standard interquartile range methods, we identified 250 chamber measurements exceeding the upper fence of 3.014 mmol m^{-2} d^{-1}, representing 14.2% of the chamber dataset. For site-level data (n=400 sites), the median is 527 mmol ha^{-1} d^{-1} while the mean is 5030 mmol ha^{-1} d^{-1}, a 9.5-fold difference. The IQR method identifies 62 sites exceeding 6,476 mmol ha^{-1} d^{-1} as outliers, representing 15.5% of sites. Importantly, the paper reports a global average methane emission rate from the globally upscaled data of 8555 mmol ha^{-1} d^{-1}, which exceeds the outlier contaminated mean of the site data reported in the paper by 1.7 x.

These outlier rates far exceed what would be expected from natural variability in a properly quality-controlled dataset. The extreme values included in Qin et al[1] are inconsistent with the published literature on mangrove stem emissions. Published studies on mangrove stem methane fluxes report chamber flux ranges of 24-1,071 µmol m^{-2} d^{-1} with typical means of 37 to 250 µmol m^{-2} d^{-1} (Table 1). Our own (unpublished) data show tree stem methane fluxes from two mangrove species range from -106 to 366 µmol m^{-2} d^{-1} with differences between day and night, and high and low tide (Figure 1). Similar to Qin et al., methane fluxes decreased with stem height, however, the maximum flux we have measured at 20 cm stem height was 366 µmol m^{-2} d^{-1}.The maximum outlier in the Qin et al. dataset (102,400 µmol m^{-2} d^{-1}) is 96 times higher than the highest stem base measurement ever published for mangroves and 680 times higher than their own dataset median, suggesting either measurement error, data entry errors, or other anomalies rather than true biological variation.

Table 1. Comparison with Published Literature on Mangrove Stem Methane Emissions

Source	**Chamber Flux Range (µmol m^{-2} d^{-1})**	**Median/Mean (µmol m^{-2} d^{-1})**	**Comments**
Jeffrey et al. (2019)[2]	24 to 1,071 (stem base)	Living: 37.5 Dead: 249	Living and dead mangroves, Australia
Zhang et al. (2022)[3]	~0 to 397	~150	Subtropical mangroves, China; pneumatophores dominated flux
Gao et al. (2021)[4]	-137 to +44	Variable	*K. obovata* stems, China; both uptake and emission
Yong et al. (2024)[5]	-99.12 to 64.08	0.96 to 11.52	4 sites, Taiwan. *Kandelia obovate* and *Avicennia marina* species. Measured at 110 cm above soil over timeseries and tides
Liao et al. (2024)[6]	-65.8 to 145.1	13.0 to 19.5 (Mean)	*Sonneratia apetala* and *Kandelia obovate.* China. Measured at 0.7, 1.2 and 1.7 m stem heights
Rosentreter et al. (unpublished)	-106 to 366	Mean = 23 Median = 12	Day and night, low and high tide, two species: *Avicennia marina, Bruguiera gymnorhiza*. Location east coast of Australia (latitude -28.86)
Qin et al. (2025) - median	—	152	Within expected range
Qin et al. (2025) - mean	—	2,020	~ 10 to 200 × literature
Qin et al. (2025) - max	—	102,400	680× median, 96 to 4,267× literature

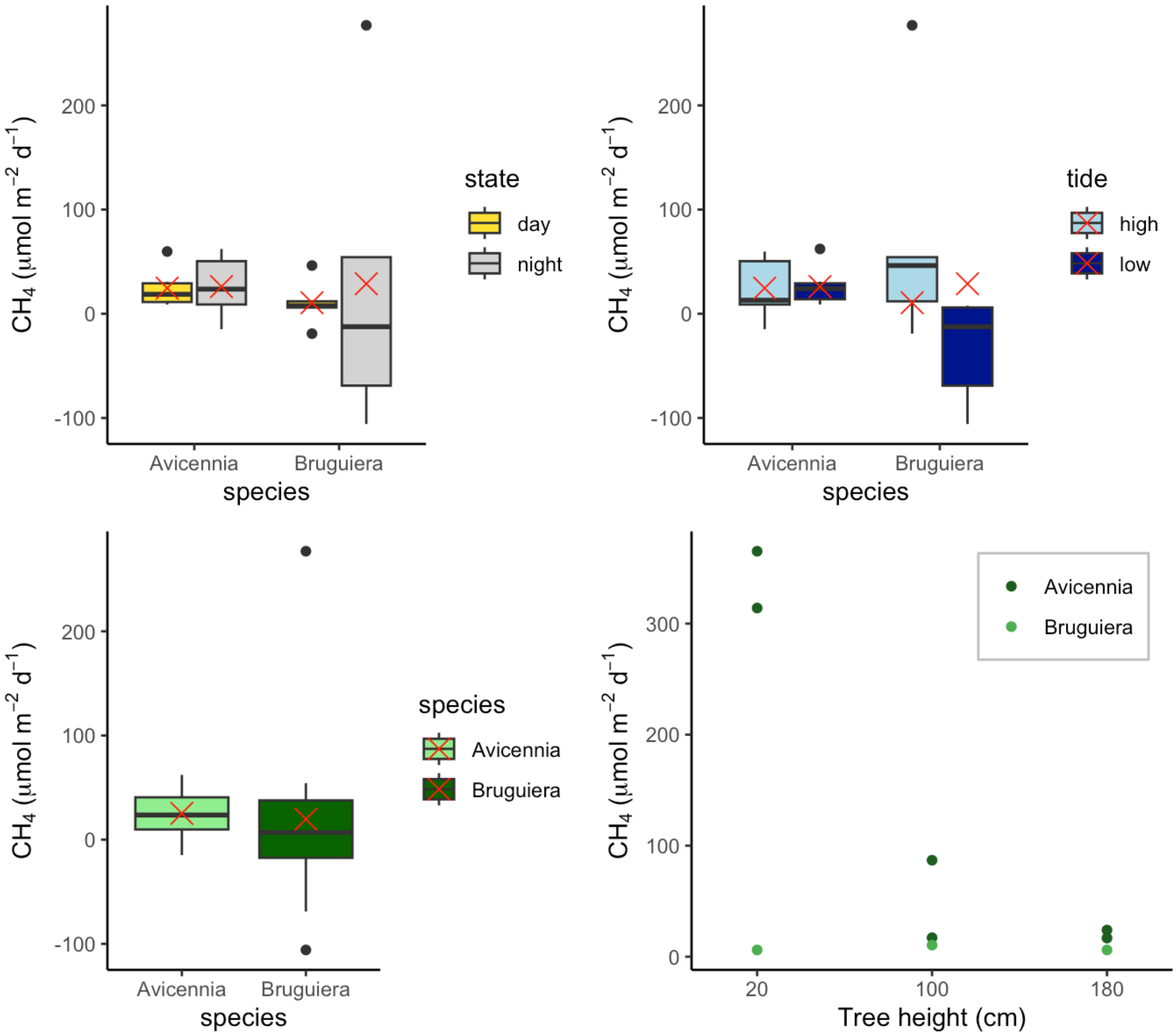

Figure 1 Tree stem methane fluxes (unpublished data) of two mangrove species (*Avicennia marina, Bruguiera gymnorhiza*) over day and night, high and low tide, and different tree height in a mangrove forest in Ballina, Australia. Data is from August 2025. Boxplots show median, Q1 and Q3. The mean is indicated by a red cross. Summary statistics are shown in Table 1.

2. MACHINE LEARNING TRAINED ON CONTAMINATED DATA

We replicated their Random Forest analysis using Python's scikit-learn library with Bayesian hyperparameter optimization (scikit-optimize BayesSearchCV) to identify optimal model settings, and obtained near-identical results when trained on the full dataset including outliers (Figure 2). Our model achieved $R^2 = 0.783$ for site data, matching their reported performance. However, these high R^2 values are misleading because the model is learning to predict extreme outliers rather than typical emissions representative of mangroves more broadly.

When we removed statistical outliers using standard IQR methods and retrained the models on appropriately cleaned data, model performance changed dramatically. The R^2 values decreased from 0.783 to 0.291 for site data, while mean absolute error (MAE) decreased substantially from 3284 to 671 mmol ha⁻¹ d⁻¹ for site predictions. This demonstrates the well-known "R^2 paradox" in outlier-contaminated data, where high R^2 reflects the model's ability to fit extreme values rather than predictive skill for representative observations. The dramatic reduction in MAE when outliers are removed confirms that the outliers inflate prediction errors and are unlikely to be representative of true biological variability.

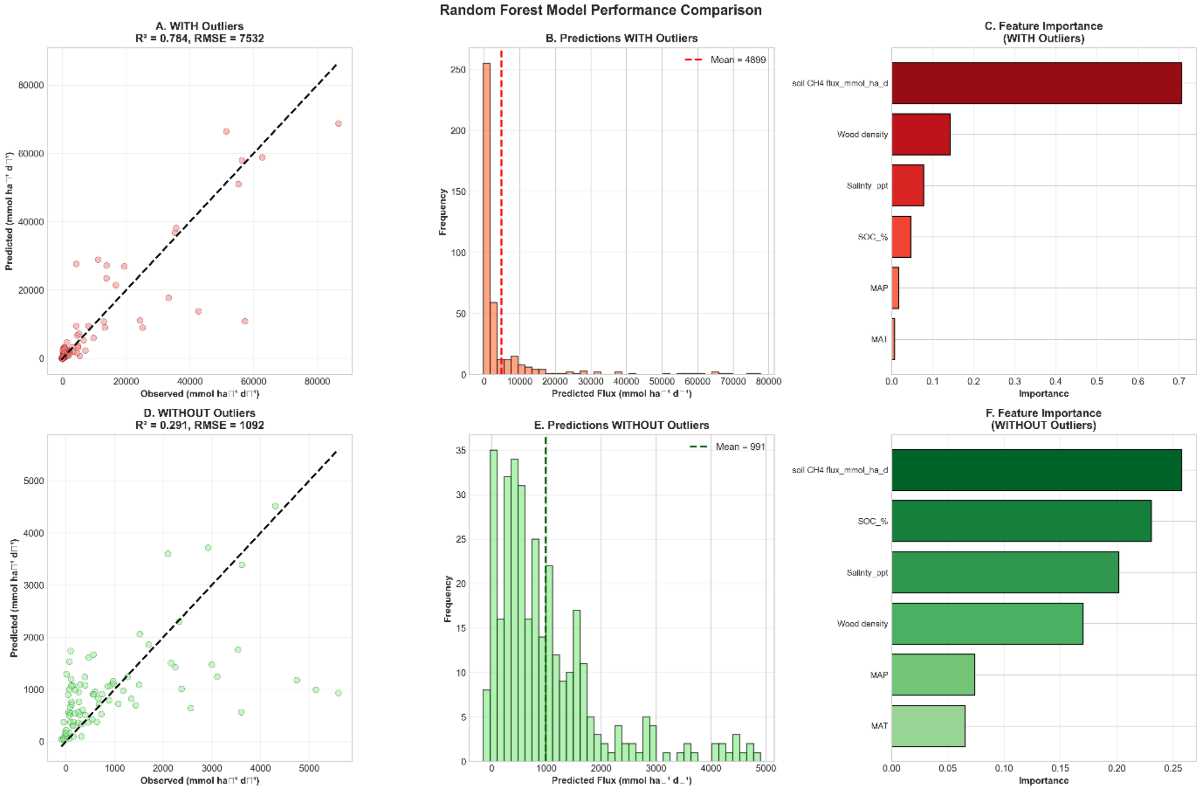

Figure 2. Random Forest Model Performance Comparison Panels A-C: Model WITH outliers A: Observed vs. predicted (R^2=0.784, MAE=3,284), B: Prediction distribution (showing extreme values) C: Feature importance (soil flux dominates at 70.7%) **Panels D-F:** Model WITHOUT outliers D: Observed vs. predicted (R^2=0.291, MAE=671) E: Prediction distribution (realistic range) F: Feature importance (more balanced, SOC at ~23%, salinity ~20%)

SHAP analysis reveals that the model trained on highly skewed contaminated data assigns high importance to predictors that correlate with outliers rather than typical emissions (Figure 3). After outlier removal, feature importance shifts toward biologically plausible drivers such as soil organic carbon, temperature and salinity. This suggests that the contaminated model has learned spurious relationships driven by extreme outliers.

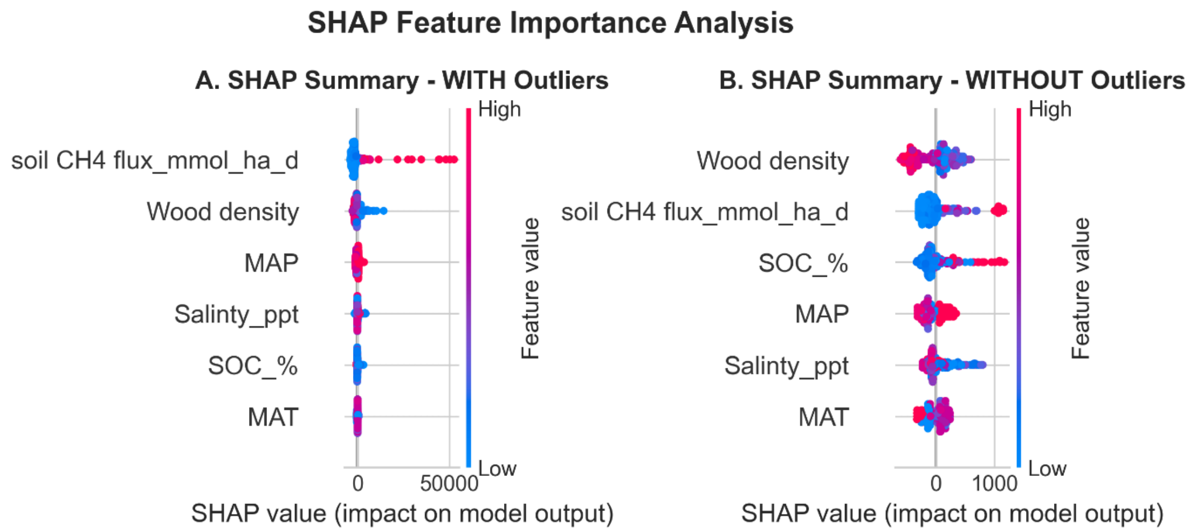

Figure 3. SHAP Feature Importance Analysis Panel A**:** SHAP summary plot for model WITH outliers (extreme SHAP values, soil flux dominates) Panel B: SHAP summary plot for model WITHOUT outliers (balanced contributions, ecologically coherent)

More fundamentally, correlation analysis reveals that the raw training data actually contains ecologically correct relationships: SOC correlates positively with stem CH_4 fluxes ($r = +0.11$) and salinity correlates negatively ($r = -0.21$), consistent with biogeochemical theory (Figure 4). Yet the trained model shows inverted patterns in SHAP dependence plots, with SOC having a negative effect ($r = -0.34$) and salinity showing no relationship ($r \approx 0$). These inversions persist even after outlier removal.

The likely explanation for this paradox is that soil CH_4 flux dominates model predictions ($r = 0.89$ with stem CH_4, 67-70% feature importance), masking the true mechanistic drivers. The model has essentially learned "stem flux $\approx f$(soil flux)" rather than transferable biogeochemical relationships. Since soil CH_4 measurements do not exist for most global mangroves, this reliance on a single correlated predictor—combined with failure to learn the actual mechanistic controls of SOC and salinity—suggests that the global extrapolation fundamentally unreliable.

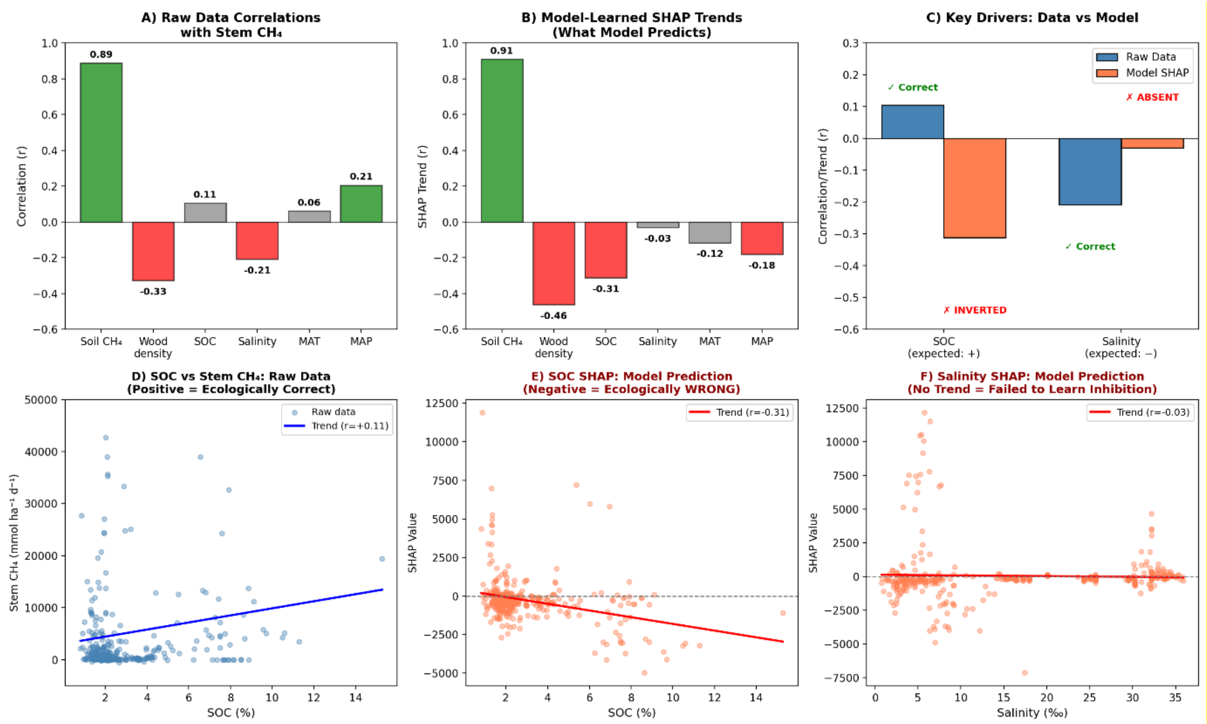

Figure 4. Ecological Incoherence in Model-Learned Relationships Panel A: Raw data correlations between predictor variables and stem CH_4 emissions show ecologically expected relationships: SOC is positive ($r = +0.11$, more organic carbon → more methanogenesis) and salinity is negative ($r = −0.21$, sulphate inhibition of methanogens). Panel B: Model-learned SHAP trends show inverted or absent relationships: SOC becomes negative ($r = −0.34$) and salinity shows no relationship ($r \approx 0$). Soil CH_4 flux dominates both raw correlations ($r = +0.89$) and model predictions ($r = +0.91$). Panel C: Direct comparison of raw data correlations versus model SHAP trends for the two key mechanistic drivers. The model has learned the opposite of established biogeochemistry for SOC and failed to detect sulphate inhibition for salinity. Panel D: Raw data scatter plot showing the positive relationship between SOC and stem CH_4 emissions. Panel E: SHAP dependence plot for SOC showing the inverted (negative) relationship learned by the model—higher SOC incorrectly predicts lower emissions. Panel F: SHAP dependence plot for salinity showing no discernible trend, indicating the model failed to learn the well-established mechanism of sulphate-mediated inhibition of methanogenesis.

---

3. IMPACT ON GLOBAL ESTIMATES

The failure to remove outliers has profound implications for global upscaling. We compared five different approaches to estimating global emissions, each representing standard statistical practices for handling skewed data with outliers (Table 2).

Table 2. Global Mangrove Stem CH_4 Emissions Under Different Methods

Method	Global CH_4 (Gg yr^{-1})	Carbon Burial Offset (%)	Fold Difference from Paper
Paper's estimate (with outliers)	730.6	16.9%	1.0× (baseline)
RF model (outliers removed, IQR)	81.2	1.8%	9.0×
RF model (outliers removed, Z-score)	205.8	4.7%	3.5×
Direct upscaling using median	22.6	0.5%	32.4×
Quantile Regression (median)	41.5	0.9%	17.6×

The paper's estimate of 730.6 Gg yr^{-1} substantially exceeds all corrected estimates by factors of 3.5 to 32.4 (Figure 5). Our central estimate, based on the mean of four outlier-corrected methods, is 88 Gg $yr^{-1}$with a plausible range of 22.6 to 205.8 Gg yr^{-1}. This corresponds to a carbon burial offset of 0.5 to 4.7%, not 16.9% as claimed. The difference between the paper's estimate and corrected values represents approximately 650 to 708 Gg yr^{-1} of spurious global emissions that according to appropriate statistical analysis, are highly unlikely to exist in reality.

This apparent overestimation, while headline-catching, has significant implications for carbon accounting. The authors claim that mangrove stem CH_4 emissions offset 16.9% of carbon burial. This claim if true, would substantially diminish the climate mitigation value of mangrove conservation and restoration. Our corrected analysis shows the offset is far more probably in the order of only 0.5 – 4.6%, meaning mangroves retain their status as highly effective "blue carbon" ecosystems. Misrepresenting the magnitude of stem emissions by a factor of 3.5 to 32.4 based on inappropriate statistical treatment of data, could lead to flawed policy decisions regarding mangrove protection and carbon credit valuation.

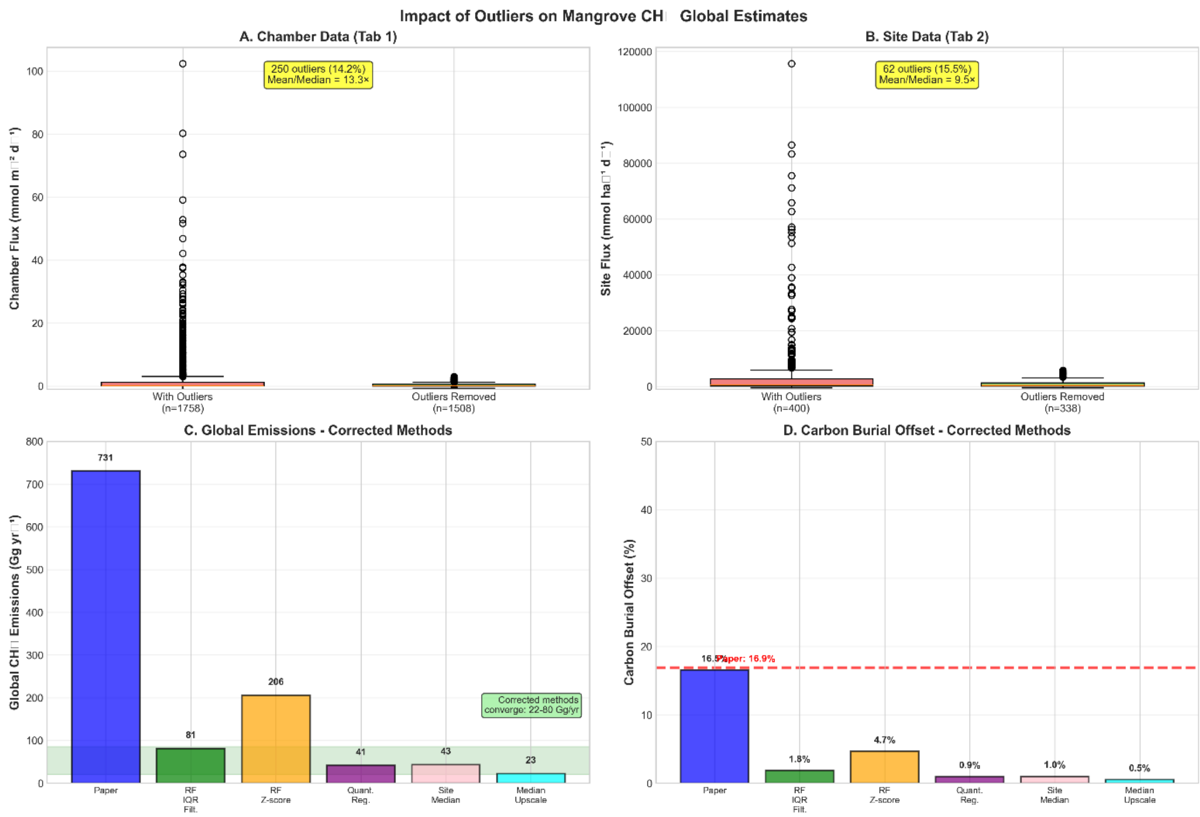

Figure 5. Impact of Outliers on Global Estimates Panel A: Chamber data box plots comparing with vs. without outliers (n=1,758 vs. 1,508), **Panel B:** Site data box plots comparing with vs. without outliers (n=400 vs. 338), **Panel C:** Global emissions comparison across five methods (bar chart), **Panel D:** Carbon burial offset comparison (16.9% → 0.5 – 4.6%)

---

4. VIOLATION OF ESTABLISHED STATISTICAL GUIDELINES

The treatment of outliers in this study violates widely accepted statistical and machine learning best practices established in foundational texts and discipline-specific guidelines. Hastie et al. (2009)[7] emphasize that outliers can have disproportionate influence on model training and should be identified and investigated before model fitting. James et al. (2013)[8] specifically warn that high leverage points in training data can substantially degrade model performance on new observations. Tukey (1977)[9] established the IQR method as a standard exploratory data analysis technique precisely for identifying values that deviate substantially from the bulk of the data. Rousseeuw and Hubert (2011)[10] provide comprehensive guidance on robust statistics for outlier detection, noting that failure to address outliers is a major source of bias in predictive modelling.

These concerns are particularly acute when using Random Forest models to extrapolate from limited regional measurements to global estimates. Hengl et al. (2018)[11] explicitly warn that "predicting values beyond the range in the training data (extrapolation) is not recommended as it can lead to even poorer results than if simple linear models are used" and emphasize that training data quality—especially spatial sampling representativeness—is critical to minimize extrapolation problems and bias. McNicol et al. (2023)[12] demonstrated this limitation empirically in their global wetland methane upscaling study: while their Random Forest model performed well in boreal and temperate regions with extensive training data (R^2 = 0.59-0.64), predictions failed in tropical regions with sparse site coverage, where "predictions at the tropical forest test site did not reproduce the seasonal signal" and spatial patterns "diverged from GCP predictions." Van der Westhuizen et al. (2023)[13] found that "although the cross-validation results for the trained models were acceptable, the extrapolation results were unsatisfactory, highlighting the risk of extrapolation. Chen et al. (2024)[14] attribute such failures to "the black-box nature of current ML approaches, which causes large uncertainty in extrapolation or out-of-sample projections. When this algorithmic constraint is combined with spatially limited, highly skewed training data containing extreme outliers, the resulting global estimates become inherently unreliable.

The authors' decision to include all measurements without outlier analysis or sensitivity testing represents a fundamental departure from established scientific practice. No justification is provided for this approach, and no investigation is presented as to what might have caused the extreme values. This lack of transparency and quality control undermines confidence in the results and violates basic principles of reproducible research.

---

5. LACK OF SENSITIVITY ANALYSIS

The paper provides no sensitivity analysis examining how global estimates vary under different data treatment scenarios. Standard practice in global upscaling studies requires reporting estimates under multiple assumptions to assess robustness. At minimum, the authors should have reported estimates using both mean and median, with and without outliers, and using different outlier detection thresholds. The absence of sensitivity analysis is particularly concerning given the obvious outlier contamination visible in the data distribution.

Our sensitivity analysis demonstrates that the conclusions do not withstand scrutiny of reasonable data cleaning procedures. The 3.6 to 32.3-fold difference between the published estimate and outlier-corrected estimates demonstrate that the primary conclusion—that stem emissions offset 16.9% of carbon burial—depends entirely on the inclusion of extreme values. Had the authors conducted and reported such sensitivity analyses, the dramatic dependence on outliers would have been apparent during peer review.

---

6. RECOMMENDED CORRECTIONS

We recommend that Nature Geoscience work with the authors to issue a correction to this paper with revised global estimates based on proper outlier removal and quality control. The authors should implement several critical changes to their analysis. First, statistical outliers should be removed using standard IQR and Z-score methods before model training, with clear documentation of the outlier detection procedure and the number and characteristics of removed observations. The Random Forest model should be retrained on cleaned data and comprehensive sensitivity analysis should be reported showing estimates with and without outliers, using both mean and median upscaling approaches, and with different outlier detection thresholds.

Given the severe right skew in the data (mean-to-median ratio of 13.3), median-based estimates should be reported as the primary result, with mean-based estimates provided as upper bounds. The authors should investigate and document the source of extreme values, determining whether they represent measurement errors, data entry issues, instrument malfunctions, or other anomalies such as undertaking measurements in atypical mangroves. Complete transparency should be provided on all data quality control procedures, including which measurements were excluded and why. The R^2 paradox should be acknowledged, with MAE and RMSE reported as primary performance metrics rather than R^2 alone, as these metrics provide a more robust assessment of prediction error.

Based on our reanalysis using statistically sound methods, we recommend the following corrections to the main text. The abstract should be revised to state that global mangrove stem CH_4 emissions total approximately 22 – 203 Gg yr^{-1} (central estimate: 88 Gg yr^{-1}), offsetting 0.5 – 4.6% (central estimate: 2.0%) of sediment carbon burial rather than the reported 730.6 Gg yr^{-1} and 16.9%. All figures and tables showing global emissions maps and carbon budgets should be regenerated using outlier-corrected estimates. The discussion should acknowledge that the original estimates were inflated by 3.6 to 32.3× due to outlier contamination and that mangrove stem emissions, while important, represent a minor rather than major offset to carbon sequestration.

---

7. IMPLICATIONS FOR THE FIELD

The issues identified in this paper have broader implications for the tree stem methane and blue carbon research communities. This study will likely be highly cited as the first global estimate of mangrove stem emissions, and the inflated values could propagate through the literature, influencing carbon budgets, earth system models, policy assessments and implementation of restoration programs linked to the blue carbon economy. It is critical that the correction be issued promptly to prevent the spread of these erroneous estimates.

More broadly, this case highlights the risks of applying machine learning techniques without adequate data quality control and cross validation with well-known ecological processes. The seductive appeal of high R^2 values can mask fundamental problems with training data. As our field increasingly adopts machine learning approaches for global upscaling, we must maintain rigorous standards for data cleaning, outlier detection, and sensitivity analysis. These traditional statistical safeguards remain essential even when using sophisticated predictive algorithms.

---

8. CONCLUSION

Our reanalysis demonstrates that the global estimate of 730.6 Gg CH_4 yr^{-1} reported by Qin et al. (2025) is inflated due to failure to remove extreme statistical outliers before machine learning model training. Using standard outlier detection methods and robust statistical practices, we estimate global mangrove stem emissions of 23 to 203 Gg yr^{-1}, offsetting 0.5 to 4.7% of carbon burial rather than 16.9%. The corrected estimates are consistent with the published literature on mangrove stem emissions and place these emissions in appropriate context as an important, but not dominant component of mangrove carbon cycling.

We have provided complete Python code and detailed documentation of our reanalysis, which fully replicates the authors' original analysis and demonstrates the impact of outlier removal. All analyses were performed using the authors' published dataset (Dataset.xlsx), ensuring complete transparency and reproducibility. We respectfully request that Nature Geoscience work with the authors to issue a correction that provides accurate estimates based on proper data quality control and statistical best practices.

Sincerely,

Professor Damien Maher
Professor of Earth Science
Southern Cross University
damien.maher@scu.edu.au

Dr Luke Jeffrey
Senior Lecturer
Southern Cross University
luke.jeffrey@scu.edu.au

Assoc. Prof. Judith Rosentreter
Associate Professor of Biogeochemistry
Southern Cross University
judith.rosentreter@scu.edu.au

Professor Scott Johnston
Professor of Biogeochemistry
Southern Cross University
scott.johnston@scu.edu.au

Professor Vincent Gauci
Birmingham Professorial Fellow
University of Birmingham
v.gauci@bham.ac.uk

Dr Sunitha Pangala
Royal Society Research Fellow

Imperial College London
s.pangala@imperial.ac.uk

DATA AND CODE AVAILABILITY

All analyses were conducted using the authors' published dataset (Dataset.xlsx, available at https://doi.org/10.57841/casdc.0004245) which was provided by the authors prior to embargo. We thank the authors for clear communication and willingness to provide data. Our complete reanalysis materials are available at https://codeocean.com/signup/nature?token=00cbcbc753df48c6bdd050941e9c8938 including Python scripts for outlier detection and removal, Random Forest model training and evaluation, SHAP analysis implementation, global emissions upscaling calculations, and all figures and tables presented in this comment.

REFERENCES

1. Qin, G. et al. Mangrove sediment carbon burial offset by methane emissions from mangrove tree stems. *Nat. Geosci.* (2025). https://doi.org/10.1038/s41561-025-01848-4

2. Jeffrey, L. C. et al. Are methane emissions from mangrove stems a cryptic carbon loss pathway? Insights from a catastrophic forest mortality. *New Phytol.* 224, 146–154 (2019).

3. Zhang, C. et al. Massive methane emission from tree stems and pneumatophores in a subtropical mangrove wetland. *Plant Soil* 473, 489–505 (2022).

4. Gao, C.-H. et al. Source or sink? A study on the methane flux from mangroves stems in Zhangjiang estuary, southeast coast of China. *Sci. Total Environ.* 790, 148158 (2021).

5. Yong, Zhao-Jun, et al. "Tidal influence on carbon dioxide and methane fluxes from tree stems and soils in mangrove forests." Biogeosciences 21.22 (2024): 5247-5260.

6. Liao, Xiaolin, et al. "Methane and nitrous oxide emissions and related microbial communities from mangrove stems on Qi'ao Island, Pearl River Estuary in China." Science of The Total Environment 915 (2024): 170062.

7. Hastie, T., Tibshirani, R. & Friedman, J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* 2nd edn (Springer, 2009).

8. James, G., Witten, D., Hastie, T. & Tibshirani, R. *An Introduction to Statistical Learning with Applications in R* (Springer, 2013).

9. Tukey, J. W. *Exploratory Data Analysis* (Addison-Wesley, 1977).

10. Rousseeuw, P. J. & Hubert, M. Robust statistics for outlier detection. *WIREs Data Min. Knowl. Discov.* 1, 73–79 (2011).

11. Hengl, T., et al. (2018). Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. PeerJ, 6, e5518.

12. McNicol, G., Fluet-Chouinard, E., Ouyang, Z., et al. (2023). Upscaling Wetland Methane Emissions From the FLUXNET-CH4 Eddy Covariance Network (UpCH4 v1.0): Model Development, Network Assessment, and Budget Comparison. AGU Advances, 4(5), e2023AV000956.

13. van der Westhuizen, S., et al. (2023). Evaluating the extrapolation potential of random forest digital soil mapping. Geoderma, 440, 116705.

14. Chen, M., et al. (2024). Quantifying Global Wetland Methane Emissions With In Situ Methane Flux Data and Machine Learning Approaches. Earth's Future, 12(10), e2023EF004330.

SUPPLEMENTARY TABLES

Table S1. Complete Outlier List - Chamber Data

Table_S1_Chamber_Outliers.csv

Table S2. Complete Outlier List - Site Data [Full list of 62 site outliers with flux values, environmental predictors, and site characteristics]

Table_S2_Site_Outliers.csv

Table S3. Model Hyperparameters from Bayesian Optimization

Parameter	With Outliers	Without Outliers
n_estimators	500	50
max_depth	18	16
min_samples_split	2	2
min_samples_leaf	2	2
max_features	0.57	0.10

Table S4. Cross-Validation Performance (5-fold)

Model	Mean CV R^2	Std Dev	Min R^2	Max R^2
With outliers	0.690	0.111	0.515	0.825
Without outliers	0.494	0.188	0.248	0.739

Table S5. Prediction Statistics

Statistic	With Outliers	Without Outliers
Mean prediction	4,899	991
Median prediction	1,048	709
SD prediction	11,637	1002
Min prediction	-219	-151
Max prediction	77,641	4,901
Q1	412	309
Q3	3059	1350
IQR	2647	1041

Table S6 Comparison of methods and offset calculations

Method	Mean Flux mmol ha^{-1} d^{-1}	Global CH4 Gg y	CO2eq TgC yr^{-1}	Carbon Offset (%)	Description
Paper Reported	8555.0	730.6	6.8	16.9	Paper (Random Forest + spatial extrapolation)
RF IQR Filtered	991.3	81.2	0.8	1.8	Random Forest with IQR outlier removal
RF Z-score Filtered	2514.2	205.8	1.9	4.7	Random Forest with Z-score outlier removal
Quantile Regression	506.8	41.5	0.4	0.9	Quantile regression (median)
Site Median	527.0	43.1	0.4	1.0	Site median and global area

Median Upscaling	275.4	22.6	0.2	0.5	Median chamber, median density, median DBH upscaling