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Quantifying global warming potential variations from greenhouse gas emission sources in forest ecosystems

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Abstract

Forest ecosystems play a crucial role in regulating greenhouse gas (GHG) emissions and mitigating climate change. This research aimed to evaluate the GHG emissions of various sources within forested ecosystems and assess their respective contributions to global warming potential (GWP), vital for developing more targeted strategies to mitigate climate change, shaping climate policies, carbon accounting, sustainable forest management, and advancing scientific comprehension of ecosystem-climate dynamics. The study comprehensively analysed carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions EDGAR data of deforestation, fires, and natural processes such as organic soil decomposition within forested ecosystems. The assessment quantified the CO_2 equivalent emissions for each category from 1990 to 2022 and forecasted till 2030. Our forecast shows that CO_2 emissions from deforestation could reach between 3,990 and 4,529 metric ton (Mt) by 2030, with forest fires contributing an additional 750 Mt. Forestland CO_2 absorption is expected to decline to -5134.80 Mt by 2030. There is uncertainty surrounding the forecasts for Organic soil CO_2 (829.78 Mt) and Other land CO_2 (-764.53 Mt). In addition, deforestation was a significant contributor to CO_2 emissions, with a GWP ranging from 4000 to 4500, highlighting the complex interplay between natural processes and human activities in shaping atmospheric warming patterns. Additionally, forest fires emit a complex mix of GHGs. The potency of these gases in warming the planet varies considerably, with CH_4 exhibiting a GWP range of 500 to 700 Mt CO_2 equivalent, and CO_2 ranging from 900 and 1350 Mt. These variations depend on fire intensity and its overall impact on the climate system. Forestland acts as powerful carbon sink, capturing atmospheric CO_2 with negative GWP values between -7000 and -6000. Researchers suggest a multifaceted strategy such as stricter enforcement of sustainable forestry regulations, investing in projects that promote carbon sequestration, and reforestation. Additionally, advancements in drone technology, satellite imagery, remote sensing and advanced data analytics can aid in detecting and mitigating climate change impacts, ultimately paving the way for carbon neutrality.

Highlights

- Deforestation exacerbates CO_2 emissions, with the additional threat of fires compounding the issue.
- Forest CO_2 sink weakens to -5,135 Mt by 2030. Soil stores 829.78 Mt, and Other land -764.53 Mt.
- Deforestation's GWP (4,000–4,500 Mt) shows complex human and nature impact on CO_2.
- Varying fire emissions (methane 550–650t, CO_2 900–1,350t) highlight need for sustainable land use.

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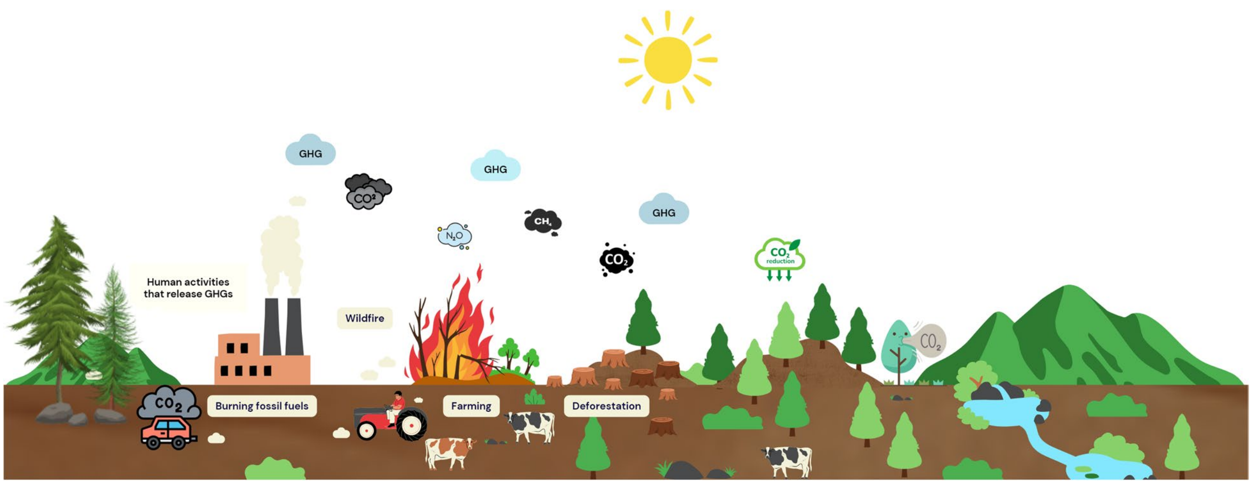
Keywords Carbon sequestration, Climate change mitigation, Deforestation, Forest ecosystem dynamics, Forest fire

Graphical Abstract



1 Introduction

Forest ecosystems significantly influence the global carbon cycle by acting as carbon sinks and sources. Trees absorb CO_2 from the atmosphere and store it in forest biomass such as trunks, branches, roots and leaves, and in soil organic matter as dead wood. This process of carbon absorption and deposition is known as carbon sequestration, which helps to mitigate climate change (Fares et al. 2017). While forests play a vital role in storing carbon, activities like deforestation, forest degradation, and land conversion can disrupt this process. This disruption releases the stored carbon back into the atmosphere, exacerbating the greenhouse effect (Houghton 2012). Furthermore, forested ecosystems are not only affected by climate change but also influence climate through biophysical processes such as evapotranspiration and albedo, which modulate the energy balance of our planet (Bagley et al. 2014).

According to the scientific consensus, our planet is experiencing an alarming rise in greenhouse gas (GHG) emissions like carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) primarily driven by human activities (Shah et al. 2024). These CO_2, CH_4, and N_2O gases act as blankets, trapping heat and causing global warming, which in turn leads to a cascade of environmental consequences. Rising temperatures and climate change disrupt weather patterns, increase sea levels, and threaten ecosystems. These disruptions also have complex and multifaceted impacts on human health and well-being (Priya et al. 2023; Rabbi and Abdullah 2024). However, climate change harms human health in both direct and indirect ways. Direct effects include heatstroke during extreme heat waves. Indirect effects arise from disruptions to our environment and societies, impacting food security, access to clean water, and air quality. This can lead to malnutrition, waterborne diseases, and respiratory problems.

Furthermore, forests play a crucial role in mitigating climate change, but their emissions can vary depending on human activities, such as deforestation, fires, management practices, and land use changes. Consequently, accurately assessing the global warming potential (GWP) of GHGs like CO_2, CH_4, and N_2O from different forest sources is essential. By understanding the biggest contributors of GWP, we can prioritize mitigation efforts and minimize the overall warming impact of these emissions.

Additionally, the GWP of GHG emissions varies depending on various factors such as emission source, GHG type, temporal scale, and spatial extent. In this context, the dynamics of CO_2 emissions from organic soils and other land types require special attention. Organic soil CO_2 refers to the carbon dioxide emissions associated with soils rich in organic matter, typically found in peatlands and wetlands (Lino et al. 2024). These soils are significant carbon reservoirs when left undisturbed, but activities like drainage or peat extraction can transform these areas into substantial CO_2 sources (Chen et al. 2024). In contrast, Other land CO_2 includes carbon dioxide emissions from various land types that do not fall into other specified categories. This includes emissions or removals from grasslands, shrublands, non-forested wetlands, and areas undergoing urbanization or other land-use changes (Souza et al. 2020). The strong positive relationship between Organic soil CO_2 and Forestland CO_2, alongside its negative association with fire and deforestation indicators, highlights its primary role in carbon sequestration (Silva et al. 2024). The sensitivity of organic soils to temperature changes makes them particularly relevant to climate change discussions, as warming can accelerate the release of CO_2. Their prevalence in both northern latitudes and tropical regions highlights their global significance in carbon dynamics.

Moreover, different sources within forested ecosystems, including natural processes such as decomposition, wildfire, and biogenic emissions, as well as anthropogenic activities like urbanization, agricultural expansion, unsustainable forest management, and biomass burning, contribute to the emission of GHGs with varying GWP. For instance, while CO_2 emissions from biomass burning and deforestation have a significant and long-lasting impact on climate, the short-term but potent effects of CH_4 and N_2O emissions from wetlands, agricultural activities, and soil management cannot be overlooked. Similarly, the emissions captured under Organic soil CO_2 and Other land CO_2 are integral to understanding the full scope of terrestrial carbon dynamics (Ramesh et al. 2019). This comprehensive view emphasizes the interconnectedness of various ecosystems and land uses in the global carbon cycle, highlighting the necessity for holistic approaches to land management and climate change mitigation.

Quantifying the variations in GWP from diverse GHG emission sources within forest ecosystems necessitates a holistic methodological framework. However, to understand the GWP variations from different GHG sources in forest ecosystems, both biophysical and socio-economic factors must be considered. Furthermore, a study by Guntuka et al. (2024) suggested to focus on reducing non-CO_2 greenhouse gas emissions from consumption and promoting international cooperation. Similarly, Gabbrielli et al. (2024) emphasized the need for more precise N_2O inventories, particularly in relation to agricultural intensification. Also, You et al. (2024) mentioned that there is still a lot we do not know about how to scale field measurements and how to represent all the different processes and factors that affect the exchange of CH_4 and N_2O between the terrestrial biosphere and the atmosphere. The study underscores the necessity for enhanced, precise global data on non-CO_2 greenhouse gas emissions, particularly in consumption trends and international trade. Consequently, further research is essential for deeper understandings the drivers behind CO_2, CH_4, and N_2O emissions.

Existing research on GHG emissions often overlooks the diversity of forest ecosystems and considers them as a uniform entity. This generalization ignores the vast diversity of forest types and their unique emission profiles. Moreover, factors such as GHG emissions from deforestation, forestland management, organic soil, and other land types, along with growing risk of wildfires are not fully integrated into current research (Gabbrielli et al. 2024; Guntuka et al. 2024; Kaske et al. 2021; Ozdemir et al. 2024; Wei et al. 2021; Withey et al. 2019; You et al. 2024).

The current understanding of the GWP of forest ecosystems is limited due to a lack of comprehensive assessments that consider the diversity of these ecosystems and their emission sources. Addressing this gap requires exploring several critical research questions (RQ).

RQ1. How do variations in forest gas emissions impact the precision of GWP assessments? Identifying these differences will help refine GWP calculations and provide a clearer understanding of forests' impact on global warming.

RQ2. What are the challenges in quantifying the variations in GWP across different forest and land types, and how can these be overcome? Accurate assessment of forest GWP necessitates improved measurement techniques for emissions from various sources and land uses.

RQ3. How do emissions from deforestation, wildfires, and other sources contribute to the overall GWP of forest ecosystems, and what key factors influence these emissions? Understanding these factors is essential for developing targeted strategies to reduce emissions and GWP (Mangla et al. 2024).

The primary goal of this research is to achieve a comprehensive understanding of forests' contributions to global warming by thoroughly quantifying their GWP. This requires an in-depth assessment of the complex nature of forests, including the distinct emissions profiles of various forest types, all relevant emission sources, and the effects of land-use changes. A detailed analysis of emissions from deforestation, wildfires, and other sources within forest ecosystems is also critical. By identifying the key factors influencing these emissions, targeted strategies can be developed to mitigate them and combat climate change.

Moreover, this research aims to bridge the identified knowledge gap by using advanced analytical techniques to predict sector-specific variations in GWP across diverse forest ecosystems. The analysis incorporated time series data on GHG emissions up to 2022, with forecasts extending to 2030. The study also examined the emissions profile of deforestation and fires, distinguishing CO_2 emissions from deforestation and breaking down fire emissions into components such as CO_2, CH_4, and N_2O.

Additionally, the impacts of organic soil management, forestland conversions, and deforestation were evaluated to pinpoint key areas for GHG mitigation in forest ecosystems. Through correlation analysis, potential relationships between emissions and other relevant factors were explored, providing insights into the drivers of rising emissions. This comprehensive examination of current and potential GHG emissions will support the development of targeted mitigation strategies to address climate change effectively.

2 Materials and methods

2.1 Study area

In this study, we focused on the global forest ecosystems as they play a crucial role in the Earth's carbon cycle and climate regulation. Forests are not only significant carbon sinks, absorbing a portion of the carbon dioxide emissions produced by human activities, but they also contribute to GHG emissions through processes such as decomposition and biomass burning. Understanding GWP variations within these ecosystems is vital for mitigating climate change.

2.2 Data collection

The analysis was based on comprehensive data collected from the EDGAR—Emissions Database for Global Atmospheric Research, a resource maintained by the European Commission (2023). This database is known for its detailed and precise spatial and temporal data on global GHG emissions.

For our study, we utilized the dataset that spans 32 years, from 1990 to 2022. This timeframe was chosen to incorporate a significant period of industrial and agricultural growth, as well as the implementation of various climate change mitigation strategies. The dataset includes emissions data for a range of GHGs, including but not limited to carbon dioxide, methane, and nitrous oxide.

Furthermore, to ensure the accuracy and reliability of our analysis, we performed a thorough data cleaning and validation process. This involved identifying and addressing any missing or inconsistent data, as well as cross-referencing our dataset with other reputable sources of GHG emissions data.

2.3 Data analysis

Time series analysis was employed to identify trends and patterns in global GHG emissions during the historical period. An autoregressive integrated moving average (ARIMA 1,1,1) model was utilized to analyze the variables. The equation used for the model is as follows:

$$Y(t) = c + \phi_1 \times Y(t-1) + \theta_1 \times e(t-1) + e(t) \quad (1)$$

This model presents the current level of GHG emissions ($Y[t]$) as a combination of factors, including a constant term (c), the influence of the previous CO_2 level ($Y[t-1]$), weighted by coefficient ϕ_1, the impact of an unexpected shock at the previous time step ($e[t-1]$), weighted by coefficient θ_1, and a new error term ($e[t]$). By considering the past values and random fluctuations, the model captures how GHG emissions evolve.

The study used the analysis of time series forecasting utilized statistical techniques to account for potential variations within the data, including trend analysis and seasonal decomposition. To provide insights into potential future scenarios, forecasting models such as the ARIMA model were used to project emission trajectories until 2030. The equation for all variables follows a general ARIMA structure, expressed as

$$y(t) = \beta_0 + \beta_1 \times y(t-1) + \beta_2 \times e(t-1) \quad (2)$$

where $y(t)$ represents the value of the emissions at time (t), (β_0), (β_1), and (β_2) are coefficients specific to each specific emission source, $y(t-1)$ is the value of the emissions at the previous time step, and $e(t-1)$ is the residual (error term) at the previous time step. This formula expresses the relationship between the current and past value and error of each emission source, with coefficients indicating the strength and direction of these relationships.

Mean and standard deviation values show the central tendency and variability of emissions data, both historically and in the future. The mean and standard deviation were calculated for both the training and testing datasets. For the training data, the mean shows the average emissions value, and the standard deviation shows how much the data varies around the mean. Similarly, for the testing data, the mean and standard deviation show how the forecasted emissions vary. To understand how different activities contribute to GHG emissions, different sectors were considered. For a given year, the contribution of each activity (deforestation, fires, etc.) to total emissions was calculated. Python's *pandas* package was used for data manipulation and *matplotlib.pyplot* for plotting. The data was collected using the *pandas* package by adding the GWP values across each sector for 100 year. The total GWP for each sector was computed by adding the GWP values for each year within that sector. This is expressed mathematically according to the following equation:

$$GWP_i = \sum_{j=1}^{100} GWP_{ij} \quad (3)$$

In the equation above, (GWP_i) is the total GWP for sector (i), and (GWP_{ij}) is the GWP value for sector (i) in year (j). Once the data was aggregated, *matplotlib.pyplot* was used to create a horizontal bar chart, with each sector represented as a horizontal bar sorted by its total GWP value. The x-axis represents the total GWP values, while the y-axis represents the sectors. This visualisation provides insight into the relative contributions of different sectors to the GWP.

In the context of the correlation plot generated in MATLAB version R2024a, each cell of the plot represents the correlation coefficient between two variables. The equation for calculating the Pearson's correlation coefficient between two variables (X) and (Y) is as follows:

$$r = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}} \tag{4}$$

Here, (X_i) and (Y_i) are individual data points for the variables (X) and (Y), respectively. ($\overline{X}$) and ($\overline{Y}$) are the means of the variables (X) and (Y), respectively. However, (n) is the number of data points. This formula calculates the covariance of the two variables $\left(\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)\right)$ divided by the product of their standard deviations $\left(\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}\right)$.

The Pearson's correlation coefficient, symbolized by (r), assessed both the strength and direction of a linear association between two variables. It was obtained by dividing the covariance of the variables by the multiplication of their standard deviations. In the provided dataset of global wildfire data, the correlation coefficient quantified how closely related pairs of variables were in terms of their linear association. Each correlation coefficient (r) varied between -1 and 1, where 1 indicated a perfect positive linear association, -1 indicated a perfect negative linear association, and 0 indicated no linear association.

In addition, to calculate the p-values associated with the correlations, the code utilizes a matrix named \`*pValues*\`. For each unique pair of variables, the \`*corrcoef*\` function was employed to determine both the correlation coefficient and its corresponding p-value. The p-value was computed through a process that involves calculating a t-statistic using the following formula:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{5}$$

Here, r denotes the sample correlation coefficient, and n is the total number of observations. The t-statistic is then compared to a t-distribution with $n-2$ degrees of freedom to derive the p-value. This p-value indicates the likelihood of obtaining the observed correlation under the null hypothesis, which assumes no actual correlation exists between the variables. The ′*pValues*′ matrix stores the calculated p-values, with diagonal elements assigned ′*NaN*′ since they do not have corresponding p-values.

The analysis assessed the impact of various land-based activities on GWP associated with diverse terrestrial activities. This approach enabled comparing the relative warming effect of each activity through a consistent unit. This standardized approach facilitated the comparative assessment of the relative warming impact attributable to each activity. Powerful computational tools played a critical role in data manipulation, analysis, and visualization of the GWP data. Python software packages, such as *Pandas*, are excellent for data management and enable to the organisation and exploration of complex datasets. In addition, *Matplotlib* and *Seaborn* allowed the creation of meaningful box-plot visualisations (Hunter 2007; Waskom 2021).

GWP measured the ability of a gas to trap heat in the atmosphere compared to carbon dioxide (CO_2) over a period, typically 100 years. The formula for this is as follows:

$$GWP_{\text{CO2-eq}} = \int_0^\infty C(t) \cdot \mathrm{GWP}_{\text{CO2}}(t)\, dt \tag{6}$$

The GWP of a gas was determined by integrating the product of its atmospheric concentration over time $C(t)$ and its time dependent GWP, denoted by $\mathrm{GWP}_{\text{CO2}}(t)$, relative to GHG emissions.

3 Results and discussion

Our analysis of global GHG emissions trends from 1990 to 2022 reveals valuable insights into how emissions have evolved over time (Fig. 1). While the analysis calculated through Eq. (1) shows a concerning upward trend in total emissions until 2010, it is followed by a period of decline. In Fig. 1, the x-axis, labelled "Year", shows the time frame, while the y-axis shows the units used, such as metric tonnes of CO_2 equivalent ($MtCO_2e$). Unlike typical emissions graphs, this graph includes negative values. This is because it consideres both the release and removal of greenhouse gases. Forests and other land types act as carbon sinks, absorbing CO_2 from the atmosphere. Therefore, a negative value on the y-axis indicated that removals outweighed emissions in that particular year.

The total emission trends increased until around 2010, followed by a decline. This fluctuation can be attributed to several factors, including changes in land use, shifts in agricultural practices, changes in the global economy,

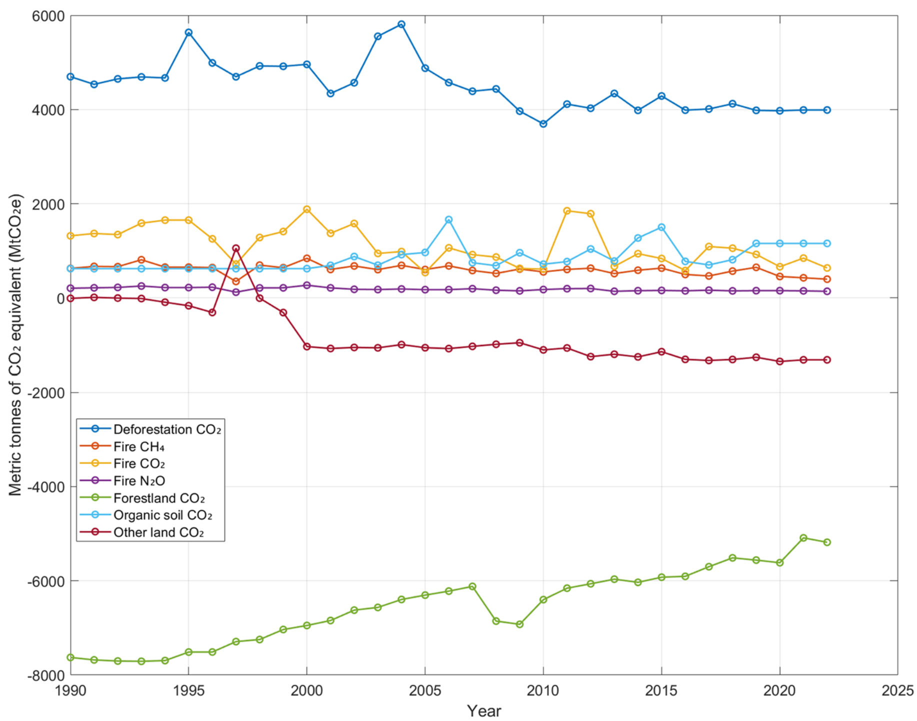


Fig. 1 Global greenhouse gas emissions trends (1990–2022)

technological advances, and policy implementation. Emissions from deforestation fluctuated over the years, with a general decline from 2010 to 2022. Similarly, emissions from fires, categorised by the dominant gas emissions (CH_4, CO_2, and N_2O), also showed fluctuations over the period.

For emissions from forests, the graph shows a decreasing trend, suggesting an increase in CO_2 sequestration or a reduction in emissions from these areas. Emissions from organic soils and other land types fluctuated over time. Total emissions increased over the period, mainly due to increased industrial activity and changes in land use practices. Significant variations in total emissions were observed, likely influenced by economic activities, policies, technological advances, and variations in agricultural practices.

Deforestation was found to be a significant contributor to emissions throughout the study period, although its relative contribution varied over time. Other sources also exhibited varying contributions from year to year. Activities such as deforestation and fires release CO_2 through the burning of forests, potentially leading to an increase in total emissions and GWP.

By analyzing the trends in each line, it was possible to determine the changes in emissions from each category over the years, whether they increased, decreased, or remained stable. The presence of several fire categories suggested that the graph differentiates between fire types based on their dominant gas emissions. Similarly, the land categories (forest, organic soil, and other) indicated whether these landscapes contribute to or remove greenhouse gases.

In Fig. 2 (calculated through Eq. [2]), the first category, Deforestation CO_2, showed a potentially positive trend. This trend indicates a decline in deforestation-related CO_2 emissions over the historical period. The forecasted emissions in 2030 ranges between 3,990 Mt and 4,529 Mt CO_2. There is a 68% chance that the actual emissions in 2030 will be in the range of 3,900 Mt and 5,500 Mt CO_2. This upward trend of CO_2 emission increases the global warming. Several categories indicate a potential rise in emissions of CH_4, CO_2, and N_2O, particularly due to fires. CH_4 emission was approximately 419 Mt with a standard deviation of ± 20.69 Mt, and a 95% confidence interval ranging from 372.8 to 452.8 units. N_2O emissions were around 144.95 Mt with a standard deviation of ± 6.50 Mt, and CO_2 emissions from fires were around 740.50 Mt with a standard deviation of ± 148 Mt. Projections signal a continuation of this upward trend in the coming years, with wider confidence intervals compared to deforestation-related CO_2 emissions, suggesting higher uncertainty in these projections. This highlights the significant contribution of fire sources to GHG emissions.

Fig. 2 Projected annual global greenhouse gas emissions (2023–2030)

Forestland CO_2 emissions have demonstrated a consistent decline over historical projections, with expectations of further decreases in emissions in the future. The forecasted emissions range were between the -5134.80 and -6,633 Mt with a standard deviation of ± 66.47 Mt and 722.60 Mt. The confidence interval for forest CO_2 emissions in later years indicates a higher carbon absorption rate. Another category, Organic soil CO_2 emissions, also displayed a declining trend based on present analysis. The forecasted emissions range between 829.78 Mt and 1157 Mt CO_2. However, the 95% confidence interval is very narrow, ranging from -735.6 to -709.6 units. This is indicating that soil organic matter is actively sequestering carbon.

Besides of these categories CO_2 is emitting from other types of lands. Other land CO_2 indicated a downward trend in CO_2 emissions. The forecasted emissions range are between -764.53 and -1314.83 Mt. However, the confidence intervals for Other land CO_2 emissions widened in later years. The emissions rate in this category will fluctuate based on factors such as land conversion, intensive agricultural practices, and forest fires.

Widening confidence intervals reflect the range of possible future values and highlight the increased uncertainty in the forecast. The underlying reasons for these emission trends are likely to be complex and include factors such as wildfire activity, land use practices, deforestation rates, and decomposition of organic matter.

While the potential reduction in CO_2 emissions from deforestation is promising, emissions from other sources must be addressed to make a significant progress in reducing GHGs. A comprehensive understanding of trends, projections, and confidence intervals across all categories can provide valuable insight into the future trajectory of GHG emissions and help identify priority areas for climate change mitigation.

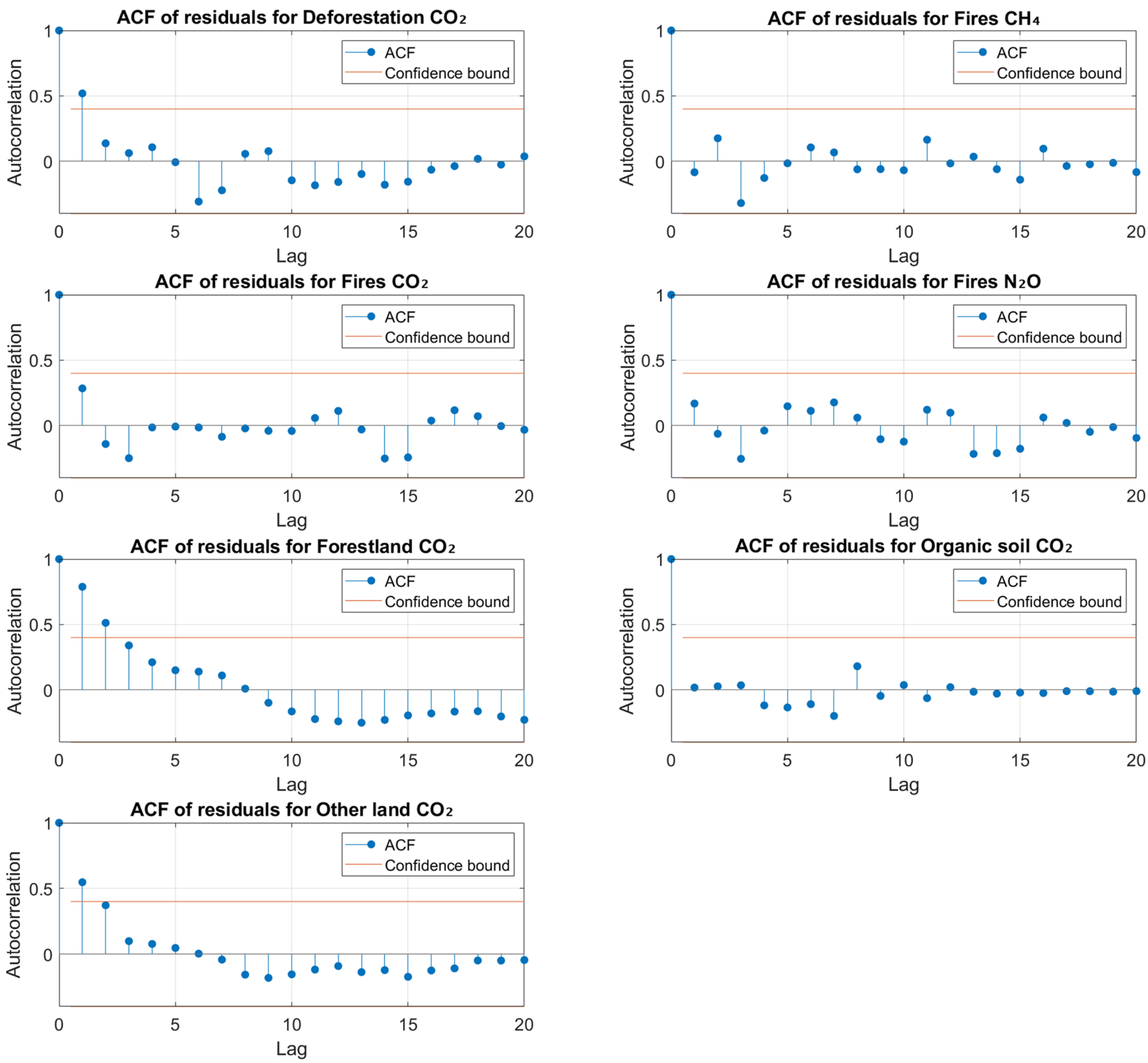


Fig. 3 Autocorrelation function (ACF) plot of residuals examining residual autocorrelation for model validation

The Autocorrelation Function (ACF) plot reveals no significant spikes at any lag ($x - axis$) points (Fig. 3). This implies that the residuals from the ARIMA model for Deforestation CO_2, Forestland CO_2, Organic soil CO_2, and Fires CO_2 exhibit white noise, which is a desirable characteristic. Ideally, the ACF plot shows spikes within the 95% confidence bound lines, which represent (±) two times the standard error of the estimate from zero. These lines delineate a confidence interval, and spikes outside this range are considered statistically significant. In Fig. 2a, the ACF plots for most residuals indicate that there are no significant spikes beyond the confidence bound line. The absence of significant spikes implies no serial correlation in the residuals across various time lags. This is a positive signal that the ARIMA model adequately captures the underlying trends and patterns in the data, with the residuals behaving similarly to random white noise.

However, the ACF plot for Deforestation CO_2 shows a potential spike at lag 1, close to the upper confidence bound, suggesting some residual autocorrelation at lag 1. The ACF plot for Fires CH_4 exhibits minor spikes around lags 5 and 10, although they do not approach the confidence bounds significantly. These spikes are likely to be insignificant and do not necessarily undermine the validity of the ARIMA model. Furthermore,

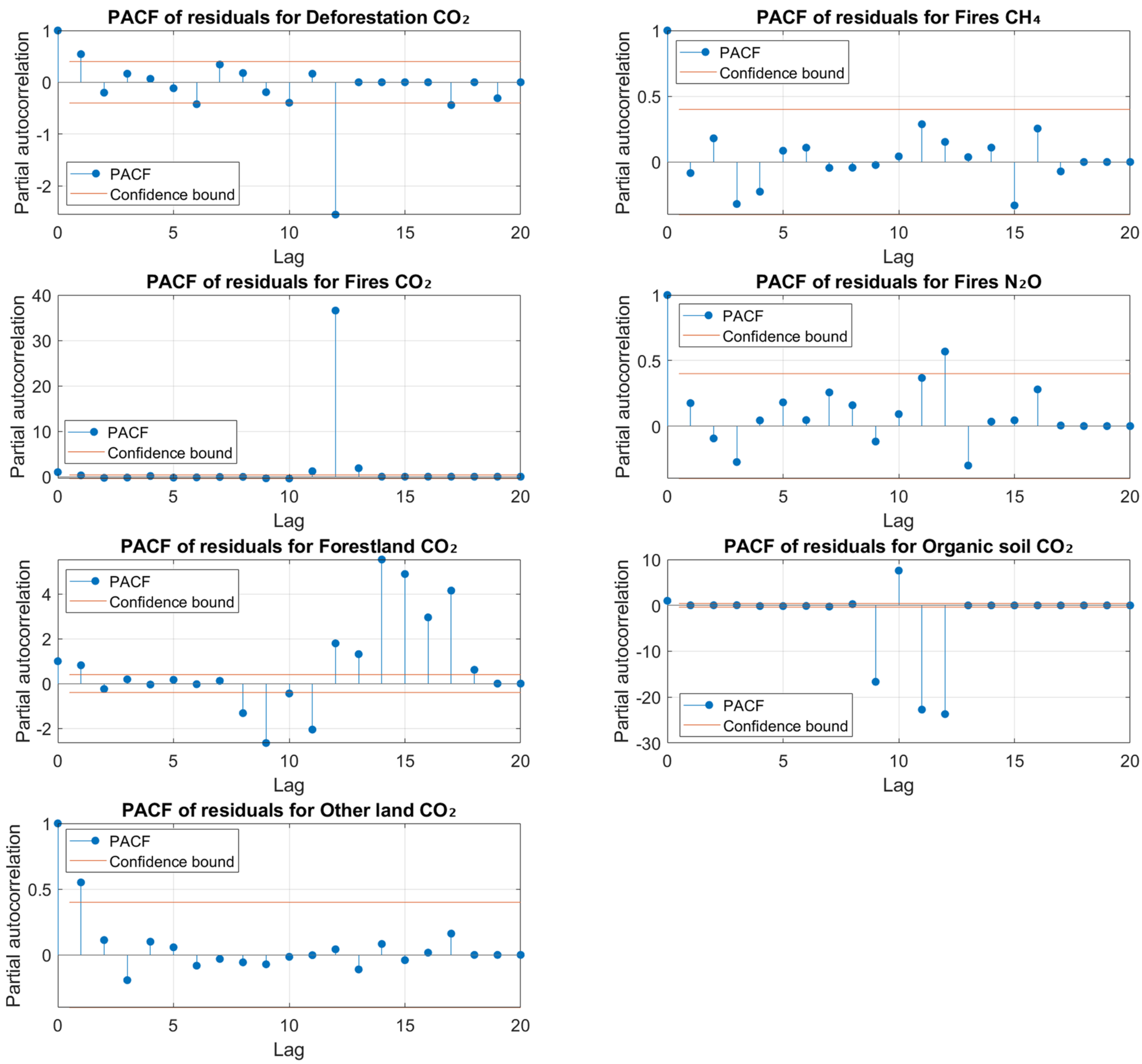


Fig. 4 Partial autocorrelation function (PACF) plot of residuals identifying autoregressive component order for model refinement

the ACF plots for fires CO_2 residuals show some small spikes. The forestland CO_2 residuals show significant autocorrelation at lag 1 and some decreasing autocorrelation up to lag 5. However, Organic soil CO_2 shows significant autocorrelation at lag 1 and minor significant levels at lags 2 and 3. In contrast, the residuals for other land CO_2 show a significant spike in autocorrelation at lag 1, indicating some structure not fully captured by the model. Beyond lag 1, the residuals exhibit a gradual decrease in autocorrelation, with values remaining within the confidence bounds, which suggests that the residuals are largely random beyond the first lag.

Examining the autocorrelation function (ACF) plots reveals minimal autocorrelation in the residuals for most sectors. Since these values fall within the confidence bounds, it suggests that the models used are generally effective in capturing the underlying trends in the data.

Nevertheless, for a more formal evaluation of residual autocorrelation, conducting statistical tests such as the Partial Autocorrelation Function is necessary.

The Partial Autocorrelation Function (PACF) plot is instrumental in pinpointing significant autoregressive (AR) components within the residuals across various time lags (Fig. 4). Ideally, in the PACF plot, significant spikes should not extend beyond the confidence bound lines representing (±) two standard deviations from zero. A notable spike at lag k implies that the residual at the

Table 1 Cross-validation results for ARIMA model performance with Root Mean Square Error (RMSE) percentage evaluation by emission source

Emission source	Training %	Test %	RMSE %
Deforestation CO_2	90.10%	101.93%	90.71%
Fires CH_4	69.38%	103.14%	70.78%
Fires CO_2	72.91%	112.33%	74.48%
Fires N_2O	82.93%	107.19%	84.11%
Forestland CO_2	-78.34%	-101.26%	-79.40%
Organic soil CO_2	123.09%	88.24%	120.26%
Other land CO_2	-164.01%	-95.25%	-145.29%

Conspicuously Table 1 presenting the emissions related to severe deforestation and fires, such as CH_4 and CO_2, demonstrated relatively low RMSE percentages of 70.78% and 74.48%, respectively, indicating accurate predictions. However, emissions linked to fires (specifically N_2O) and Organic soil CO_2 displayed higher RMSE percentages of 84.11% and 120.26%, respectively, suggesting potential challenges in prediction accuracy. Interestingly, forestland CO_2 emissions exhibited a negative RMSE percentage of -79.40%, indicating systematic underestimation by the model. A paired sample t-test was conducted to examine the consistency between the training and test datasets. The analysis revealed a mean difference of 0.944, and statistical tests showed no significant difference between the datasets (t = -0.391; p = 0.509), suggesting that the model's performance remains consistent across different data subsets

present time (t) correlates with the residual k time steps prior ($t - k$), even after considering the influences of residuals at lags 1 to $k - 1$.

The PACF plot of Deforestation CO_2 uncovers substantial autocorrelation at lags 1 and 2. This is because the partial autocorrelation values at these lags surpass the confidence bounds, suggesting the presence of significant autoregressive influences. and Forestland CO_2 residuals unveil no significant spikes at 1, 3, 4, 10, 20 lags. This indicates a complex autoregressive relationship in the residuals for the datasets, indicating that the selected ARIMA model likely captures relevant AR terms.

Similarly, the PACF plots for Other land CO_2 residuals showcase significant spikes at lag 1 and 2 beyond the confidence bounds. This suggests that an AR (2) model might be suitable for capturing the residual structure. However, the PACF plots for Fires CH_4 and Fires CO_2 exhibit significant partial autocorrelation at lag 1, closely nearing the upper confidence bound. This hints at an autoregressive relationship between the current residual and the residual from one time step ago, even after factoring in the influence of lag 0. Meanwhile, the PACF plot for Organic soil CO_2 exhibits a minor spike at lag 1, and a significant negative spike at lag 10 is also observed. Although it remains distant from the confidence bounds, suggesting its insignificance and would not invalidate the ARIMA model.

In general, this PACF plots reveal significant autoregressive patterns in the residuals of our gas emission models. This suggests room for improvement in capturing the full complexity of the data. While the current models provide valuable insights, further refinement is needed to enhance predictive accuracy. By incorporating the lags highlighted by the PACF analysis, future models can achieve a more comprehensive understanding of gas emission dynamics.

In Fig. 5, the X-axis has both positive and negative values (calculated through Eq. [3]) because forestland is absorbing the carbons from the atmosphere. The graph value shows 32 years of global GHG emissions data, with a ranging from -200,000 to 15,000, representing different GWP values. Negative values mean that CO_2 emissions are being absorbed, which lowers the GWP, while positive values mean emissions, with an elevated GWP, indicating a greater contribution to global warming compared to CO_2 over 100 years. When the Y-axis shows negative values, it means that emissions from a specific sector are cooling relative to CO_2. This is exceptional but can occur with certain industrial processes that temporarily cut off greenhouse gases from the atmosphere, resulting in a negative GWP. On the other hand, positive values on the y-axis mean that a sector's emissions have a warming effect greater than that of CO_2. For instance, methane has a much higher GWP than CO_2, so even lower methane emissions can significantly contribute to global warming. As a result, this is contributing to temperature rise.

Electricity and heat production, including deforestation for fuel, stood out as the largest contributors to the GWP, accounting for approximately 150,000 Mt. In addition, agriculture, which included fires and soil organic matter decomposition, contributed about 30,000 Mt. Interestingly, forestry, which included deforestation, fires, and forestland, appeared to have a negative value of about -200,000 Mt, indicating its capacity to absorb emissions. However, this absorption dependeds on how forests are managed. In addition, other sectors such as industry, transport, and waste, also played a significant role in global GHG emissions.

Figure 6 shows the relationships among seven variables associated with greenhouse gas emissions from forest ecosystems (calculated through Eqs. [4] and [5]). The matrix uses colour intensity and numerical values to represent the strength and direction of correlations, with darker blue indicating both stronger positive and negative correlations.

The relationships between different sources of GHG emissions can be complex, but examining the correlations between them can provide valuable insights. A key question was how fire emissions of methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O) relate to emissions from forests and soils. In Fig. 6, Deforestation CO_2 shows strong positive correlations with Fires CH_4

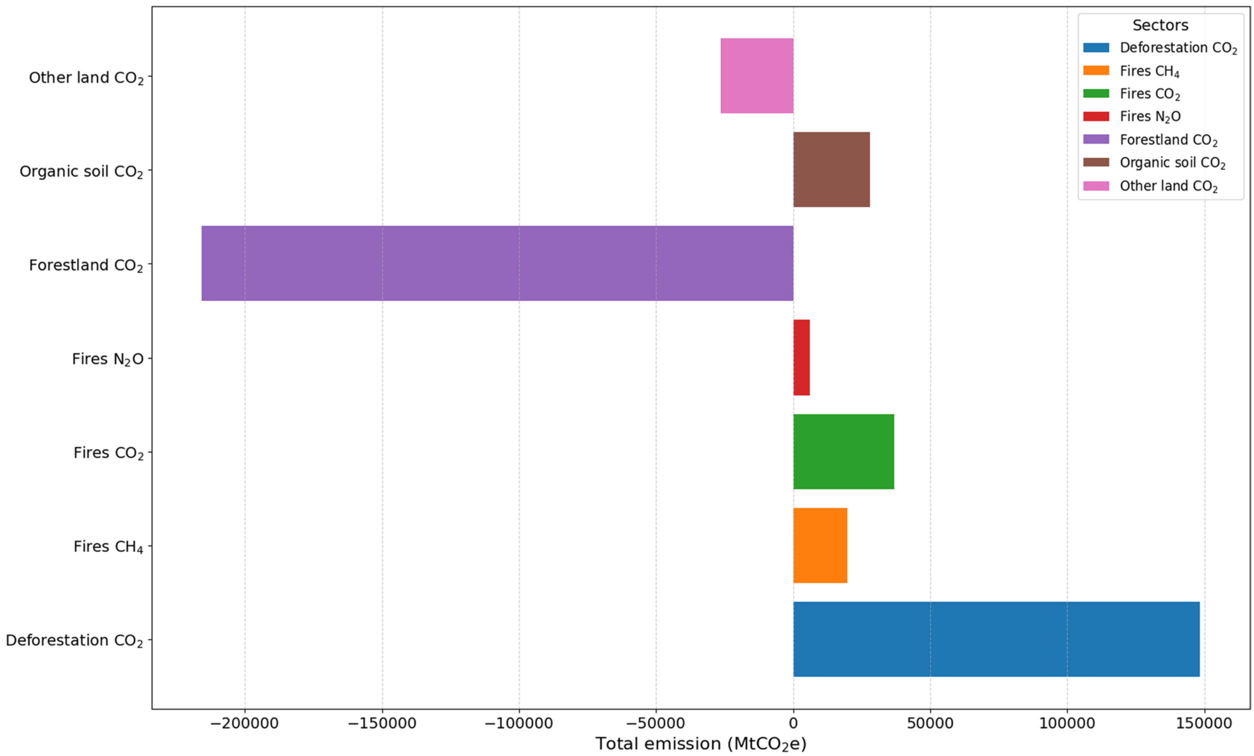


Fig. 5 Breakdown of global greenhouse gas emissions by seven key sectors

(0.46), Fires CO_2 (0.32), and Fires N_2O (0.49). This suggests that as deforestation increases, emissions from fires also tend to increase across multiple greenhouse gases. Interestingly, Deforestation CO_2 has a moderate negative correlation with Forestland CO_2 (-0.56) and Organic soil CO_2 (-0.36), implying that as deforestation increases, carbon storage in forests and organic soils decreases.

Fires significantly influence the co-emission of CH_4, CO_2, and N_2O, as indicated by strong positive correlations ranging from 0.46 to 0.80 among these gases. This suggests that fire-related emissions of these greenhouse gases are closely linked and tend to increase or decrease simultaneously. A positive correlation indicates that as fire emissions rise, emissions from forests or organic soils also increase, likely due to drier conditions. These conditions can fuel wildfires, accelerate forest dieback, and enhance soil respiration. Consequently, this leads to more decomposition and the release of CO_2 from dead trees. Similarly, drier conditions can increase soil respiration, the process by which microbes break down organic matter in the soil and release CO_2 (Li et al. 2024). Conversely, a negative correlation suggests that increased wildfires correspond with reduced human impact on forests and soils. For example, a negative correlation between fire emissions and CO_2 emissions from forests indicates a decrease in deforestation in areas with more frequent fires (Aragão et al. 2018). However, fire-related variables also show moderate negative correlations with Forestland CO_2 and Organic soil CO_2, ranging from -0.37 to -0.52. Fire emissions could fluctuate due to factors independent of human activities affecting forests and soils.

A robust positive correlation (0.64) existed between CO_2 emission levels in forestland and organic soil, suggesting that carbon sequestration in these ecosystems tends to fluctuate together. Conversely, these variables exhibit negative correlations with factors linked to fire and deforestation, underscoring the inherent tension between carbon storage and emissions resulting from land disruptions.

Other land CO_2 shows positive correlations with Deforestation CO_2 (0.46) and fire-related emissions (0.17 to 0.38), but negative correlations with Forestland CO_2 (-0.83) and Organic soil CO_2 (-0.55). This indicates that when deforestation and fire emissions escalate, emissions from Other land types tend to rise accordingly. Conversely, as the carbon storage capacity of forests and soil increases, emissions from these alternative land types tend to decrease.

In addition to correlation coefficients, the matrix provides p-values for each variable pair. All p-values are below 0.05, indicating statistically significant

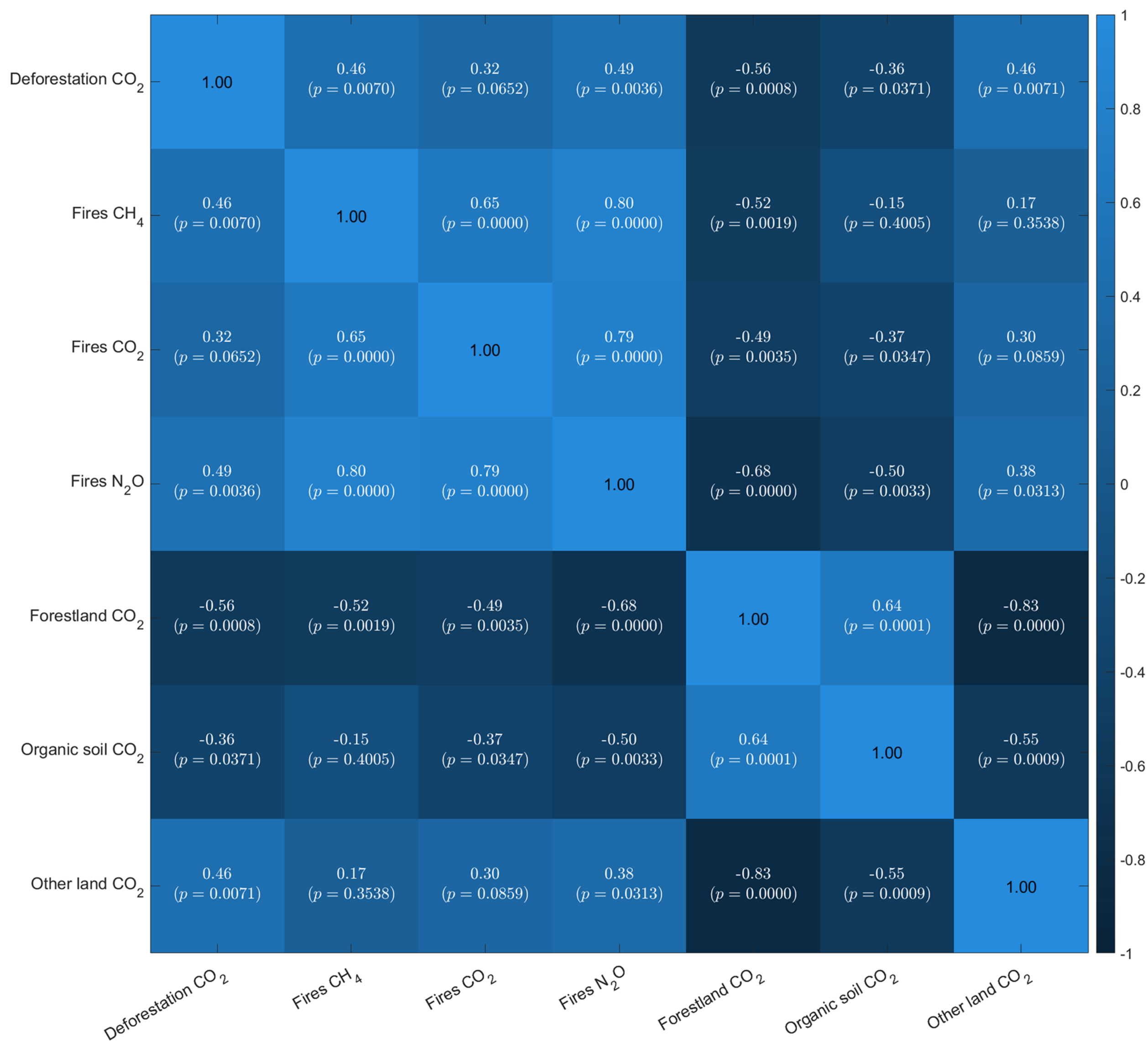


Fig. 6 Correlation analysis of key greenhouse gas emissions from forest ecosystems

relationships. Notably, the most robust correlations, such as those among fire-related variables and between Forestland CO_2 and Other land CO_2, exhibit exceptionally low *p*-values ($p < 0.0001$). This further underscores the high degree of confidence in these observed associations.

Figure 7 shows box plots for different categories of GHG emissions, revealing interesting patterns in their GWP (calculated through Eq. [6]). The central box represents the middle 50% of the data, with the median as the midpoint. The width of the box indicates the spread of the data within this middle range. The whiskers extend outwards to capture most of the remaining data points, with the outliers falling beyond the whiskers.

Figure 7 also shows that the variations in GWP were the apparent CO_2 emissions from deforestation activities, with a GWP ranging from 4000 to 4500 metric tons CO_2e. The interquartile range (IQR) spanned from approximately 4200 to 4700 metric tons CO_2e. This underlined the significant warming effect associated with deforestation activities.

In addition, CH_4 emissions from fires had a GWP of 550 to 650, resulting in IQR of 500 to 700 Mt CO_2 equivalent. These emissions contributed to atmospheric warming, although to a lesser extent than other sources. However, CO_2 emissions from fires with a GWP between 900 and 1350 resulted in IQR between 1000 and 1400 Mt CO_2 equivalent emissions. The wide range underlined the differences in the intensity of their warming effect.

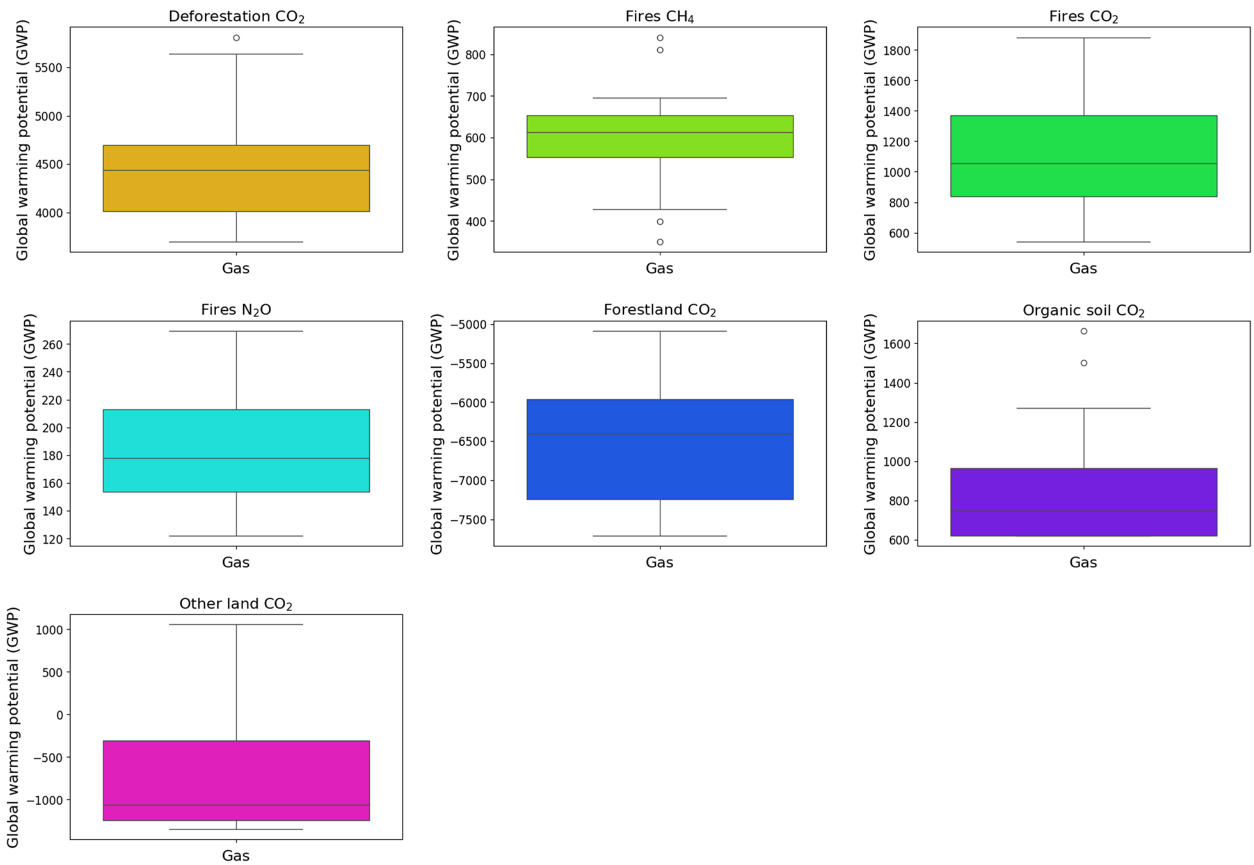


Fig. 7 Comparison of global warming potential (GWP) of seven major greenhouse gases (1990–2022)

Furthermore, N_2O emissions from fires had a median GWP of about 180 Mt CO_2 equivalent. This indicated their contribution to atmospheric warming, but with some variability. The median value of Fire CH_4 emission was approximately 600 metric tons of CO_2 equivalent. The interquartile range suggests a typical emission range of 500 to 700 metric tons CO_2e. It is important to note that there are several outliers exist on both ends of the spectrum, with some emissions falling below 400 Mt and others exceeding 800 Mt CO_2e.

On the other hand, the three land-based sources represented different scenarios. The median value of CO_2 emissions from forestland was approximately -6500 Mt CO_2e. The IQR ranged from about -7000 to -6000 metric tons CO_2e, indicating net negative emissions, likely due to carbon sequestration. A negative GWP indicates that forests function as carbon sinks. This means they absorb carbon dioxide from the atmosphere instead of releasing it. However, CO_2 emissions from organic soils with a GWP of 700 to 900 Mt CO_2 equivalent resulted in IQR ranges of 600—1000 Mt CO_2 equivalent, contributing to heat trapping. CO_2 emissions from Other land types IQR spanned from -1500 to -500 (negative GWP indicated a carbon sink) suggested that Other land types also act as carbon sinks, absorbing CO_2 from the atmosphere.

Based on these calculated CO_2 equivalent emissions and the characteristics of each category, it was clear that forest CO_2 and Other land CO_2 acted as carbon sinks with negative GWPs, whereas Fire CH_4, Fire CO_2, and Organic soil CO_2 contributed positively to heat trapping. In addition, Deforestation CO_2 and Fire N_2O had positive GWPs, indicating their contribution to warming.

Overall, some sectors, like Fires CH_4 and Organic soil CO_2, show significant outliers, indicating occasional extreme emission events. However, Forestland CO_2 exhibited net negative emissions, suggesting effective carbon sequestration in forested areas.

The study reveals several crucial insights into the dynamics of global greenhouse gas emissions.

1. Forests act as nature's frontline defenders to combat climate change. Forest also functions as massive carbon sinks; they absorb and store a staggering amount of carbon dioxide. This research reveals that forests globally absorb about 175,000 $MtCO_2e$, helping to mitigate climate change. This underscores the paramount importance of forest conservation and reforestation initiatives.
2. However, deforestation disrupts this vital equilibrium. Deforestation releases stored carbon into the air, substantially increasing atmospheric greenhouse gases. Our estimates identified that this process contributes around 150,000 $MtCO_2e$ emissions globally. This emphasizes the urgent need for robust strategies to curb deforestation.
3. Fire emissions present another significant challenge, albeit with greater variability. Wildfires and controlled burns release a complex mixture of greenhouse gases, including CO_2, methane, and nitrous oxide. Carbon dioxide released from wildfires contributes approximately 40,000 $MtCO_2e$ to global emissions. This underscores the urgent need for more effective approaches to fire prevention and control.
4. The importance of organic soils in carbon capture is frequently underestimated. These soils serve as natural reservoirs for atmospheric carbon dioxide, effectively trapping and storing significant quantities of this greenhouse gas. Research suggests their carbon sequestration capacity is considerable, with estimates indicating that they may hold roughly 75,000 $MtCO_2e$. This finding suggests that implementing sustainable soil management practices holds significant potential for enhancing carbon capture and storage capabilities.
5. From a broader perspective, a clear contrast emerges. On one side, forests and organic soils steadily absorb carbon. On the other side, deforestation and fires release varying amounts of emissions. This situation calls for a dual strategy. First, we need focused plans to cut down on emissions from clearing forests and burning land. At the same time, it is crucial to protect and improve our natural carbon absorbers. By tackling both sides of this issue, we can make real progress in managing carbon levels.

Overall, this study underscores the complex interplay between GHG emission sources, ecosystem dynamics, and human activities in forested ecosystems, highlighting the need for integrated approaches to climate mitigation and sustainable forest management. By advancing our understanding of GWP variations and informing evidence-based policymaking, this research contributes to global efforts to address climate change and build resilient ecosystems for future generations.

4 Conclusion

Our study explored the complex relationship between global greenhouse gas emissions and their impact on climate change, using a variety of analytical methods. The findings revealed concerning patterns in emissions and their role in the planet's rising temperatures, emphasizing the urgent need to address climate change.

Employing advanced predictive methods, the research projected changes in greenhouse gas emissions and carbon sequestration from 2023 to 2030. The forecasts indicate that without significant intervention, the increasing release of carbon dioxide from forested areas is likely to continue through the decade. Effective reduction strategies are essential to counter this troubling trend. The sectoral analysis revealed key contributors to emissions, including deforestation, soil organic matter, and fires, particularly emissions of CH_4 and N_2O, in addition to CO_2 emissions from changes in land use. These insights pinpoint specific areas where targeted policies and interventions could have substantial effects.

Current research informs policy governments and policy makers that mitigation strategies should be initiated to reduce GHG emissions for human well-being. Several tactics have been proposed to address this challenge through several key strategies:

1. A large-scale tree planting programmes in previously bare areas and in areas recovering from deforestation can significantly increase the amount of carbon dioxide captured from the atmosphere (Ohashi et al. 2024). Protection of existing forests and restoration of degraded forests are equally important. In addition, sustainable forest management practices are essential. These prioritise conservation, minimise logging and protect old-growth forests. In addition, stopping illegal logging and deforestation is essential to maintain the health of these natural carbon sinks.
2. A transition to clean energy sources such as solar, wind and hydropower is also crucial for reducing dependence on fossil fuels (Rabbi et al. 2022). While these sources are generally cleaner, it is important to acknowledge that they are not entirely without environmental impact. For instance, hydropower facilities can have varying climate impacts (Ocko and Hamburg 2019), solar panels pose end-of-life management challenges (Duran et al. 2022), and wind energy projects can have ecological effects (National Research Council 2007). Therefore, a nuanced approach is required to accelerate this shift while mitigating potential impacts.
3. Governments and policymakers also need to develop better strategies to prevent and manage wildfires (Arango et al. 2024). Early warning systems, con-

trolled burns under safe conditions, and involving local communities in fire prevention efforts can all help reduce emissions from burning forests. Pricing carbon through carbon taxes or cap-and-trade systems can incentivise companies to reduce pollution. The revenue generated can then be reinvested in projects such as tree planting and renewable energy development.

4. Sustainable agricultural practices are another way to reduce emissions (SaberiKamarposhti et al. 2024). These practices, such as minimising soil disturbance, improving the accuracy of fertiliser application and integrating trees into farms, can reduce methane and nitrous oxide emissions from agricultural activities. They can also improve soil carbon storage and reduce emissions associated with fertilisers.
5. Finally, fostering international cooperation and providing financial support to developing countries for climate change mitigation and adaptation is crucial (Irshad Ahmad et al. 2024). This can include technology transfer, capacity building and financial support for sustainable land management and forest conservation projects.

Furthermore, implementing responsible forest management practices and enforcing stricter regulations against deforestation can significantly reduce emissions from forestry activities (Rana and Sills 2024). The use of satellite imagery and remote sensing technologies should be used to observe the changes in forest cover. Additionally, capturing high-resolution images by using drones equipped with LiDAR sensors, along with advanced data analytics and machine learning algorithms, can help detect illegal logging, land use change, and forest degradation.

Similarly, improving wildfire prevention and management techniques can also reduce emissions from fires (Purnomo et al. 2024). Drones equipped with thermal imaging cameras can be used to detect potential fire outbreaks in remote and inaccessible forest areas, as they can patrol large forests areas as well as industrial sites frequently.

The GWP analysis provided valuable insights by showing the relative warming impact of different land-based activities. Forest CO_2 and Other land CO_2 have the lowest GWPs and acted as carbon sinks, while Fire N_2O and Organic soil CO_2 contributed positively to heat trapping. The GWPs of Fire CH_4, Fire CO_2, and Deforestation CO_2 had a wider range, indicating differences in the intensity of their warming effects. Understanding the combined impact of these greenhouse gases helps prioritize mitigation efforts based on their overall warming potential. Activities with higher GWP footprints may require more urgent attention and stricter regulation.

The findings shed new light on worldwide carbon emissions and highlight the importance of natural ecosystems in addressing climate challenges. This approach significantly enhances our knowledge of climate dynamics and informs strategic environmental decision making.

While the study offers comprehensive insights into global greenhouse gas emissions, several limitations should be acknowledged. Projections from 2023 to 2030 are based on past trends and assumptions that may not fully capture future socio-economic, political, and environmental changes. Potential limitations of predictive models inherently involved uncertainties, and the projections of future emissions came with confidence intervals that needed to be considered. Future research should aim to refine forecasting models by incorporating more dynamic variables and scenarios that account for unexpected changes in policy, technology, and natural events. Additionally, the scope of green-house gases studies should be expanded to include fluorinated gases and other minor, but impactful emissions will provide a more comprehensive understanding of their contributions to global warming.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions
All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Dr. Mohammad Fazle Rabbi. The first draft of the manuscript was written by Dr. Mohammad Fazle Rabbi, and Dr. Kovács Sándor and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Mohammad Fazle Rabbi performed conceptualization, data curation, formal analysis, investigation, methodology, project administration, resource coordination, software supervision, draft writing, and editing. Kovács Sándor conducted conceptualization, project administration, resource coordination, software supervision, draft editing, and overall coordination.

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Availability of data and materials
The datasets used or analyzed during the current study are available at the following website: https://edgar.jrc.ec.europa.eu/report_2023.

Declarations

Competing interests
The authors have no relevant financial or non-financial interests to disclose.

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