Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 5 (No. 2), pp. 42-55, 2025
doi: 10.5541/aair.PID
Published online:Dec 25, 2025

Temporal and Spatial Analysis of the Relationship Between Atmospheric CO_2 Concentration and Precipitation in Türkiye Based on Satellite Data

İnayet KARADAŞ[1] *, Tuncay YİĞİT [2], İsmail Serkan ÜNCÜ [3], Mevlüt ERSOY [2]

[1] Süleyman Demirel University, Institute of Graduate Studies in Science, Computer Engineering, Isparta, Türkiye;
[2] Süleyman Demirel University, Department of Computer Engineering, Faculty of Engineering, Isparta, Türkiye;
[3] Isparta University of Applied Sciences, Department of Electronics and Automation, Isparta, Türkiye

Abstract

This study examines the relationship between atmospheric carbon dioxide (CO_2) concentrations and precipitation amounts over Türkiye using satellite-based data. CO_2 concentration data from the Orbiting Carbon Observatory-2 (OCO-2) satellite developed by NASA (National Aeronautics and Space Administration) were combined with precipitation data derived from Integrated Multi-satellite Retrievals for GPM (IMERG). After performing spatiotemporal matching, the two datasets were directly compared and subjected to statistical analyses.
The results revealed a weak positive correlation between CO_2 concentrations and precipitation amounts ($r \approx 0.17$). Moreover, by examining temporal lags, the maximum correlation was observed at a 12-month delay. Regression analyses showed that CO_2 concentrations have limited explanatory power for precipitation variability ($R^2 \approx 0.03$).
These findings indicate that CO_2 concentrations do not directly drive changes in precipitation but should be considered alongside other atmospheric dynamics. The study aims to contribute to a better understanding of atmospheric processes over Türkiye in the context of climate change.

Keywords: *CO_2 concentration; precipitation analysis; OCO-2; IMERG; climate change; Türkiye.*

1. Introduction

The increase in greenhouse gases in the atmosphere is one of the most fundamental indicators of climate change, leading to global temperature rise, sea level rise, and fluctuations in meteorological events. Carbon dioxide, being one of the most abundant greenhouse gases in the atmosphere, plays a critical role in the disruption of the energy balance and the acceleration of climate change. Therefore, monitoring atmospheric CO_2 levels and understanding their relationship with meteorological events—particularly precipitation—is of great importance for developing sustainable environmental and climate policies.

Precipitation is a critical variable within the climate system due to its direct link to the water cycle [1]. Many sectors such as agriculture, energy production, and water resource management depend on precipitation patterns. However, climate change has caused significant fluctuations in precipitation regimes, increasing the risk of extreme drought in some areas and floods in others [2]. Türkiye, located in the Mediterranean climate zone, is one of the vulnerable regions particularly susceptible to these changes. Therefore, investigating the relationship between regional CO_2 concentrations and changes in precipitation can provide valuable insights for measures against climate change.

In recent years, satellite-based observation systems have become important tools for collecting and analyzing atmospheric and meteorological data. The OCO-2 satellite developed by NASA provides high-resolution measurements of atmospheric CO_2 concentrations [3]. Similarly, the IMERG mission allows for accurate determination of global precipitation amounts. These datasets can be effectively used to investigate the relationship between CO_2 and precipitation through temporal and spatial analyses.

In the literature, there are limited studies that directly examine the relationship between CO_2 levels and precipitation amounts. Most studies have focused on CO_2's radiative effects in the atmosphere, temperature increases, and evaporation processes; however, the indirect role of CO_2 on precipitation has not been sufficiently explored. Nonetheless, it is known that factors such as aerosol density, surface temperatures, and evaporation affect precipitation formation, and these processes may be linked to CO_2 levels. Understanding the potential effects of CO_2 levels on precipitation requires a detailed examination of these processes.

This study aims to understand the potential relationship between CO_2 concentrations and precipitation amounts over Türkiye. CO_2 data obtained from NASA's OCO-2 satellite and precipitation data from the IMERG satellite mission were combined, and both temporal and spatial analyses were conducted.

In the temporal analysis, the focus was on the changes in CO_2 concentrations and precipitation amounts over a specific time period. Particularly, OCO-2 data from January 2018 to February 2022 and IMERG data from January 2018 to December 2022 were used to examine the trends, seasonal variations, and possible long-

*Corresponding author
E-mail address: d2240138006@ogr.sdu.edu.tr

Received: 01/Aug/2025; Accepted: 02/Dec/2025.

term connections between the two variables over time. A lagged correlation analysis was conducted to explore the temporal relationship of CO_2 levels' effects on precipitation.

In the spatial analysis, regional differences in CO_2 concentrations and precipitation were compared across Türkiye. Türkiye was divided into seven geographical regions. For each region, monthly average CO_2 and precipitation values were calculated and visualized as time series to reveal regional variability. The strength of the relationship between CO_2 and precipitation was quantified using Pearson correlation coefficients. Furthermore, simple linear regression models were developed to evaluate whether regional CO_2 concentrations could statistically explain changes in precipitation. Finally, lagged correlation graphs were used to assess whether fluctuations in CO_2 levels influenced precipitation with a temporal delay. By applying these methods, the study aimed to numerically and visually explore the spatial and temporal links between CO_2 and precipitation over Türkiye. The findings are expected to provide insights into the influence of atmospheric CO_2 on precipitation dynamics and contribute to predicting potential climate change impacts in the region.

2. Related Work

The impacts of atmospheric CO_2 concentrations on global climate change have been revealed through extensive research in recent years [4, 5, 2]. In particular, the IPCC reports have thoroughly examined the effects of CO_2 emissions on global temperature rise, sea level increase, and extreme weather events [2]. These reports emphasize that the increase in CO_2 directly affects the hydrological cycle, causing changes in precipitation patterns.

The effects of CO_2 on climate have been analyzed using various modeling approaches. Elliott at al. conducted global analyses with linear models to investigate the influence of changes in atmospheric CO_2 levels on tropical sea surface temperatures and precipitation patterns [6]. Yang and Wang evaluated the role of CO_2 increases on climatic variables in China using atmospheric modeling techniques [7]. Similarly, Zhou at al. studied ecosystem responses through nonlinear models and demonstrated the potential effects of CO_2 increases on humidity, temperature, and precipitation changes [8]. The effects of CO_2 on precipitation occur through both direct and indirect processes. Betts at al. emphasized that increased CO_2 can cause significant changes in continental runoff by altering evapotranspiration processes on land [9]. In addition, the impacts of CO_2 levels on soil moisture, water vapor transport, and atmospheric circulation have also been addressed in the literature.

In recent years, satellite-based data have provided great advantages in understanding the spatial and temporal variability of atmospheric CO_2 concentrations. Eldering at al. analyzed the regional distribution of global carbon emissions using data from the OCO-2 satellite [10]. Satellite-derived CO_2 data allow for more precise monitoring of atmospheric variability. Similarly, Mousavi et al. analyzed the changes in CO_2 levels in Iran between 2003 and 2020 using satellite data from SCIAMACHY (Scanning Imaging Absorption Spectrometer for Atmospheric CHartographY) and GOSAT (Greenhouse Gases Observing Satellite), and revealed the effects of CO_2 on atmospheric variables [11]. Conducting such analyses in countries like Türkiye, which have diverse climatic conditions, can contribute to a more detailed understanding of CO_2 and precipitation dynamics.

Precipitation data provided by the Integrated Multi-satellite Retrievals for GPM (IMERG) and the Global Precipitation Measurement (GPM) missions are highly important for evaluating global precipitation patterns. Huffman at al. analyzed global precipitation distribution using IMERG data and emphasized that such satellite-based measurements can improve the accuracy of meteorological analyses [12]. NASA conducted comprehensive analyses using OCO-2 and OCO-3 data to better understand the global carbon cycle [13].

In a study conducted in the Cape Rama region on the western coast of India, Tiwari at al. examined changes in atmospheric CO_2 concentrations between 1993 and 2002 and showed that CO_2 levels decreased during the summer monsoon due to increased precipitation [14]. This study revealed a complex relationship between atmospheric CO_2 concentrations, the hydrological cycle, and vegetation changes. Similarly, Leuzinger at al analyzed the effects of CO_2 emissions on precipitation patterns, and Sponseller at al. evaluated the influence of precipitation fluctuations on soil CO_2 flux [15, 16].

In the context of Türkiye, most studies have focused on the relationship between changes in precipitation regimes and climatic processes. Türkeş and Erlat evaluated regional climate impacts by linking precipitation changes in Türkiye to the North Atlantic Oscillation (NAO) [17]. Ersoy at al. analyzed extreme precipitation events in the Eastern Anatolia Region and aimed to improve the predictability of these events using machine learning methods. However, comprehensive studies directly addressing the relationship between atmospheric CO_2 concentrations and precipitation patterns in Türkiye remain quite limited [18]. Crane at al. evaluated changes in precipitation under a doubled CO_2 scenario in the Susquehanna River Basin; applying similar approaches to Türkiye could contribute to understanding the connection between regional carbon emissions and the hydrological cycle [19].

In recent years, machine learning methods have been increasingly used for analyzing and forecasting climate data. Reichstein at al. examined how machine learning and deep learning techniques can be used in climate prediction models, showing that these approaches offer significant advantages, especially in temporal forecasting processes [20]. Machine learning algorithms can analyze variations in atmospheric CO_2 concentrations and allow for long-term predictions and modeling of regional climate change impacts.

The effects of rising CO_2 on vegetation play a critical role in understanding the carbon cycle. Keenan at al. revealed that the increase in CO_2 enhances plant carbon uptake, which in turn affects atmospheric CO_2 concentrations [21]. Carbon storage processes in ecosystems have the potential to balance the presence of CO_2 in the atmosphere. Furthermore, Fischer and Knutti stated that increasing CO_2 levels raise the frequency of extreme precipitation and high-temperature events, thereby highlighting the influence of CO_2 on the hydrological cycle and extreme weather patterns [22].

Table 1. *Summary of methods and study areas in research on atmospheric CO_2 and precipitation dynamics*

References	Algorithms / Methods Used	Study Area / Region
Elliott (1991)	Linear models, statistical analysis	Global
Yang and Wang (2000)	Statistical analysis, atmospheric modeling	China
Zhou et al. (2008)	Nonlinear models, ecosystem response analysis	Global
Betts et al. (2007)	Hydrological modeling, vegetation impact analysis	Global
Eldering et al. (2017)	Satellite-based data analysis (OCO-2)	Global
Leuzinger et al. (2009)	CO_2–precipitation impact modeling, vegetation analysis	Global
Mousavi et al. (2022)	Satellite-based data analysis (SCIAMACHY, GOSAT)	Iran
Tiwari et al. (2013)	Atmospheric CO_2–precipitation relationship analysis	India (Cape Rama Region)
Sponseller et al. (2006)	Effect of precipitation variability on soil CO_2 flux	Global
Ersoy et al. (2023)	Machine learning methods, weather prediction models	Türkiye (Eastern Anatolia Region)
Türkeş and Erlat (2003)	Analysis of precipitation variability and NAO	Türkiye
Crane et al. (1998)	CO_2 doubling scenario modeling	Susquehanna Basin (USA)
Huffman et al. (2021)	Precipitation analysis using IMERG and GPM data	Global
NASA (2015)	Analysis using OCO-2 and OCO-3 satellite data	Global
Reichstein et al. (2019)	Machine learning, climate prediction models, deep learning	Global
Keenan et al. (2016)	Carbon cycle modeling, ecosystem analysis	Global
Fischer and Knutti (2015)	Analysis of extreme weather events	Global

The present study aims to temporally and spatially analyze atmospheric CO_2 concentrations and precipitation dynamics across Türkiye. These analyses are intended to provide a more detailed understanding of the CO_2–precipitation relationship and to assess regional differences, ultimately contributing to a deeper insight into Türkiye's climate processes.

3. Materials and Methods

This section first describes the data sources used in the study and the procedures applied to process the information derived from them. Subsequently, the data matching procedures and the analytical methods employed are explained in detail. The study is designed to evaluate potential relationships between CO_2 concentrations and precipitation amounts by considering not only temporal changes but also spatial differences. This methodological approach contributes to both understanding atmospheric processes and clarifying climate dynamics.

3.1. Data and data sources

The datasets used in this study include global and high-resolution measurements of both carbon dioxide (CO_2) concentrations and precipitation amounts. The data were obtained from two main sources:

3.1.1. OCO-2 data

The OCO-2 satellite was launched by NASA in 2014 to measure atmospheric carbon dioxide concentrations. This satellite enables high-resolution spatial and temporal investigation of global greenhouse gas emissions. In this study, monthly CO_2 concentration data covering the years 2018–2022 across Türkiye were obtained from NASA's Jet Propulsion Laboratory [23].

OCO-2 data have a spatial resolution of 0.5° × 0.625° and focus on the area within Türkiye's borders, between 36°–42° north latitude and 26°–45° east longitude. The data were downloaded in Network Common Data Form (NetCDF) format and processed for analysis using the xarray library in Python. The spatial and temporal details of the data are crucial for understanding variations in atmospheric CO_2 concentrations. All data processing and analysis procedures were conducted on a laptop equipped with a 12th-generation Intel®

Core™ i7-12700H processor (2.30 GHz, 14 cores), 16 GB DDR4 RAM, and 512 GB SSD storage. The operating system used was Windows 11 Pro, and the analyses were performed using Python 3.10 along with data processing and visualization libraries such as pandas, xarray, matplotlib, and numpy. This setup enabled the efficient handling and analysis of large-volume satellite datasets.

Temporally, the data were organized on a monthly basis to represent average atmospheric CO_2 concentrations for each month. The concentration unit is expressed in parts per million (ppm). This structure allows for the analysis of both temporal trends and spatial distribution.OCO-2 data were used to analyze changes in atmospheric carbon levels over time and to identify potential relationships with precipitation amounts.

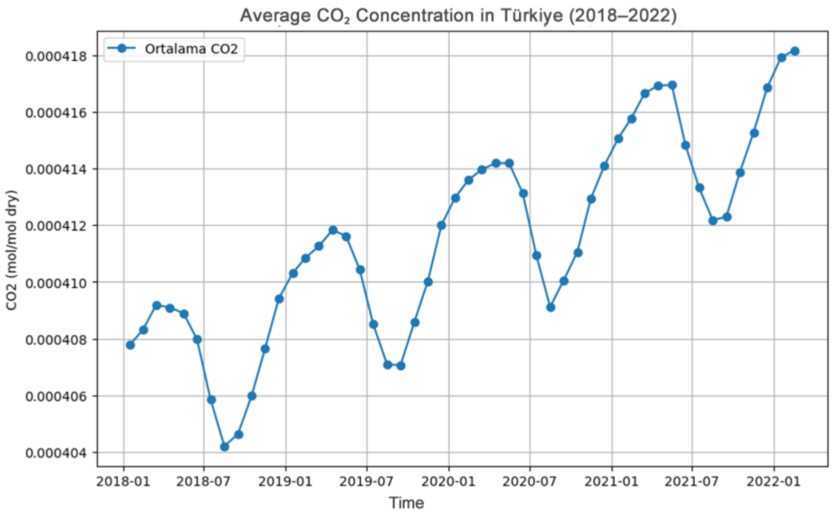

Figure 1. *Average CO_2 concentration in Türkiye (2018–2022)*

Figure 1 shows the temporal distribution of monthly average atmospheric CO_2 concentrations across Türkiye between 2018 and 2022, based on data obtained from the OCO-2 satellite. The graph reveals a clear upward trend in CO_2 levels over time. This increasing trend reflects the impact of global greenhouse gas emissions and provides valuable insights into the understanding of atmospheric dynamics.

3.1.2. IMERG Precipitation Data

IMERG provides high-resolution precipitation data as part of NASA's Global Precipitation Measurement (GPM) mission. In this study, IMERG precipitation data covering the period from 2018 to 2022 were obtained from NASA's Precipitation Processing System [24]. The data were processed within selected geographic boundaries across Türkiye and prepared for temporal analysis.

IMERG data are generated by integrating satellite-based precipitation measurements with observations from ground-based meteorological stations. This combination allows for more accurate investigation of atmospheric and surface dynamics. While the original data are recorded hourly, they were restructured into monthly average values to facilitate analysis and enable comparative studies. This reorganization made it possible to evaluate precipitation trends at a monthly temporal resolution.

In the IMERG dataset, precipitation amounts are expressed in millimeters (mm), enabling quantitative comparison of rainfall patterns. The data are provided in a consistent and comparable format, allowing for the analysis of precipitation variability across different geographic regions of Türkiye.

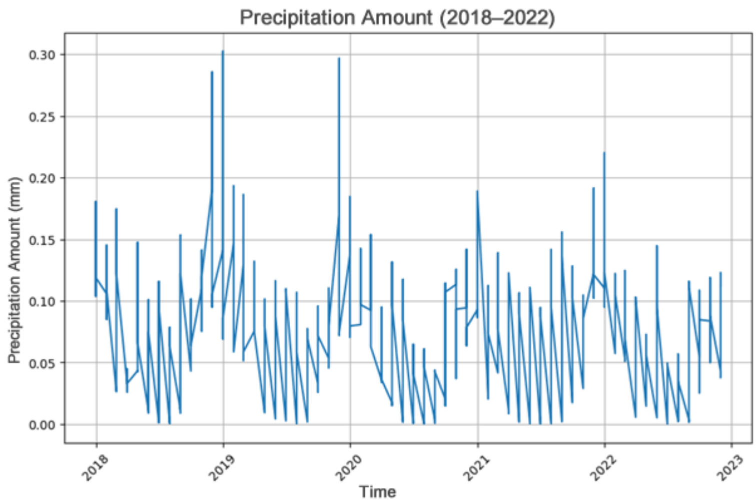

Figure 2. *IMERG precipitation amount graph (2018–2022)*

Figure 2 illustrates the temporal variation in precipitation amounts between 2018 and 2022, based on IMERG data. Monthly fluctuations in precipitation are clearly visible in the graph. These variations contribute to the understanding of seasonal changes and anomalies. For instance, sudden increases in rainfall observed during specific periods may be associated with changes in atmospheric conditions.

The atmospheric CO_2 and precipitation datasets used in this study underwent similar preprocessing steps prior to analysis. Both datasets were converted into CSV format and analyzed using the Python programming language. Specifically, data cleaning and restructuring were performed using data analysis libraries such as pandas and xarray, allowing for the calculation of monthly average values. CO_2 data were derived from the original NetCDF files obtained from the OCO-2 satellite and converted into mean values (in ppm) for the grid cells corresponding to Türkiye. Likewise, IMERG satellite data were derived from hourly precipitation records and aggregated into monthly averages in millimeters. During this process, missing data points in both datasets were identified and filled using interpolation methods. Following this, temporal and spatial alignment was performed to create a unified dataset suitable for analysis. This combined dataset enabled a holistic evaluation of the relationship between CO_2 concentrations and precipitation amounts.

3.2. Data processing

In this study, the data processing procedure was carried out in several stages to ensure the accuracy and reliability of the analyses. The process included key steps such as identifying and handling missing data, temporal alignment, and geographic subsetting. Each step was designed to preserve data integrity and enhance the validity of the analysis results.

In the first step, missing values within the datasets were examined. Since missing data can disrupt the continuity of the series, such values were either filled using interpolation methods or excluded from the analysis when deemed inappropriate. In particular, linear interpolation was employed to fill missing values in the time series. This method enabled the completion of data points in a manner consistent with natural trends, thereby improving usability for analysis.

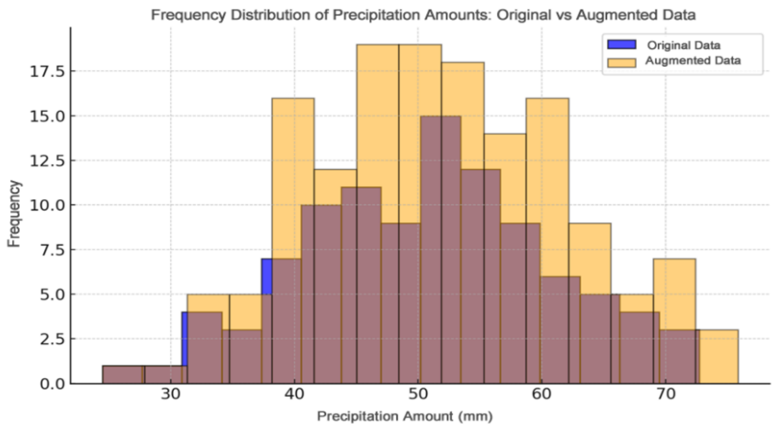

Figure 3. *Frequency distribution of original and interpolated precipitation data*

This graph compares the frequency distribution of the original IMERG precipitation data with the interpolated dataset obtained after missing observations were filled. The enhanced dataset exhibits a distribution similar to the original, and it was evaluated for modeling suitability during the data processing stage.

During the temporal alignment process, harmonization between CO_2 and precipitation data was achieved due to their collection at different time intervals. IMERG precipitation data were downscaled from hourly measurements to monthly averages and adjusted to match the temporal resolution of the OCO-2 data. Data manipulation was performed using the Python programming language along with the pandas and numpy libraries. Temporal alignment allowed the CO_2 and precipitation datasets to be directly compared within the same time periods.

To assess potential relationships between CO_2 concentrations and precipitation amounts across different regions of Türkiye, a regional analysis was conducted. In this process, Türkiye was divided into seven geographical regions, and regional averages of precipitation and CO_2 were calculated separately for each.

In the spatial analysis, CO_2 and precipitation data were converted into raster grid format to enable regional-scale comparisons. To focus solely on the areas within Türkiye, the geographic boundaries were defined as follows:

- Latitude: 36°–42° N
- Longitude: 26°–45° E

Regional CO_2 and precipitation analyses were performed using grid cells defined across Türkiye to observe spatial variations in CO_2 concentrations and precipitation.

Finally, the overall distribution of precipitation amounts was analyzed. The results indicated that the majority of precipitation events across Türkiye were concentrated in the 0.00–0.10 mm range.

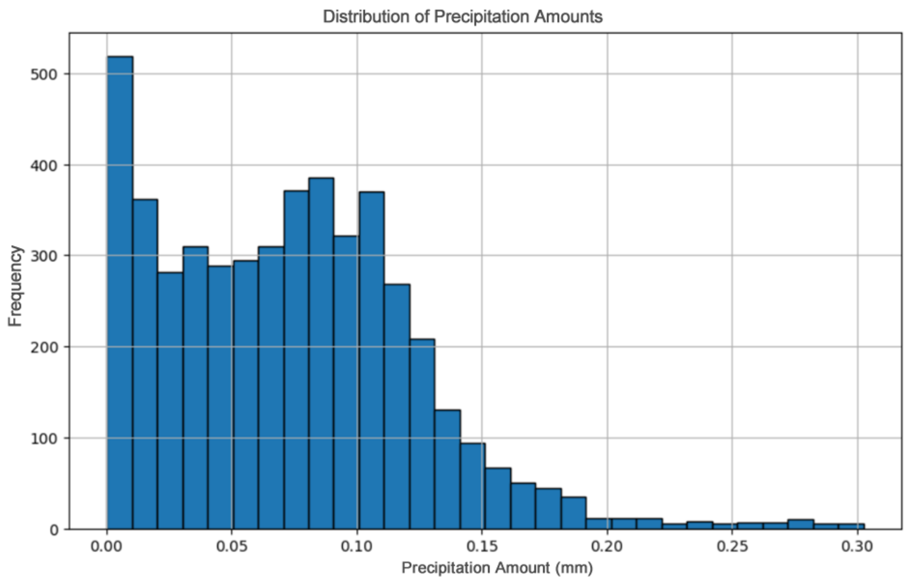

Figure 4. *Frequency distribution of precipitation amounts*

Figure 4 presents the frequency distribution of precipitation amounts, offering important insights into Türkiye's rainfall regime.

Through these data processing steps, the accuracy and reliability of the analyses have been improved. The datasets were processed and prepared for analysis in a way that facilitates a better understanding of the relationship between CO_2 concentrations and precipitation amounts.

3.3. Algorithms and analytical methods used

This section provides a detailed explanation of the mathematical models, algorithms, and analytical methods employed in the study. The aim is to comprehensively present the rationale and implementation processes of the techniques selected to investigate the potential relationship between atmospheric CO_2 concentration and precipitation amount.

3.3.1. Time series analysis

Time series analysis is a method used to identify trends, seasonal patterns, and anomalies in data that change over time. In this study, time series methods were applied to analyze both CO_2 concentration and precipitation data.

The time series analysis focused on the following model components:

One of the primary components of the time series analysis is trend analysis, which is used to understand the overall direction of the data and to evaluate long-term changes. For instance, increasing trends in annual average CO_2 levels and decreasing trends in precipitation amounts were examined.

The trend component can be mathematically expressed as follows (1):

$$T_t = \beta_0 + \beta_1 t \quad (1)$$

Where *Tt* denotes the trend component, *t* is the time variable, *β0* and *β1* represent the model coefficients.

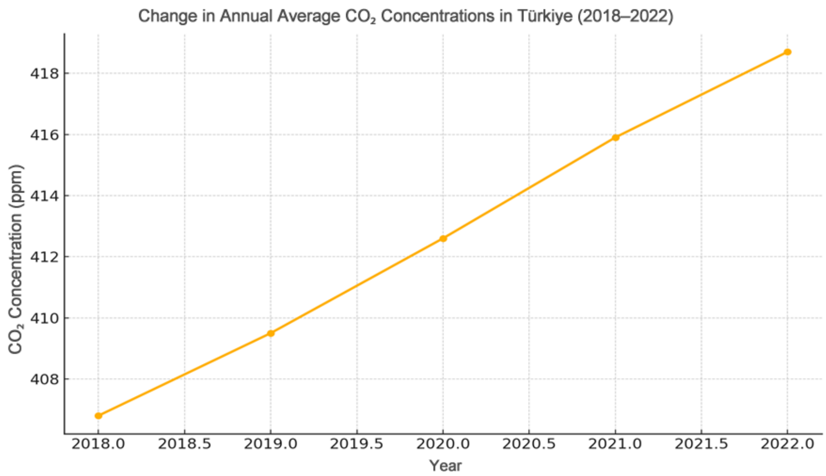

Figure 5. *Amounts Annual average CO_2 concentration trend (2018–2022)*

This graph illustrates the trend in atmospheric carbon dioxide (CO_2) levels observed across Türkiye over the years. The figure reveals a clear upward trend in CO_2 concentrations.

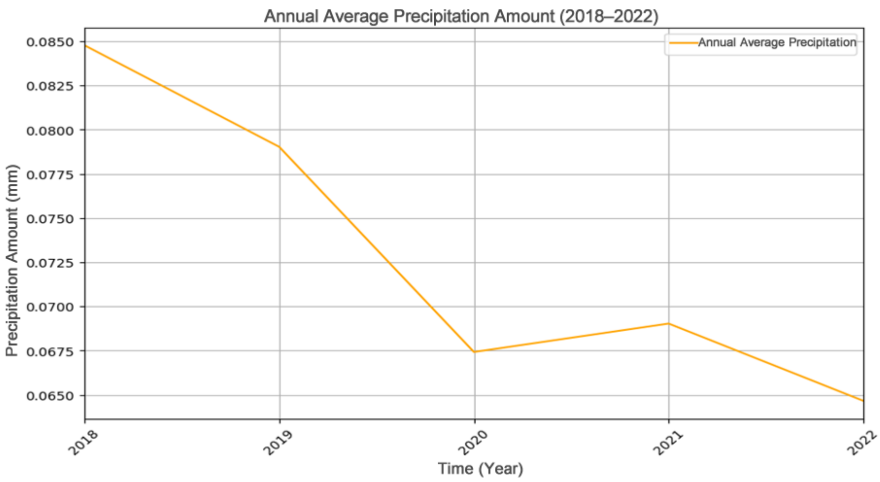

Figure 6. *Annual average precipitation trend (2018–2022)*

The graph clearly illustrates the overall decreasing trend in precipitation amounts. The data, derived from annual measurements across Türkiye, indicate potential long-term climatic changes and shifts in precipitation regimes.

One of the key components of the time series analysis is seasonality analysis, which aims to identify periodic patterns in CO_2 concentrations and precipitation amounts. In this study, Fourier transformation and moving average methods were used to detect seasonal effects. Fourier transformation enables the decomposition of the data into fundamental frequency components, allowing for the identification of recurring patterns. The moving average method smooths short-term fluctuations, making seasonal variations more visible within the time series.

Mathematically, seasonality can be expressed as follows (2):

$$S_t = A_k + cos\ (2\pi f_k t + \phi_k) \tag{2}$$

where S_t represents the seasonal period length, A_k is the amplitude coefficient, f_k denotes the harmonic frequency, t is time, ϕ_k is the phase angle.

This analysis plays a critical role in identifying and comparing periodic patterns in CO_2 concentration and precipitation data.

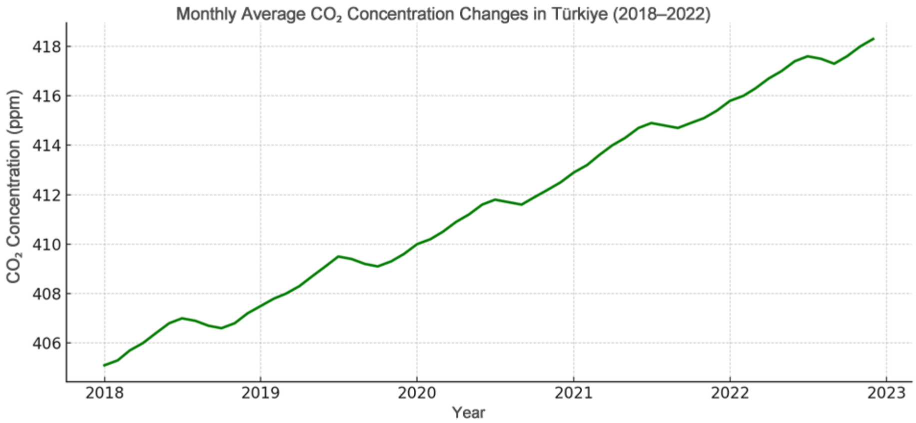

Figure 7. *Monthly average CO_2 concentration changes (2018–2022)*

Figure 7 illustrates the variation in monthly average atmospheric carbon dioxide concentrations observed across Türkiye between 2018 and 2022. The graph shows a consistent upward trend in CO_2 levels throughout the year. This trend reflects both the increase in global carbon emissions and the influence of region-specific anthropogenic activities. In addition, seasonal fluctuations are observed, which are attributed to vegetation dynamics and the effects of photosynthesis during different times of the year.

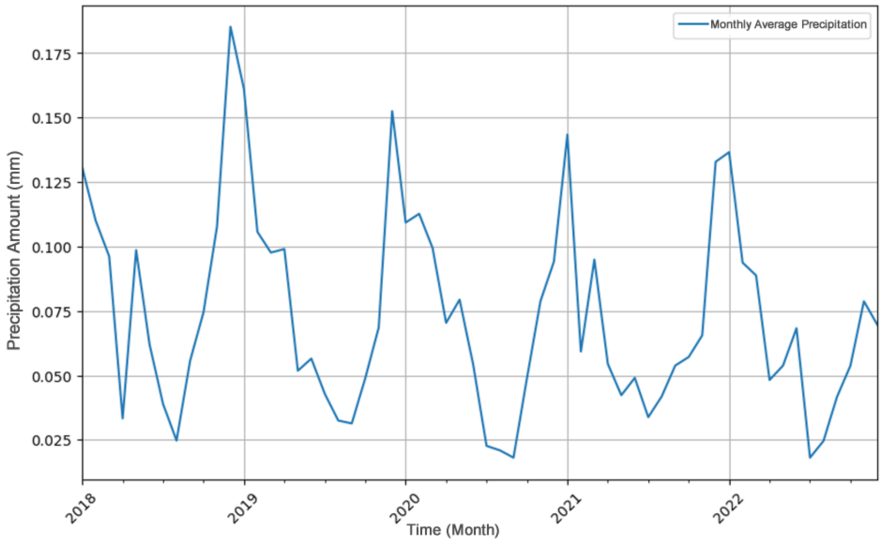

Figure 8. *Monthly average precipitation variation (2018–2022)*

Figure 8 is used to visualize seasonal patterns, allowing for the examination of trends and recurring structures within the dataset.

3.3.2. Correlation analysis

Correlation analysis was conducted to evaluate the relationship between atmospheric CO_2 concentration and precipitation amount. The Pearson correlation coefficient (r) is a metric that measures the linear relationship between two variables, and it is calculated using the following formula (3):

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{3}$$

where x_i represents the CO_2 concentration, y_i is the precipitation amount, $\overline{x}$ is the mean of CO_2 values, and $\overline{y}$ is the mean of precipitation values. The correlation coefficient r takes values between -1 and $+1$. A value of $r>0$ indicates a positive linear relationship, while $r<0$ suggests a negative linear relationship. If $r=0$, it implies that there is no linear relationship between the two variables.

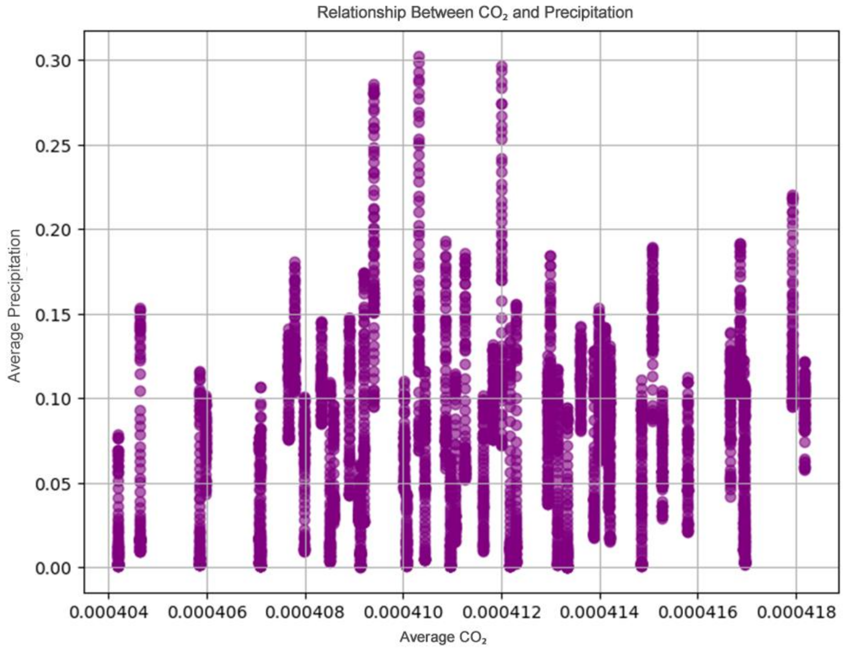

Figure 9. *Relationship between CO_2 concentration and precipitation*

Figure 9 presents a visual representation of the relationship between CO_2 concentration and precipitation amount. In the graph, the horizontal axis represents CO_2 concentration (ppm), while the vertical axis shows precipitation amounts (mm). Each point on the graph corresponds to the CO_2 and precipitation values for a specific time period.

As can be observed, no clear linear relationship exists between the two variables. The scatterplot indicates that increases in CO_2 concentration do not have a pronounced effect on precipitation levels. This suggests that the relationship may be more complex or potentially explained by a non-linear model. Additionally, the low correlation coefficient (r) obtained during the analysis confirms the weakness of this relationship.

3.3.3. Regression analysis

In this study, linear regression analysis was employed to model the relationship between CO_2 concentration and precipitation amount. The model is defined as follows (4):

$$Y = \beta_0 + \beta_1 x + \varepsilon \tag{4}$$

where Y denotes the dependent variable representing precipitation amount, x is the independent variable representing CO_2 concentration, $\beta 0$ is the intercept term, $\beta 1$ is the coefficient of the independent variable, and ε represents the error term.

The regression coefficients were estimated by minimizing the residual sum of squares using the ordinary least squares (OLS) method, expressed as follows (5):

$$min \sum_{i=1}^{n}(Y_i - (\beta_0 + \beta_1 X_i))^2 \tag{5}$$

The regression results suggest that CO_2 concentration, as the independent variable, has limited ability to explain variations in precipitation amount.

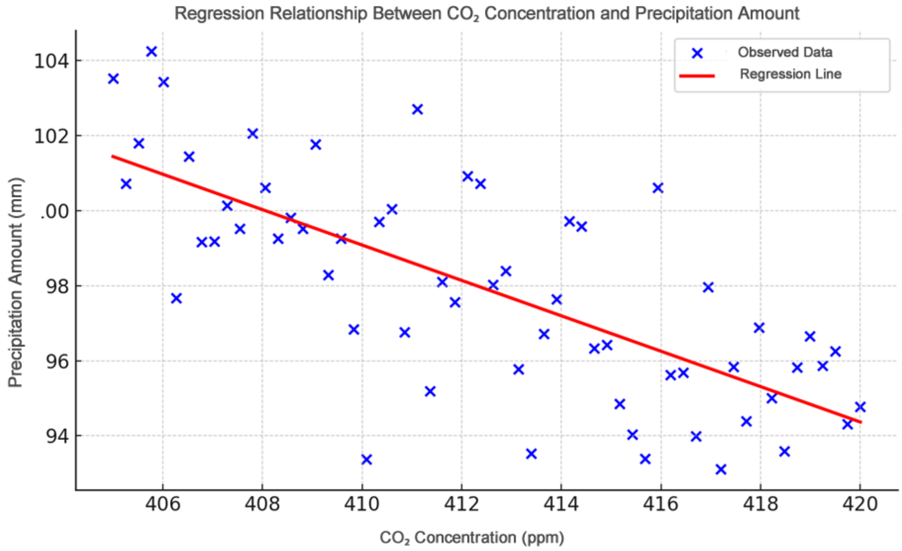

Figure 10. *Linear regression relationship between CO_2 concentration and precipitation*

This graph illustrates the linear regression model representing the relationship between monthly average CO_2 concentrations and precipitation amounts across Türkiye from 2018 to 2022. The blue dots represent the individual monthly observations, while the red line indicates the linear relationship predicted by the model. The resulting regression line shows that changes in CO_2 levels have limited explanatory power over precipitation amounts ($R^2 \approx 0.03$). This finding suggests that the relationship between CO_2 and precipitation may be nonlinear or influenced by indirect atmospheric processes.

3.3.4. Lagged correlation analysis

To understand how the relationship between CO_2 concentration and precipitation amount changes over different time intervals, a lagged correlation analysis was conducted. This analysis is based on the assumption that the impact of CO_2 levels on precipitation may emerge with a time delay. The lag analysis examines the correlation between CO_2 and precipitation across various temporal lags.

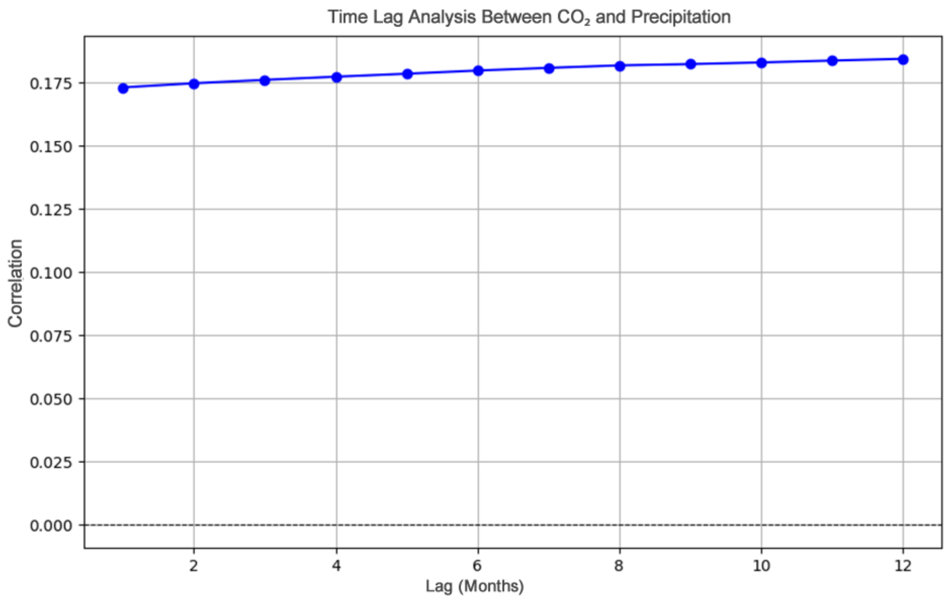

Figure 11. *Lagged correlation analysis between CO_2 concentration and precipitation*

Figure 11 illustrates how the correlation between CO_2 concentration and precipitation amount changes as a function of time lag. The horizontal axis represents the lag (in months), while the vertical axis shows the correlation coefficient (r). The results indicate that the correlation coefficient gradually increases with longer lag periods, although it generally remains at low levels.

This suggests that the effect of CO_2 concentration on precipitation is neither immediate nor direct, and that more complex atmospheric processes may be involved. For instance, the impact of rising CO_2 levels on atmospheric systems may accumulate over time, potentially leading to delayed changes in precipitation dynamics. However, a more detailed explanation of this relationship would require the use of alternative or more advanced modeling approaches.

4. Results

In this study, the potential relationship between atmospheric carbon dioxide (CO_2) concentrations and precipitation amounts across Türkiye was comprehensively investigated using satellite-based data. High-resolution CO_2 concentration data obtained from the OCO-2 satellite were combined with precipitation measurements derived from IMERG data, covering the period from 2018 to 2022. The study aimed to understand the relationship between these two key atmospheric variables from both temporal and spatial perspectives, and to offer a deeper insight into atmospheric processes over Türkiye.

From a spatial perspective, Türkiye was divided into seven geographical regions, and separate averages for CO_2 and precipitation were calculated for each. These values were analyzed comparatively. It was observed that regions with intensive industrial or agricultural activity—such as Marmara, Aegean, and Central Anatolia—exhibited higher CO_2 levels. However, no distinct inverse relationship with precipitation amounts was identified. This suggests that the relationship between CO_2 and precipitation may not be linear, but rather influenced by regional characteristics, land use patterns, and atmospheric circulation dynamics.

The correlation analysis revealed a weak positive relationship ($r \approx 0.17$) between CO_2 concentration and precipitation amount. This indicates that there is no strong or direct link between the two variables, although a limited interaction may exist. The findings suggest that increasing CO_2 levels could have an indirect influence on precipitation dynamics.

Lagged correlation analysis indicated that the effects of CO_2 concentration on precipitation may emerge over time. The highest correlation coefficient was observed with a 12-month lag, suggesting that CO_2 may influence atmospheric processes through gradual accumulation. However, the low correlation value ($r \approx 0.17$) indicates that the relationship is not direct and is likely associated with more complex atmospheric mechanisms.

The linear regression analysis showed that the model's explanatory power was notably low ($R^2 \approx 0.03$). This result indicates that CO_2 concentration alone is insufficient to explain variations in precipitation amounts, implying that the relationship may not follow a linear structure but may instead be governed by more intricate mechanisms.

Spatial analyses across Türkiye demonstrated that both CO_2 concentrations and precipitation amounts vary at the regional level. However, no statistically significant trend was identified between these variations. For instance, regions with higher CO_2 concentrations did not show a clear increase or decrease in precipitation. In some areas, weak positive or negative correlations were observed (with r values around ±0.05), yet these were statistically insignificant ($p > 0.05$). These findings suggest that the relationship between CO_2 and precipitation does not follow a linear pattern at the regional scale and may be shaped by more complex atmospheric dynamics. Therefore, it is recommended that regional analyses be supported by more advanced methods, such as multivariate analyses or artificial intelligence-based models.

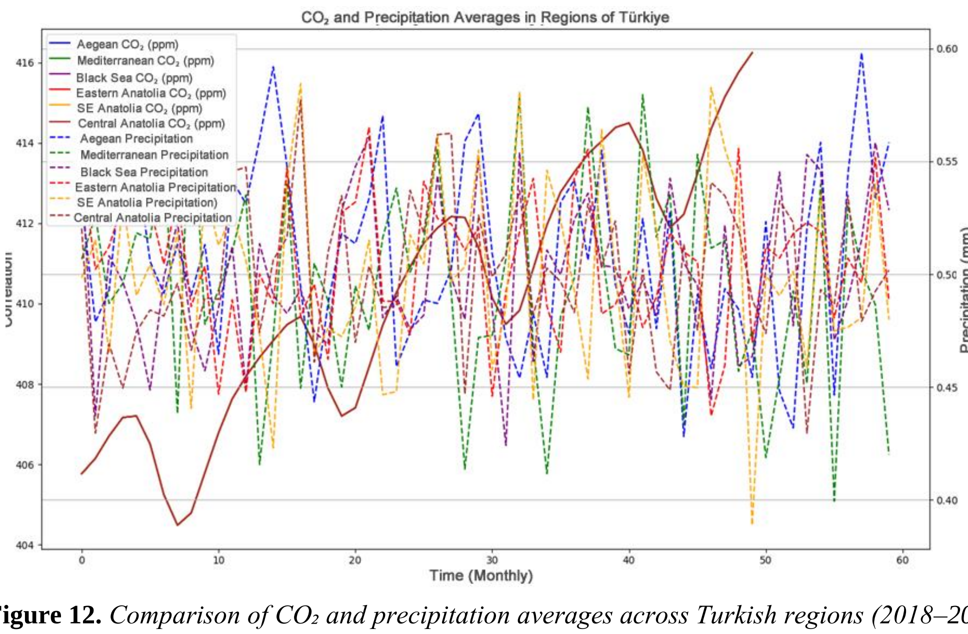

Figure 12. *Comparison of CO_2 and precipitation averages across Turkish regions (2018–2022)*

Figure 12 illustrates the trends in monthly CO_2 concentrations and precipitation amounts across various regions in Türkiye. The results show spatial differences in CO_2 and precipitation levels among regions; however, these differences do not reveal any distinct correlation or trend. For instance, while CO_2 levels exhibited an upward trend in industrially and agriculturally active regions such as Marmara and the Aegean, no significant change in precipitation was observed. In regions like Southeastern and Eastern Anatolia, precipitation showed seasonal fluctuations, but changes in CO_2 concentrations did not appear to significantly influence rainfall dynamics. These findings underscore the importance of conducting more detailed regional analyses.

5. Discussion and Future Work and Recommendations

The results of this study indicate that atmospheric CO_2 concentrations are not a direct or decisive factor in precipitation dynamics; rather, their effects should be considered within a broader atmospheric context. This finding aligns with previous studies in the literature. For example, Zhou et al. emphasized that increases in CO_2 influence intermediate processes such as humidity, cloud formation, and radiative effects, but do not directly determine precipitation amounts [8]. Similarly, research by Sponseller et al. has shown that soil CO_2 fluxes and precipitation variability are part of a complex web of interactions [16].

In the context of Türkiye, this study makes a significant contribution to the limited literature exploring the influence of CO_2 concentrations on precipitation dynamics. Particularly given Türkiye's location within the Mediterranean climate zone—a region highly sensitive to climate change—such research is of growing importance. These findings highlight that the effects of atmospheric CO_2 levels on precipitation should be assessed in conjunction with other atmospheric processes such as temperature, humidity, and evapotranspiration.

In conclusion, while this study marks an important step toward understanding atmospheric processes in Türkiye, the relationship between CO_2 concentration and precipitation dynamics likely involves more complex mechanisms and should be supported by further modeling studies. Future research should incorporate longer-term datasets and explore these interactions using non-linear models to gain deeper insights.

This study serves as a valuable starting point for investigating the relationship between CO_2 concentration and precipitation dynamics. However, the results suggest that this relationship is linked to more complex atmospheric processes, necessitating more comprehensive analyses in future work. Subsequent studies should utilize datasets covering longer time periods, as extended data can enhance understanding of long-term trends and improve the robustness of current findings.

Furthermore, the application of non-linear models may offer more effective insights into the complex interactions between CO_2 and precipitation. In particular, machine learning methods such as artificial neural networks and support vector machines can provide a deeper understanding of these relationships. Given the non-linear nature of CO_2's influence on precipitation, the inclusion of such algorithms in future analyses is recommended.

Incorporating additional atmospheric variables will allow for a more holistic examination of this relationship. Factors such as temperature, humidity, surface pressure, and wind speed play critical roles in precipitation formation. Integrating these variables into models will enable a more detailed analysis of atmospheric processes.

The findings of this study may serve as a scientific basis for Türkiye's climate policy development and contribute significantly to the advancement of sustainable environmental management strategies. Moreover, a more comprehensive understanding of atmospheric processes will help inform effective strategies in the global fight against climate change. In this regard, this study provides a framework for future, more extensive research efforts.

Declaration of interest

The authors declare that there is no conflict of interest.

Acknowledgements

The authors gratefully acknowledge NASA and the Jet Propulsion Laboratory for providing access to the OCO-2 and IMERG datasets. The OCO-2 data were obtained from the NASA Jet Propulsion Laboratory, California Institute of Technology, and the IMERG precipitation data were provided by NASA's Precipitation Processing System. These datasets were essential for conducting the temporal and spatial analyses presented in this study.

Symbol Description

Latin symbols

A_k	amplitude coefficient
β_0,β_1	regression coefficients
f_k	harmonic frequency
ϕ_k	phase angle
S_t	seasonal component
t	time
T_t	trend component
x_i	CO_2 concentration (ppm)
$\overline{x}$	mean of CO_2 values
y_i	precipitation amount(mm)
$\overline{y}$	mean of precipitation values

Greek symbols

ε	error term
ϕ_k	phase angle

Abbreviations and units

CPU	central processing unit
CSV	comma-separated values – a plain text file format
GB	gigabyte
GHz	gigahertz
GOSAT	greenhouse gases observing satellite
GPM	global precipitation measurement (NASA-JAXA satellite mission)
IMERG	integrated multi-satellite retrievals for GPM (NASA precipitation product)
mm	millimeter
NASA	National Aeronautics and Space Administration
NAO	North Atlantic Oscillation
NetCDF	network common data form – scientific multidimensional data format
OCO-2	orbiting carbon observatory-2 (NASA CO_2 satellite mission)
ppm	parts per million
RAM	random access memory
SCIAMACHY	scanning imaging absorption spectrometer for atmospheric CHartographY
SSD	solid state drive

References

[1] Trenberth, K. E., Fasullo, J. T., & Kiehl, J. (2011). "Earth's global energy budget", *Bulletin of the American Meteorological Society*, 90(3), 311–323. https://doi.org/10.1175/2008BAMS2634.1

[2] IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/

[3] Wunch, D., Toon, G. C., Blavier, J. F. L., et al. (2017). "Validation of the OCO-2 XCO_2 measurements against TCCON data using the TCCON network.", *Atmospheric Measurement Techniques*, 10, 2209–2238. https://doi.org/10.5194/amt-10-2209-2017

[4] Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Bakker, D. C. E., Hauck, J., ... & Peters, G. P. (2022). Global Carbon Budget 2022. *Earth System Science Data*, *14*(11), 4811–4900. https://doi.org/10.5194/essd-14-4811-2022

[5] Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., ... Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

[6] Elliott, W. P., Angell, J. K., & Thoning, K. W. (1991). Relation of atmospheric CO_2 to tropical sea and air temperatures and precipitation. *Tellus B: Chemical and Physical Meteorology*, 43(2), 144–155. https://doi.org/10.3402/tellusb.v43i2.15259

[7] Yang, X., & Wang, M. (2000). Monsoon ecosystems control on atmospheric CO_2 interannual variability: Inferred from a significant positive correlation between year-to-year changes in land precipitation and atmospheric CO_2 growth rate. *Geophysical Research Letters*, 27(11), 1671–1674. https://doi.org/10.1029/1999GL006073

[8] Zhou, X., Weng, E., & Luo, Y. (2008). Modeling patterns of nonlinearity in ecosystem responses to temperature, CO_2, and precipitation. *Ecological Applications*, *18*(3), 453–466. https://doi.org/10.1890/07-0626.1

[9] Betts, R. A., Boucher, O., Collins, M., Cox, P. M., Falloon, P. D., Gedney, N., ... & Woodward, F. I. (2007). Projected increase in continental runoff due to plant responses to increasing carbon dioxide. *Nature*, *448*(7157), 1037–1041. https://doi.org/10.1038/nature06045

[10] Eldering, A., Wennberg, P. O., Crisp, D., Schimel, D. S., Gunson, M. R., Chatterjee, A., Liu, J., Schwandner, F. M., Sun, Y., O'Dell, C. W., Frankenberg, C., Taylor, T., Fisher, B., Osterman, G. B., Wunch, D., Hakkarainen, J., Tamminen, J., & Weir, B. (2017). The Orbiting Carbon Observatory-2 early science investigations of regional carbon dioxide fluxes. Science, 358(6360), eaam5745. https://doi.org/10.1126/science.aam5745

[11] Mousavi, S. M., Dinan, N. M., Ansarifard, S., & Sonnentag, O. (2022). Analyzing spatio-temporal patterns in atmospheric carbon dioxide concentration across Iran from 2003 to 2020. *Atmospheric Environment: X*, *14*, 100163. https://doi.org/10.1016/j.aeaoa.2022.100163

[12] Huffman GJ, Bolvin DT, Braithwaite D, Hsu K, Joyce R, Xie P, et al. "Integrated Multi-satellitE Retrievals for the Global Precipitation Measurement (GPM) mission (IMERG)", in *Satellite Precipitation Measurement* (Advances in Global Change Research, vol. 67), Springer, 2020, pp. 343–353. https://doi.org/10.1007/978-3-030-24568-9_19

[13] NASA. (2015). *OCO-2 Science Team: OCO-2 Data User's Guide*. Jet Propulsion Laboratory, California Institute of Technology.

[14] Tiwari, Y. K., Revadekar, J. V., & Ravi Kumar, K. (2013). Variations in atmospheric Carbon Dioxide and its association with rainfall and vegetation over India. *Atmospheric Environment*, *68*, 45-51. https://doi.org/10.1016/j.atmosenv.2012.11.040

[15] Leuzinger, S., Körner, C., Asshoff, R., & Gehrig, R. (2009). Rainfall distribution is the main driver of runoff under future CO_2. *Global Change Biology*, *15*(8), 2124–2138. https://doi.org/10.1111/j.1365-2486.2009.01937.x

[16] Sponseller, R. A., Virginia, R. A., & Schimel, J. P. (2006). Precipitation pulses and soil CO_2 flux in a Sonoran Desert ecosystem. *Global Change Biology*, *12*(4), 653–665. https://doi.org/10.1111/j.1365-2486.2006.01307.x

[17] Türkeş, M., & Erlat, E. (2003). Precipitation changes and variability in Türkiye linked to the North Atlantic Oscillation during the period 1930–2000. *International Journal of Climatology*, *23*(14), 1771–1796. https://doi.org/10.1002/joc.962

[18] Ersoy, A., Uğuz, H., & Yurdusev, M. A. (2023). Rainfall forecasting with hybrid and machine learning models based on hyperparameter optimization. *Journal of Hydrometeorology*, *24*(5), 755–770. https://doi.org/10.1061/JHYEFF.HEENG-5960

[19] Crane, R. G., Hewitson, B. C., & du Plessis, J. A. (1998). Doubled CO_2 precipitation changes for the Susquehanna Basin: Down-scaling from the GENESIS general circulation model. *International Journal of Climatology*, *18*(1), 65–76. https://doi.org/10.1002/(SICI)1097-0088(199801)18:1<65::AID-JOC222>3.0.CO;2-9

[20] Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1

[21] Keenan, T. F., Williams, C. A., Gray, J., Lindenmaier, R., Michaelis, A. R., Campbell, J. E., ... & Wang, H. (2016). Recent pause in the growth rate of atmospheric CO_2 due to enhanced terrestrial carbon uptake. *Nature Communications*, *7*, 13428. https://doi.org/10.1038/ncomms13428

[22] Fischer, E. M., & Knutti, R. (2015). Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nature Climate Change*, *5*(6), 560–564. https://doi.org/10.1038/nclimate2617

[23] Jet Propulsion Laboratory (JPL). (2015). *Orbiting Carbon Observatory-2 (OCO-2) Data Product User's Guide: Operational L1 and L2 Data Versions 6*. California Institute of Technology. Retrieved from https://ocov2.jpl.nasa.gov/

[24] NASA Precipitation Processing System (PPS). (2023). *Integrated Multi-satellite Retrievals for GPM (IMERG) [Data set]*. NASA. Retrieved from https://gpm.nasa.gov/data/imerg