CA22057-ANIS AYU SYAFIQAH.pdf

by AYUANIS

The Review of Visualisation Technique: Time Series in Climate Change

Anis Ayu Syafiqah binti Mohamad Nazham
CA2205
Faculty of Computing
Faculty of Computing, University Malysia Pahang Al-Sultan Abdullah, Pahang.

Abstract—The use of time series visualisation as a vital tool for comprehending and sharing advancements made towards Sustainable Development Goal (SDG) 13: Climate Action is reviewed in this research. To uncover trends, patterns, and anomalies in climate-related variables, the basic idea behind time series visualization is to show data points successively over time. These visualizations make it easy for stakeholders to see progress, setbacks, and the effects of interventions by charting temporal data, including greenhouse gas emissions, temperature anomalies, rates of adoption of renewable energy, and climate-related disaster events. The core principles of time series visualization are discussed in this review, with a focus on how it may be used to make difficult facts into understandable stories of change. When line charts, bar charts, and area charts are used effectively in this context, they help people make well-informed decisions and increase public awareness of the pressing need for and effects of climate action in the pursuit of the 2030 Agenda

Keywords—template, Scribbr, IEEE, format

I. VISUALISATION TECHNIQUE TIME SERIES

Time series technique is a foundational technique in climate science as it allows researchers, policymakers, and the public to track, understand, and project changes in climate variables over time.Visplore enables accurate data quality assessment and validation of synthetic meteorological time series, reducing erroneous inferences in thermal performance assessments[1]. As the world intensifies efforts to achieve the United Nations Sustainable Development Goals notably SDG 13 which is climate action, visualization technique time series have become essential for monitoring progress, detecting trends, and guiding interventions. This review examines the evolution, methodologies, and impact of time series visualization in the context of climate change, drawing on recent peer-reviewed literature and authoritative tools
.

A. The Role of Time Series Technique in Climate Change

In climate science, these visualizations allow the detection of long-term trends and anomalies, which are significant for distinguishing anthropogenic influences from natural variability. Furthermore, they facilitate the recognition of seasonal and cyclical patterns, such as annual temperature cycles or recurring climate phenomena. By conveying complex climate dynamics in an accessible format, time series visualizations support effective communication to both scientific and non-specialist audiences. Importantly, these visual tools inform policy development and the tracking of progress by providing clear data-driven insights into ongoing changes and the effectiveness of interventions.

The development of time series visualization techniques has been crucial in advancing climate change analysis. Traditional approaches primarily employ the static visualizations such as line graphs, bar charts, and scatter plots. While effective for basic trend identification, these methods struggle with the complexity and scale of modern climate datasets, specifically in representing multidimensional or high-frequency data.

Modern interactive methods have addressed these limitations through dynamic platforms such as NOAA's Climate at a Glance and NASA's GISS Surface Temperature Analysis. These tools integrate web-based dashboards, spatial-temporal animations, and user-customizable parameters, allowing the researchers to explore climate variables across geographic regions and temporal scales. Such platforms can enhance data accessibility for policymakers and the public while supporting advanced analytical workflows.

B. Methodological advancements in time series analysis.

a) *Trend Detection:* Statistical methods like the Mann-Kendall test, LOESS smoothing, and Theil-Sen estimator are commonly used to identify monotonic trends, filter out noise, and estimate trend slopes in climate time series. These techniques are crucial for distinguishing anthropogenic climate change signals from natural variability.

b) *Seasonal and Pattern Recognition:* Advanced decomposition techniques, such as STL (Seasonal-Trend decomposition using LOESS) and Fourier analysis, help isolate recurring seasonal patterns and periodic signals, which are vital for understanding phenomena like El Niño and annual CO_2 cycle.

c) *Multivariate and Causal Analysis:* Modern frameworks, such as the SDG Track, Trace & Forecast (SDG-TTF) model, employ multivariate time series analysis to account for causal relationships within and between geographic entities, improving the accuracy of SDG attainment forecasts.

C. Recent advances and Future Direction of Time Series

Recent progress in time series visualization for climate change analysis has been driven by the combination of machine learning, geospatial analytics, and real-time data

processing. The application of deep learning models, like Long Short-Term Memory (LSTM) networks, has greatly improved the ability for pattern recognition and predictive modeling in complex climate time series. These models are particularly adept at identifying non-linear dependencies and long-range temporal correlations, which are essential for forecasting climate variables and extreme occurrence.

The integration of satellite and terrestrial data has facilitated the development of high-resolution, spatiotemporal visualizations, which are critical for local adaptation planning and for comprehending regional climate impacts. Platforms like Google Earth Engine and ArcGIS facilitate the integration and analysis of multi-dimensional climate datasets, aiding the advanced spatiotemporal clustering and pattern detection. Furthermore, cloud-based systems such as Pangeo and Google Earth Engine have reinvented the field by enabling rapid, scalable analysis and visualization of massive, streaming climate datasets. These infrastructures support real-time monitoring and immediate response to evolve the climate patterns, thereby enhancing both research and policy decision-making capabilities.

In spite of these developments, several challenges remain. Data quality issues, such as absent values and irregular temporal sampling, necessitate sophisticated preprocessing, interpolation, and quality assurance techniques to ensure the reliability and consistency. As visualization models and tools become more complex, maintaining the interpretability and accessibility for non-expert audiences becomes increasingly challenging, highlighting the need for intuitive interfaces and transparent methodologies.

Time series visualization technique remains central to climate change analysis and monitoring. The transition from static charts to interactive dashboards and machine learning-powered analytics has changed our ability to detect trends, communicate risks, and inform policy. As climate datasets continue to emerge in scale and complexity, ongoing advancement in time series visualization will be indispensable for advancing global sustainability goals.

II. TIME SERIES TECHNIQUES PROCESS FLOW

A. The Steps Flow

1. Data Acquisition: Collect climate data from reliable sources. For example temperature, precipitation, and CO_2 levels data using ground stations, satellites, or open databases.

2. Data Preparation: Clean the data and handle missing values, remove outliers, and ensure temporal consistency. Then convert the data into a time series object, specifying frequency (e.g., daily, monthly, yearly) and time range.

3. Exploratory Visualization: Generate initial plots like line graphs, scatter plots to observe overall trends and identify anomalies.

4. Trend Detection: Apply statistical methods such as Mann-Kendall test, LOESS smoothing, or Theil-Sen estimator to detect long-term trends.

5. Seasonal and Pattern Analysis: Decompose the time series using STL (Seasonal-Trend decomposition using LOESS) or Fourier analysis to isolate seasonal/cyclical patterns. Visualize seasonal effects and periodic signals such as the CO_2 cycles.

6. Advanced Visualization: Integrate geospatial data for spatiotemporal analysis like the mapping temperature changes across regions over time.

7. Interpretation and Communication: Annotate the visualizations to highlight key findings, trends, and anomalies. Use clear legends, color schemes, and explanatory notes for policymakers, educators, or the public.
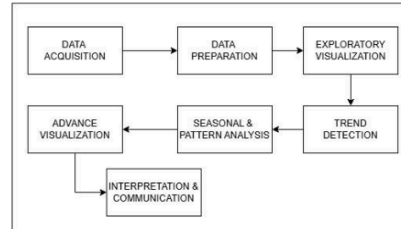

FIGURE 1 PROGRESS THROUGH TIME SERIES ANALYSIS

Analyzing periodic phenomena like climate variables requires the use of time series data, which are measurements made at regular intervals and are characterized by their sample frequency and time unit. When this data is broken down, trends for a long term changes, seasonality such as cyclic patterns, and random variables can be found. The figure below shows an annual cycle and increasing trend of Mauna Loa CO_2 time series.
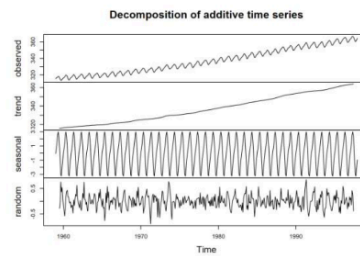

FIGURE 2 DECOMPOSITION OF MAUNA LOA CO_2 DDATA

III. Advantageous and Limitations

A. The Advantages

a) Uncovering Trends and Patterns

Time series visualization is highly effective in uncovering long-term trends, seasonal cycles, and anomalies within climate datasets. This capability allows researchers to differentiate between natural fluctuation and anthropogenic influences, supporting robust climate change evaluations. For instance, recent research using time series visualization have identified the deceleration of carbon emissions in high-income countries and rapid increase in developing economies, findings that are critical for policy development and the monitoring of Sustainable Development Goals (SDGs).

b) Enhance Communication and Decision Making

Modern time series visualization tools, including interactive dashboards and animated charts, facilitate the conversion of complex climate data into accessible and engaging visual narratives. These tools play a crucial role in communicating scientific results to both expert and non-expert audiences, thereby supporting informed decision making at multiple governance levels.

c) Enabling Advanced Analytical Methods

Time series visualization is not limited to basic plotting; it is closely linked with advanced statistical and machine learning techniques, like trend detection, decomposition, clustering, and forecasting. This integration facilitate for deeper insights into climate dynamics, the recognition of causal relationships, and the projection of future scenarios, which are important for climate modeling and adaptation planning.

B. The Limitations

a) Data Integrity and Deficiency

A major limitation of time series visualization in climate science is the prevalence of missing data, irregular sampling intervals, and measurement inconsistencies. These issues can undermine the reliability and accuracy of visualizations, necessitating sophisticated preprocessing and interpolation methods to reduce their impact. Even with such methods, residual uncertainty may affect the resilience of conclusions[4].

b) Complexity and Interpretability

As visualization techniques incorporate more advanced features such as machine learning, multidimensional data, and interactivity, they can become less transparent and challenging for non expert users to interpret. Ensuring accessibility and preventing confusion or information overload remains an ongoing challenge in the field.

c) Risk of Oversimplification or Misrepresentation

While visualizations are designed to summarize and highlight key features of large datasets, there is a risk of oversimplifying the complex climate processes or overlooking the important but subtle patterns. For example, focusing solely on aggregate trends may obscure regional imbalance or short-term extremes, which are crucial for local adaptation and risk evaluation.

Summary—Visualising time series is a critical technique for both industry and academia in the context of climate change analysis monitoring. Research has demonstrated its value in uncovering patterns in global carbon emissions, revealing the influence of economic development, policy interventions, and industrial shifts on emission trajectories across diverse national context[9]. This analytical capability is crucial for advancing climate science, informing cross-disciplinary research, and supporting evidence based recommendations.

In industry, time series visualization transforms complex climate datasets into accessible, practical insights for resource managers, policymakers, and stakeholders. Interactive dashboards and advanced visual analytics enable real-time monitoring, risk evaluation, and scenario planning, which are important for sectors such as energy, agriculture, water management, and disaster response. The technique supports the communication of scientific findings to non-expert audiences, enhancing public involvement and facilitating knowledgeable decision-making at multiple levels. Furthermore, the integration of time series visualization with machine learning and geospatial analytics enable high-resolution, spatiotemporal analysis, enhancing the precision and relevance of climate adaptation and mitigation strategies. Overall, time series visualization bridges the gap between complex climate data and practical action, empowering both academic and industrial stakeholders to track progress, evaluate interventions, and contribute effectively to global sustainability objectives[10].

References

[1] (2025)Map Library: Review of modern climate data visualization techniques and tools https://www.maplibrary.org/1462/exploring-temporal-changes-in-climate-data-visualization/

[2] (2021)Yassir Alharbi, Sustainable Development Goals Monitoring and Forecasting using Time Series, https://pdfs.semanticscholar.org/6f4c/b2e855f64d4fc81c179b7cf7c7e9427e07f3.pdf

[3] (August,2021), James Cheshire, Why dynamic data visualization is key to covering climate change. (n.d.). https://gijn.org/stories/why-dynamic-data-visualization-is-key-to-covering-climate-change/

[4] (April, 2025)Jerry Davis, SFSU Institute for Geographic Information Science. *Chapter 12 Time Series Visualization and Analysis | Introduction to Environmental Data Science.* https://bookdown.org/igisc/EnvDataSci/ts.html (September,2021)Armstrong, I. J. M. F. Z., *How to analyze and visualize time series data.* Observable. https://observablehq.com/blog/analyzing-time-series-data

[5] Liu, X., Zhao, M., & Miao, Q. (2023). Global carbon dioxide emissions analysis based on time series visualization. *Frontiers in Physics*, *11.* https://doi.org/10.3389/fphy.2023.1201983

[6] (2020) Wu, J., Wang, Y., Wang, J., & Qin, Y. A survey of time series data visualization methods. *Journal of Quantum Computing,* *2*(2), 105–117. https://doi.org/10.32604/jqc.2020.07242

[7] (March 2019), Manfred Mudelsee, Vol 190, Trend analysis of climate time series: A review of methods https://www.sciencedirect.com/science/article/pii/S0012 825218303726

[8] (2020) M.Vuckovic et al.,Visual Analytics Approach to Comprehensive Meteorological Time-Series Analysis https://consensus.app/papers/visual-analytics-approach-to-comprehensive-vuckovic-schmidt/9dbc98347f2f526ca604934fd18a960b/

[9] Thomas NOCKE, Till STERZEL, Michael BÖTTINGER and Markus WROBEL,Visualization of Climate and Climate Change Data: An Overview https://citeseerx.ist.psu.edu/document?repid=rep1&type =pdf&doi=4931e11d5dba0bf3a102d394931778c673b8 b049

CA22057-ANIS AYU SYAFIQAH.pdf

3% SIMILARITY INDEX

3% INTERNET SOURCES

1% PUBLICATIONS

1% STUDENT PAPERS

PRIMARY SOURCES

1	**Submitted to Manchester Metropolitan University** Student Paper	**1**%
2	www.maplibrary.org Internet Source	**1**%
3	www.peeref.com Internet Source	**1**%
4	dalspace.library.dal.ca Internet Source	**1**%
5	stripe.com Internet Source	**1**%
6	www.researchgate.net Internet Source	**1**%

Exclude quotes	On	Exclude matches	< 10 words
Exclude bibliography	On		