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AI-Generated Narratives and Infographic Synthesis for Visualizing Climate Temperature Anomalies

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Abstract

Communicating long-term climate trends to non-specialist audiences remains a persistent challenge, despite the availability of well-validated global temperature datasets. While existing climate visualizations and reports provide accurate information, they often rely on expert-driven interpretations or static representations that limit accessibility and scalability. This study presents a proof-of-concept system that integrates analytical processing, rule-based narrative generation, and infographic synthesis to transform structured climate data into coherent public-facing communication artifacts. The proposed framework uses the NASA GISTEMP v4 dataset, covering annual global temperature anomalies from 1880 to 2024. It applies linear trend estimation and deterministic anomaly highlighting to extract salient temporal patterns. These analytical outputs are then translated into traceable natural language summaries and integrated with visual encodings within a single reproducible pipeline. The results confirm a persistent long-term warming trend, with several recent years exceeding high-anomaly thresholds, and demonstrate that analytical values, narrative descriptions, and visual emphasis can be generated consistently from a shared data source. Rather than introducing new climate indicators or predictive models, this study's contribution lies in system-level integration: coupling data analysis, narrative synthesis, and visual composition into a unified, communication-oriented workflow. The framework is explicitly positioned as a proof of concept and does not claim causal attribution or empirical validation of user impact. Nonetheless, it demonstrates how transparent automation can reduce reliance on expert mediation while preserving scientific fidelity, supporting scalable climate communication systems.

Keywords: AI-generated narratives; climate data visualization; GISTEMP; sustainable communication; temperature anomaly detection;

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1. Introduction

Climate change continues to accelerate, with observable consequences across atmospheric, terrestrial, and marine systems. Among the most cited indicators of this phenomenon is the increase in global surface temperature anomalies, which reflect long-term shifts in Earth's energy balance. According to the Intergovernmental Panel on Climate Change (IPCC AR6, 2021) [1], global temperatures have risen by approximately 1.1°C since the pre-industrial era, and the rate of warming has significantly increased over the past four decades. However, while the data supporting these conclusions is extensive and rigorously validated, effectively communicating this information to non-specialist audiences remains a persistent challenge.

This communication gap impedes public understanding, policy urgency, and educational dissemination, especially in the Global South, where scientific literacy and access to technical resources may be limited. In such contexts, the challenge is not only the availability of reliable climate data but also the ability to transform this information into formats that can be understood and applied by communities, educators, and policymakers with limited technical

capacity. Therefore, a lightweight, open-source, and executable system is critical for enabling broader adoption in resource-constrained settings, ensuring that climate communication tools are accessible to regions disproportionately affected by climate change yet underserved by traditional scientific infrastructure.

Traditional climate communication mechanisms, such as scientific reports, academic publications, and governmental bulletins, often rely on statistical charts or dense textual descriptions that can be difficult for laypersons to interpret [2]. Studies in science communication have highlighted that raw data and static graphs, when presented without accompanying explanation or narrative structure, tend to generate low engagement and limited retention among general audiences [3], [4]. In response, recent interdisciplinary efforts have focused on improving public access to complex environmental data through narrative-driven approaches such as visual storytelling [5-7].

A key development in this domain is narrative visualization, a concept popularized by Segel and Heer [8], which combines data visualization with narrative elements to guide viewers through the data coherently and engagingly. Subsequent works, such as [9] and [10], reinforced the importance of blending visual, textual, and temporal elements to enhance comprehension in scientific communication. Within the climate domain specifically, visual dashboards and interactive graphics have been adopted by institutions such as NOAA, NASA, and the WMO to present real-time environmental indicators [11]. Yet, these visual outputs are typically hand-crafted, requiring teams of designers, scientists, and communicators to collaborate, an approach that, while effective, is labor-intensive and lacks scalability.

From a technological perspective, recent advancements in artificial intelligence offer potential to automate some of these communicative tasks. Natural Language Generation (NLG) has shown promise in fields such as automated journalism [12], medical reporting [13], [14], [15], and business intelligence [16], where structured data can be converted into human-readable summaries. Within climate science, however, applications of NLG remain limited. Most existing AI research has focused on modeling (e.g., temperature forecasting, extreme event detection) or climate prediction using deep learning [17], [18], rather than on communicating findings through interpretable, audience-oriented outputs. The integration of NLG with data visualization, especially for automated public communication, remains an underexplored area in both AI and climate informatics.

This study addresses this gap by proposing a framework that combines rule-based NLG and design communication principles to generate narrative-driven visualizations of long-term climate trends. Using the GISTEMP v4 dataset from NASA, the system analyzes global temperature anomalies from 1880 to 2024, detects major anomaly events, and automatically produces natural-language summaries and infographic panels. The system architecture follows a reproducible, modular pipeline that includes data preprocessing, linear trend modeling, anomaly classification, narrative construction, and visual assembly. Outputs are designed to balance scientific accuracy with public accessibility, grounded in design principles from Visual Communication Design (Desain Komunikasi Visual - DKV) and narrative science.

The primary objective of this research is to evaluate whether such a system can effectively transform structured climate data into self-contained, accessible artifacts that support public environmental literacy. The resulting framework is intended not only as a tool for automated climate communication but also as a proof-of-concept that AI can help bridge the gap between technical data and public understanding, particularly in the context of global sustainability agendas.

The contribution of this study is not to advance climate modeling accuracy, but to rethink how long-term climate data can be systematically transformed into interpretable, public-facing communication artifacts through an integrated systems engineering approach. Unlike existing climate visualization platforms that primarily emphasize interactive dashboards or expert-curated graphics, the proposed framework operationalizes a complete data-to-narrative-to-infographic pipeline within a single reproducible workflow. The novelty lies in explicitly coupling rule-based natural language generation with structured visual composition. Analytical results, explanatory text, and visual emphasis are generated coherently from the same data source rather than as independent post-processing steps.

By adopting deterministic narrative templates and lightweight visualization modules, the system prioritizes transparency, traceability, and deployability on modest computational resources, which are often overlooked in automated visualization research. Importantly, the framework is deliberately presented as a proof-of-concept for scalable climate communication rather than a production-ready decision-support system. This positioning enables a clear methodological contribution. It demonstrates how automation, narrative structure, and visual communication principles can be jointly engineered to reduce reliance on expert mediation while preserving scientific fidelity. In this respect, the study advances existing work by shifting the focus from isolated visualization outputs toward an integrated communicative system designed explicitly for accessibility, reproducibility, and public climate literacy.

2. Methods

This research adopts a cross-disciplinary approach that integrates AI-driven data summarization with automated visual generation to enhance climate literacy. The overall methodological workflow consists of three main stages: (1) climate data acquisition and

preprocessing, (2) AI-based narrative and visual generation, and (3) evaluation of infographic effectiveness.

The proposed framework (Figure 1) is engineered as a modular pipeline that converts structured climate records into communicative artifacts through tightly coupled analytical, narrative, and visual components. At the input layer, annual temperature anomaly data are ingested from NASA GISTEMP v4 and normalized into a clean time-indexed series. The analytics core then performs two deterministic operations: (i) linear trend estimation to obtain an interpretable long-term warming rate and (ii) extreme-year flagging using a fixed anomaly threshold to select salient events for emphasis. These analytical outputs are passed to a narrative synthesis module that applies rule-based, template-driven NLG to produce traceable textual statements whose content can be directly mapped to computed values, thereby avoiding uncontrolled linguistic variation. Finally, an infographic renderer integrates the time-series plot, trend overlay, anomaly markers, and generated narrative into a single panel with a consistent layout strategy. Importantly, architecture is intentionally positioned as a proof-of-concept communication system rather than a production-grade decision-support platform: it does not attempt causal attribution, regional inference, or policy recommendation, but instead demonstrates a reproducible systems workflow for transforming validated climate datasets into accessible narrative-visual summaries.

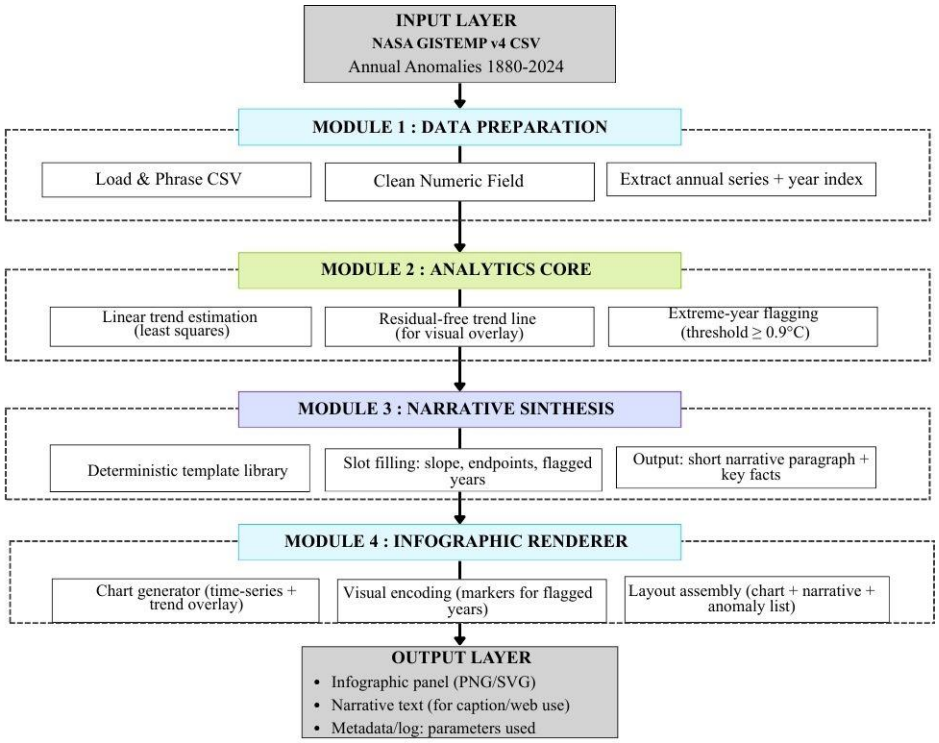


Figure 1. System architecture of the proposed data-to-narrative-to-infographic pipeline. The framework ingests annual global temperature anomalies, performs trend estimation and extreme-year detection, generates deterministic narrative summaries via template-based NLG, and renders an infographic panel that integrates the chart, explanatory text, and highlighted anomaly years in a reproducible workflow.

2.1 Data Acquisition and Preprocessing

This study used the GISTEMP v4 dataset [19], a publicly available global surface temperature record from NASA's Goddard Institute for Space Studies (GISS). The dataset contains monthly and annual temperature anomalies calculated relative to the 1951–1980 mean baseline. Data were acquired via the official NASA GISS portal in CSV format, ensuring up-to-date values through 2024, compiled from NOAA's Global Historical Climatology Network (GHCN v4) and the Extended Reconstructed Sea Surface Temperature version 5 (ERSST v5).

The scope of this study required only annual mean anomalies (January to December), extracted from the dataset and used as the basis for subsequent trend modeling and narrative generation. Monthly or seasonal data were excluded to maintain focus on long-term global-scale analysis and to reduce noise that may interfere with aggregate interpretations.

Data preprocessing was performed using Python 3.11 in Google Colab. The process began with standardizing the header to consistently map the year and anomaly values into a structured tabular format. Anomaly values, initially in string format, were converted into floating-point numbers through type coercion. Any rows containing null markers or non-numeric placeholders were removed to ensure data integrity. Finally, a time index was assigned to each row so that each entry corresponded to its calendar year, enabling reliable chronological sorting and analysis. The complete source code and example outputs are publicly available

at https://github.com/abigailazeda/climate-ai-visualization for reproducibility.

The output of this stage was a clean, chronologically ordered annual anomaly dataset spanning 1880 to 2024. The dataset was stored in a structured DataFrame and used as the primary input to the system's analytical and generative components. No interpolation or imputation was applied to preserve data integrity and alignment with the source. This preprocessing phase followed established practices in climate informatics [19-21] and ensured reproducibility by maintaining a clear, code-driven transformation pipeline from raw data to structured input.

2.2 Linear Trend Estimation and Anomaly Thresholding

To characterize long-term global temperature dynamics for public interpretation, the system applies a linear trend to the annual anomaly series derived from the GISTEMP v4 dataset. Linear regression was selected due to its interpretability, low computational overhead, and widespread use in summarizing long-horizon climate trends. The model is defined as in Equation 1, where the slope parameter represents the average annual rate of change in global surface temperature anomalies. The resulting trend line is not intended for inferential climate modeling, but rather as a structural abstraction that supports narrative explanation and visual emphasis.

$$y_t = \alpha + \beta_t + \varepsilon_t \quad (1)$$

In parallel, the system implements an extreme-year identification mechanism to highlight salient warming events within the time series. A fixed anomaly threshold is applied to classify years exhibiting exceptionally high temperature deviations. This thresholding operation is treated as a deterministic filtering step rather than a statistical test, enabling consistent identification of emphasized years across narrative and visual outputs. The flagged years serve as anchors for both textual explanation and graphical annotation in subsequent stages. Importantly, no causal interpretation or attribution is inferred from this classification; the procedure is strictly designed to support communicative clarity by isolating values that are visually and narratively salient within the long-term trend.

2.3 Template-Based Narrative Synthesis

Narrative generation in the proposed framework is implemented using a rule-based, template-driven natural language generation (NLG) approach. This module transforms analytical outputs, such as the estimated trend rate, temporal range, and identified extreme years, into concise explanatory text through deterministic sentence templates. Each template is constructed with fixed syntactic structures and variable placeholders, ensuring that generated narratives remain stable, interpretable, and directly traceable to their numerical sources. Template-based NLG is commonly used in domains requiring explainable and deterministic output, particularly when the input structure is consistent and the communicative goal is tightly scoped [22], [23].

The choice of a template-based NLG is motivated by the system's communicative objectives [24], [25]. Unlike neural language models, which may introduce semantic variability or unverifiable interpretations, the rule-based approach guarantees transparency and reproducibility, both essential in scientific communication contexts. The generated narratives are intentionally descriptive rather than interpretive: they summarize observed patterns without introducing causal explanations or predictive claims. This design choice reinforces the system's positioning as a proof-of-concept communication pipeline, demonstrating how structured climate data can be translated into standardized explanatory statements for non-expert audiences.

2.4. Infographic Assembly and Visual Encoding Strategy

The final stage of the pipeline integrates analytical results and generated narratives into a single infographic panel. This visual synthesis module combines three coordinated components: a time-series plot of annual temperature anomalies, a trend overlay representing long-term change, and a textual narrative summarizing key observations. The infographic is constructed using a reproducible plotting environment, ensuring consistent rendering across executions.

Visual encoding decisions are guided by established principles of visual communication and information design, including hierarchy, alignment, and emphasis. The time-series plot occupies the primary visual field to establish temporal context, while highlighted markers are used to draw attention to extreme years identified in the analytical stage [26], [27]. The narrative text is positioned to directly reference visual elements, reinforcing coherence between numerical trends and explanatory statements. The design deliberately avoids decorative elements or interactive features, prioritizing clarity and low cognitive load over aesthetic complexity.

At this stage, the visual module functions purely as a presentation layer and does not introduce additional analytical computation. While layout refinement and typographic adjustments may involve limited manual intervention in the current implementation [28], the overall structure is modular and reproducible. As such, the infographic assembly serves as a demonstrative implementation of how analytical, narrative, and visual components can be systematically integrated within a single communication-oriented system architecture. This approach aligns with emerging trends in communicative visualization for public science, where narrative-visual coupling improves message retention and engagement [29], [30].

3. Results and Discussions

This section presents the results of the proposed AI-based framework for climate trend visualization and discusses its relevance to environmental communication. The findings are interpreted based on the processed GISTEMP v4 dataset [31] and the performance of the AI-driven narrative generation, along with a visual infographic output. The discussion is grounded in comparisons with existing studies and reflects on the theoretical and practical implications for climate data literacy and sustainable development.

3.1 Automated Climate Trend Interpretation and Narrative Generation

The proposed system produced a coherent set of analytical, narrative, and visual outputs derived from the GISTEMP v4 annual anomaly series spanning 1880–2024. Linear trend estimation revealed a persistent upward trajectory in global surface temperature anomalies, with a slope consistent with long-term warming rates reported in major climate assessments [1], [31], [32]. While such trend characteristics are well established in the literature [31], the contribution of this study does not lie in rediscovering the warming signal but in operationalizing how this signal is communicated through an integrated system.

In contrast to conventional climate reporting formats, where charts and textual explanations are typically produced as separate artifacts, the proposed framework generates narrative descriptions and visual elements from a shared analytical backbone. This tight coupling ensures that numerical values referenced in the narrative (e.g., trend rate, temporal range, extreme years) correspond directly to the visual encodings displayed in the infographic. Prior studies in narrative visualization emphasize that coherence between visual and textual elements is critical for non-expert comprehension [8], [29], [33]. The present results demonstrate that such coherence can be achieved through deterministic automation, rather than through manual editorial intervention.

The generated narratives are intentionally restrained in scope, focusing on descriptive interpretation rather than causal explanation. This design choice aligns with recommendations in science communication research, which caution against overstating inference when presenting complex environmental data to general audiences [34]. By limiting the narrative to observable patterns supported by the data, the system preserves scientific fidelity while improving accessibility.

Compared with manually authored climate reports, such as those by the IPCC or the World Meteorological Organization, the AI-generated narrative requires no human intervention, significantly reducing the time and cost of producing such interpretations. While previous research as [35-37] has explored how visual aids can improve the communication of complex climate data, the combination of automated data analysis and natural-language generation remains underdeveloped in climate informatics.

From a systems engineering standpoint, this approach provides a scalable, repeatable methodology for transforming raw environmental data into structured, public-facing outputs. In educational or policy communication contexts, such tools can serve as a bridge between climate science and the public, especially when scientific literacy is limited.

Nonetheless, it must be acknowledged that while the AI summary captures the macro-trend, it does not yet offer causal interpretation. For instance, the system cannot attribute warming to greenhouse gas emissions or distinguish anthropogenic influences from natural variability. These limitations are also noted by [38-40], who highlight the importance of complementing automation with expert-driven interpretation to ensure scientific validity.

3.2 Detection of Extreme Temperature Years and Visual Infographic Generation

Applying a fixed anomaly threshold enabled the system to consistently identify years exhibiting exceptionally high temperature deviations. The resulting list of extreme years, summarized in Table 1, corresponds closely with those highlighted in institutional climate summaries and monitoring reports [1], [11], reinforcing the validity of the underlying analytical step. Within the proposed framework, however, the primary value of this mechanism lies not in the novelty of detection but in its function as a communicative filter that isolates salient temporal points from a long-term climate record.

To translate these analytical results into an accessible visual form, the identified extreme years are integrated into a narrative infographic. As shown in Figure 2, the long-term global temperature anomaly series is presented alongside a linear trend line, with highlighted markers indicating years that exceed the predefined anomaly threshold. This visual composition allows viewers to simultaneously perceive the overall warming trajectory and the relative prominence of recent extreme years within the historical record. Prior studies in visual communication indicate that such selective visual emphasis can support pattern recognition and memory retention when users engage with extended time-series data [28], [29]. By aligning visual markers with the analytical results summarized in Table 1, the infographic reduces the cognitive burden commonly associated with dense climate plots [3], [41].

Importantly, the thresholding mechanism is treated as a deterministic highlighting strategy rather than a statistical classification. This distinction is essential to avoid misinterpretation of the output as an attribution or risk assessment tool. The framework is therefore best understood as a communicative layer built atop validated climate data, rather than as an analytical system for climate diagnosis.

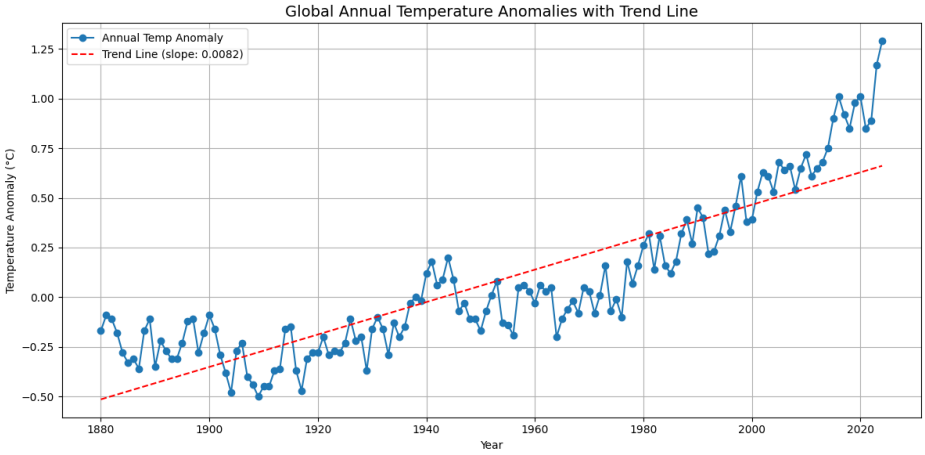


Figure 2. Infographic Panel Generated by AI-Based Visual Storytelling System

Table 1. Years with Extreme Temperature Anomalies (≥ 0.9°C)

Year	Annual Mean (°C)
2015	0.90
2016	1.01
2017	0.92
2019	0.98
2020	1.01
2023	1.17
2024	1.29

The robustness of the template-based logic becomes evident when the underlying data changes. For example, if future annual anomalies exceed previously observed thresholds, the system automatically updates the narrative clause describing "recent extreme years" and adjusts the highlighted markers in the infographic without altering the structural template. Conversely, if anomaly values stabilize below the threshold, the narrative shifts to emphasize long-term trend continuity rather than extreme-year escalation. This behavior illustrates that the communicative output dynamically reflects data updates while preserving deterministic structure, reinforcing transparency and reproducibility.

3.3 Scope and Limitations

Compared with existing climate communication tools, the proposed framework occupies a distinct position. Interactive dashboards developed by organizations such as NASA or NOAA provide rich exploratory capabilities but typically require users to interpret charts independently and often assume a degree of data literacy [11]. Conversely, narrative-driven reports, such as IPCC summaries, offer carefully curated explanations but depend on extensive expert authorship and editorial resources [1].

The present system bridges these approaches by automating the generation of both narrative and visual components within a single pipeline. Unlike automated visualization tools that focus primarily on chart generation, the framework explicitly incorporates narrative synthesis as a first-class system component. At the same time, unlike free-form natural language generation systems, it employs deterministic templates to maintain traceability and prevent semantic drift [23], [25]. This combination enables scalability while preserving control over scientific content, a balance that remains underexplored in climate informatics [17], [18].

3.4. Practical Implications

The results should be interpreted considering the framework's intended scope. The system is explicitly designed as a proof-of-concept communication pipeline that demonstrates how validated climate datasets can be transformed into coherent narrative-visual artifacts through modular automation. It does not aim to replace expert-driven climate analysis, nor does it provide causal attribution, regional assessment, or predictive modeling.

The absence of empirical user evaluation represents a key limitation. While prior studies provide strong theoretical support for narrative visualization as an effective communication strategy [8], [30], [33], the actual impact of the generated infographics on comprehension and engagement has not yet been measured. As such, claims regarding effectiveness are grounded in design theory and comparative reasoning rather than direct behavioral evidence. This limitation is acknowledged to avoid overstating the system's current capabilities.

3.5. Future Work

Future research is required to extend the current proof-of-concept into a more empirically grounded climate communication system. A primary direction is to conduct systematic user-centered evaluation to assess whether the generated narratives and infographics effectively improve comprehension, retention, and perceived clarity among non-expert audiences. Such evaluation can be conducted through controlled user studies comparing multiple presentation conditions, including chart-only visualizations, narrative-only summaries, and the integrated narrative–infographic outputs proposed in this study. Quantitative measures may include comprehension accuracy, recall performance, and task completion time, complemented

by qualitative feedback on interpretability and visual clarity.

A second avenue for future work concerns the expansion of both data sources and analytical granularity. While the present framework focuses on long-term global temperature anomalies, integrating additional climate indicators, such as regional temperature series, precipitation anomalies, or extreme event indices, would enable broader communicative coverage. Incorporating multiple datasets would also facilitate cross-source consistency checks and more nuanced narrative construction without altering the core system architecture.

Further development is also needed in the narrative generation component. Although the rule-based approach ensures transparency and reproducibility, future iterations may explore hybrid strategies that combine deterministic templates with constrained generative language models. Such integration could allow greater linguistic variation while preserving traceability and preventing unsupported inference, thereby maintaining scientific reliability in public-facing communication.

Finally, the infographic assembly process offers opportunities for deeper automation. Future work may investigate constraint-based layout engines or rule-driven design grammars to reduce manual intervention in visual composition. By formalizing design principles into programmable constraints, the system could evolve toward fully automated, scalable deployment while retaining the communicative clarity demonstrated in the current implementation.

4. Conclusions

This study presents a system framework that bridges climate data analytics and visual communication to support public interpretation of long-term temperature anomalies. Using the GISTEMP v4 dataset, the proposed system processes historical global temperature records from 1880 to 2024 and translates analytical outputs into structured narrative summaries and infographic-based visualizations. These outputs are designed to enhance accessibility for non-expert audiences while maintaining consistency with validated climate data.

The primary contribution of this work lies in systems-level integration: combining data processing, rule-based narrative generation, and infographic composition into a reproducible communication-oriented pipeline. The study does not advance climate science or artificial intelligence theory; rather, it demonstrates how integrated systems engineering can support scalable climate communication. Rather than introducing new climate indicators or analytical models, the framework demonstrates how existing datasets can be transformed into coherent communicative artifacts without reliance on extensive expert mediation. From a systems perspective, the architecture exhibits modularity and extensibility, allowing future enhancements in data granularity, language variation, or interaction mechanisms.

While the current implementation remains a proof-of-concept and requires further refinement, particularly in automating visual layout and empirically evaluating user impact, it provides a foundational model for communication-oriented environmental information systems. By combining computational analysis with design communication principles, this study contributes to an interdisciplinary approach for translating complex climate trends into accessible public knowledge and supports broader efforts in digital sustainability communication, including alignment with Sustainable Development Goal 13 (Climate Action).

Conflict of Interest Declaration

The authors declare that they have no known competing financial or personal interests that could have appeared to influence the work reported in this paper.

Data and Code Availability

All datasets used in this study are publicly accessible from the NASA GISTEMP v4 repository. The processing scripts, narrative generation templates, and visualization modules are available on GitHub at https://github.com/abigailazeda/climate-ai-visualization.

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