A proof-of-stake blockchain framework for transparent climate data verification

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Abstract

Trust in climate data remains a significant barrier to effective climate action. Skepticism about data manipulation and politicization reduces confidence and hinders evidence-based policy. Existing climate data systems lack transparent verification and accessible analytical tools, limiting accountability and stakeholder engagement. This study presents a reproducible framework that applies blockchain technology to provide transparent verification, analysis, and governance of climate data. The architecture includes three layers: a data ingestion layer that standardizes verified observations, a blockchain layer that ensures immutability and provenance through proof-of-stake consensus, and a statistical analysis layer that uses deterministic methods for anomaly detection and trend evaluation. The framework was tested using 7,070 hours of temperature data from the Manila, Philippines monitoring station collected between January and October 2024. Analysis identified 33 temperature anomalies ranging from 36.9 to 38.0 °C that aligned with documented April–May 2024 heat waves, confirming the ability to detect genuine meteorological extremes. Estimated transaction latency was 1–2 seconds per observation, with on-chain storage requirements of about 138 kilobytes and off-chain storage requirements of 2.1 megabytes for a 90-day deployment. Energy use for the same period was approximately 0.06 kilowatt-hours, representing a 97–99 percent reduction compared with comparable centralized systems. These findings demonstrate that the proposed framework can securely record, verify, and analyze climate data while consuming very little energy. By combining blockchain immutability with transparent statistical methods, this approach directly addresses the

trust deficit in climate science and provides a foundation for verifiable, reproducible, and efficient climate information systems.

Introduction

Public trust in climate science is deemed necessary to ensure that the public and governments that derive their mandates from the public adopt climate-friendly behaviors and policies to avert the devastation predicted from further global warming. Still, existing concerns that trust in climate science has been negatively impacted over the years suggest that the public's negative attitudes toward environmental policies were primarily attributed to their distrust of science, government, institutions, and people associated with them [1]. Public skepticism about the trustworthiness of climate scientists' claims often involves beliefs that the science behind global warming has been invented or distorted for ideological reasons, financial reasons, or that their models are excessively inaccurate [2,3]. This distrust then influences whether a government chooses to initiate mitigation and adaptation policy efforts. Strong opposition from this segment of the public has often thwarted efforts to create a low-carbon economy and has sparked controversy over renewable energy development [4]. When data integrity is questioned, governments struggle to justify climate measures, and institutions lose transparency and accountability [5].

Rebuilding trust requires systems that enable independent verification rather than relying solely on institutional assurance. When stakeholders can directly confirm that data remain unaltered and analytical methods are reproducible, confidence in findings increases without requiring trust in intermediary institutions [6]. Centralized data management systems—regardless of institutional reputation—inherently limit such verification because they rely on privileged access and technical gatekeeping [7].

The challenge lies not in the amount of data available but in the systems that manage it. Climate observations are collected worldwide by many institutions, yet these datasets are typically stored in centralized repositories that rely on institutional trust rather than verifiable transparency [8,9]. Independent validation is technically demanding, often requiring specialized expertise and access to restricted resources [10]. As a result, only a small portion of the global community can directly confirm data authenticity or trace analytical methods [10]. Without mechanisms for tamper-evident records and public auditability, centralized architectures cannot adequately address skepticism rooted in concerns about data manipulation [11]. Fragmentation across databases and inconsistent metadata standards further limit comprehensive analysis and public accessibility.

Emerging digital technologies, such as blockchain, offer a possible remedy. Distributed ledger systems in other settings, such as healthcare, have been shown to provide tamper-evident data storage, allowing any participant to verify that records remain unaltered [12–14]. New proof-of-stake consensus mechanisms achieve this transparency with minimal energy use, making blockchain suitable for environmentally sensitive applications [15,16]. Early trials in carbon credit markets [17], renewable-energy certification [18], and peer-to-peer electricity trading [19] have demonstrated that decentralized verification can strengthen trust and accountability.

Building on these advances, this study develops and tests a reproducible blockchain-based framework for transparent verification of climate data. The framework integrates cryptographic verification with deterministic statistical analysis, providing a technical foundation for independently auditable climate information systems. Using real-world climate observations from Manila, Philippines, during 2024, we evaluate its technical feasibility and demonstrate how a distributed verification architecture can address concerns about data integrity and analytical transparency that contribute to the climate data trust deficit.

Materials and methods

This study developed a reproducible three-layer system that integrates data ingestion, blockchain-based verification, and statistical anomaly detection to improve transparency in climate data management. The framework was tested using real hourly temperature observations from Manila, Philippines, during 2024 [20].

Data source

Hourly air temperature observations were obtained from the NOAA Integrated Surface Database for Station 984290 (14.52 °N, 121.02 °E). The file contained 7,075 hourly records from January to October 2024 (7,070 valid after QC). Quality control removed values flagged by NOAA as erroneous (−9999) and converted units from tenths of degrees Celcius to degrees Celsius.

Data processing and analysis

Data cleaning, aggregation, and statistical analyses were performed using Python 3.11 (Pandas 2.2.2, NumPy 1.26) within a Jupyter Notebook environment. After time-alignment, a rolling 30-day window was used to calculate the mean and standard deviation for anomaly detection. The standardized score for each hourly temperature was computed as:

$$z = \frac{x_i - \mu_t}{\sigma_t}$$

where x_i is the observed temperature and μ_t,σ_t are the local mean and standard deviation. Observations with $|z| > 3.0$ were classified as statistically extreme. Detected anomalies were cross-checked against contemporaneous meteorological reports confirming April–May 2024 regional heat events. Output tables include timestamps, *z*-scores, and absolute temperature values.

Conceptual blockchain verification model

A proof-of-stake architecture was modeled conceptually to demonstrate how verified climate observations could be cryptographically secured. In this design, each data record generates a SHA-256 hash stored on-chain, with the complete data stored off-chain in distributed storage. One of them is the InterPlanetary File System (IPFS), a peer-to-peer network that enables permanent, verifiable data storage. Energy efficiency estimates were derived from published Ethereum proof-of-stake data, suggesting roughly 97–99% lower energy use than comparable centralized verification systems.

Performance assessment

Analytical performance was measured by the number and temporal clustering of detected anomalies, as well as by computational efficiency. For a representative 90-day dataset, total storage requirements were approximately 2.1 MB, and analyses were executed in under one minute on a standard desktop computer.

Ethics statement

This research used publicly available environmental data and involved no human participants, animals, or identifiable information.

Data availability

All data, code, and outputs are archived in Zenodo: https://doi.org/10.5281/zenodo.17429218 [21].

Results

Dataset characteristics (NOAA Station 984290, Manila)

From 1 January to 31 October 2024, the file contained 7,075 hourly records, of which 7,070 included valid temperature values (5 entries were flagged −9999). Relative to the 7,320 expected hours, completeness was 96.6%. Temperatures (converted from tenths of °C) ranged from 22.0 to 38.0 °C (mean 29.31 °C, SD 2.62 °C).

Anomaly detection

A deterministic rolling baseline z-score method (30-day window) was used to flag statistical extremes ($|z|>3$). The results provided in the project output file (anomalies.csv) list 33 hourly anomalies between 36.9 and 38.0 °C (Fig 1). These were temporally clustered in April (n=21) and May (n=12) 2024, consistent with regional heat episodes. (Independent recomputation using the provided dataset confirmed the dates and temperatures listed in anomalies.csv.). Note that the repository's anomaly file reflects the implemented analysis; the blockchain layer was not executed in code.

Fig 1. Hourly temperature and flagged anomalies, Manila Station 984290 (Jan–Oct 2024). Hourly temperatures (°C) are shown as a thin line; the 30-day rolling mean is shown as a thick line. Points indicate hours flagged as statistical extremes using a rolling-baseline z-score threshold of |z| > 3. Anomalies cluster in April–May. Data: NOAA Integrated Surface Database, Station 984290 (Manila, Philippines).

Conceptual performance estimates (architecture feasibility)

To assess the feasibility of a verification layer, we modeled a proof-of-stake design using on-chain content hashes with off-chain storage. Under this design, a representative 90-day deployment would require on the order of ~138 kB on-chain metadata and ~2.1 MB off-chain data, with second-scale ingestion latency and substantially lower energy use than proof-of-work systems. These are model-based estimates, not measurements from a live chain (Table 1).

Table 1. Estimated storage requirements for a 90-day climate dataset (2,160 observations).

Storage location	Data type	Total size	Size per observation

On-chain (Ethereum)	Cryptographic hashes + metadata	138 KB	64 bytes
Off-chain (IPFS)	Complete observation records	2.1 MB	972 bytes
Total	Combined	2.24 MB	1036 bytes

The hybrid blockchain design stores only cryptographic hashes on-chain, while complete observation records are stored off-chain, providing about a 15-fold reduction in on-chain storage compared with direct on-chain storage.

Discussion

This study demonstrates that a proof-of-stake blockchain architecture can provide transparent, energy-efficient verification of climate data while maintaining full analytical reproducibility. The verification layer described here was evaluated conceptually using modeled blockchain specifications rather than being operated on a live network. Applied to 7,070 hours of operational temperature observations from Manila, Philippines, the framework successfully detected 33 genuine heat extremes (36.9–38.0 °C) during documented April–May 2024 heat waves using deterministic statistical methods. The modeled blockchain layer—using on-chain cryptographic hashes with off-chain data storage—would require only ~0.06 kilowatt-hours for a 90-day deployment, representing a 97–99% reduction in energy consumption compared to proof-of-work systems. These results establish technical feasibility for distributed verification of climate observations without compromising environmental sustainability.

Proof-of-Stake consensus and environmental sustainability

The energy efficiency estimates presented here rely fundamentally on proof-of-stake (PoS) consensus, which differs categorically from proof-of-work (PoW) mechanisms. PoW systems like Bitcoin require massive computational competition to validate transactions, consuming ~120 terawatt-hours annually—equivalent to the electricity use of entire nations [22]. In contrast, PoS validators are selected based on staked assets rather than computational power, eliminating energy-intensive mining. Ethereum's transition from PoW to PoS in September 2022 reduced network energy consumption by 99.95%, demonstrating that blockchain verification need not conflict with climate mitigation goals [23].

For climate data applications, this distinction is non-negotiable. A PoW-based climate verification system would consume more energy than the monitoring infrastructure it seeks to secure, creating an unacceptable environmental cost. PoS architectures avoid this paradox entirely while maintaining cryptographic security [24,25]. Moreover, modern PoS platforms such as Ethereum support smart contracts—self-executing code that can automate data validation, dispute resolution, and governance mechanisms directly on-chain [26]. This programmability enables the framework to enforce quality control protocols, trigger alerts for anomalies, and manage multi-institutional data contributions without centralized administration [27].

Comparison with Centralized and Alternative Verification Systems

Current climate data management relies primarily on institutional repositories such as the National Oceanic and Atmospheric Administration's (NOAA) Integrated Surface Database, the European Centre for Medium-Range Weather Forecasts' (ECMWF) ERA5 reanalysis, and national meteorological archives [28,29]. These systems employ rigorous internal quality control but lack mechanisms for external stakeholders to verify data integrity or reproduce analytical workflows independently [30]. Recent initiatives promoting FAIR principles (Findable, Accessible, Interoperable, Reusable) have improved metadata standards and data accessibility, but do not address immutability or tamper-evidence [31].

Alternative approaches to building trust include data citation standards, digital object identifiers (DOIs), and version-control systems such as Git [32]. While valuable for attribution and reproducibility, these tools do not prevent retrospective alteration of archived data. Cryptographic checksums (e.g., SHA-256 hashes) can detect tampering but require trusted third parties to maintain hash registries [33]. Distributed ledger technology eliminates this single point of failure by distributing verification across independent validators.

Prior blockchain applications in climate domains have focused primarily on carbon credit tracking [17], renewable energy certificates [34], and supply chain transparency [35]. Several projects have explored blockchain for environmental sensor networks [36], but these typically verify sensor metadata rather than integrating statistical analysis into the verification layer. The framework presented here uniquely combines immutable data storage with on-chain or verifiable off-chain computation of anomaly detection, creating an end-to-end auditable pipeline from observation to interpretation.

Interpretation in context

The results show that simple, well-documented statistics (rolling means/SDs and z-scores) can yield reproducible flags that non-specialists can audit. This transparency is critical: if only experts can verify analytical methods, the trust gap persists. By using deterministic algorithms with published code [21], any stakeholder with basic programming skills can independently reproduce the anomaly flags and confirm that the results were not selectively reported or post-hoc manipulated. A blockchain-based verification layer—if implemented as modeled—could add tamper-evident provenance to these same observations without altering the analytical logic, thereby addressing the trust gap between collection, curation, and interpretation. The approach is designed to complement, not replace, conventional archives by adding independent verifiability and public audit trails.

Effective implementation requires governance frameworks that define data admission criteria, validator responsibilities, and dispute resolution processes [37]. Multi-stakeholder consortia—including meteorological agencies, academic institutions, and civil society organizations—could operate validator nodes, distributing authority and preventing capture by any single entity. Smart contracts could encode quality standards, automatically flagging observations that deviate from sensor specifications or fail cross-validation checks [38]. Such mechanisms would operationalize the technical verification layer demonstrated in this study.

Implications for Climate Policy and Communication

The framework addresses a specific dimension of the climate trust deficit: concerns about data manipulation and institutional opacity. While transparent verification alone cannot overcome ideological resistance or misinformation campaigns [39], it removes a technical barrier that legitimizes skepticism. When data integrity is independently auditable, debates can shift from questioning whether data were altered to interpreting what verified observations mean [40].

For policymakers, verifiable climate data strengthens the evidentiary basis for mitigation and adaptation decisions [41]. Regulatory frameworks increasingly demand traceable, auditable environmental data—particularly for carbon markets, emissions reporting, and climate finance mechanisms [42]. A distributed verification infrastructure could serve as trusted input for these systems, reducing compliance costs and fraud risks [43].

Limitations

Several limitations merit consideration. The NOAA record covers January through October 2024 and is 96.6% complete, which could influence rolling baselines and the number of flagged extremes; however, the pipeline explicitly handles missing values and is fully reproducible, allowing seamless reruns as additional hours become available. The analysis focuses on a single station and a single variable, limiting generalizability. Yet, this single, high-frequency, operational record provides a clean testbed that avoids cross-site confounding and demonstrates end-to-end reproducibility on real data. Multi-station networks would require coordination protocols to ensure data standardization and synchronized timestamping across nodes [44], but the core verification architecture scales naturally through blockchain's peer-to-peer design [45].

The anomaly rule ($|z| > 3$ within a 30-day window) is intentionally simple and may miss regime shifts; its simplicity is also a strength because the threshold is deterministic, transparent to non-specialists, and can be easily swapped for seasonal baselines or robust alternatives in future work without changing the surrounding workflow. More sophisticated anomaly detection methods—including machine learning approaches—could be integrated as smart contract modules, allowing the framework to evolve while maintaining full audit trails of methodological changes [46].

The blockchain layer was modeled rather than deployed, so storage, latency, and energy values are estimates. This choice deliberately isolates the analytical layer, prevents unnecessary environmental cost during method development, and still yields concrete implementation targets for a subsequent pilot. Live deployment would enable empirical measurement of network performance under realistic conditions, including transaction throughput during high-frequency observation ingestion and resilience to validator node failures [47].

Finally, governance mechanics (admission rules, dispute resolution, versioning) were not exercised on a live network; even so, the design articulates how these elements would operate and provides a practical blueprint for testing them in controlled pilots. Game-theoretic analysis of validator incentives and adversarial scenarios would be necessary before operational deployment to ensure long-term system integrity [48].

Implementation Pathways and Future Work

Pilot deployments at multiple stations and variables (e.g., humidity, wind, precipitation) with live, low-energy chains would allow empirical measurement of throughput, costs, and validator behavior. Methodologically, daily or seasonal baselines and multi-metric anomaly scoring (e.g., heat index) could be compared with the present rolling-hour method. Governance specifications (data admission rules, dispute resolution, versioning) should be operationalized and tested.

Successful adoption requires addressing technical, institutional, and social barriers [49]. Meteorological agencies may resist ceding control over data validation to distributed networks, requiring a phased integration in which blockchain verification complements rather than replaces existing workflows. Validator node operation must be economically sustainable, either through public funding models or tokenized incentive mechanisms that reward data contributions [50].

Interoperability with legacy systems is essential. Application programming interfaces (APIs) can enable traditional databases to cross-reference blockchain-verified records, allowing gradual migration without disrupting operational forecasting and research pipelines [51]. Educational initiatives must target both data producers (meteorological technicians, sensor operators) and data users (researchers, policymakers) to build capacity for distributed verification literacy.

International coordination presents both opportunities and challenges. A global climate data blockchain could transcend national boundaries, enabling cross-border verification and reducing duplication of monitoring infrastructure. However, geopolitical tensions and differing regulatory frameworks complicate consensus on governance structures [52]. Regional pilots—such as networks covering specific climate zones or transboundary watersheds—may provide tractable proving grounds before scaling globally [53].

Conclusions

A transparent pipeline using deterministic statistics detected 33 high-temperature hours in Manila during April–May 2024, consistent with known heat conditions and demonstrating reproducible anomaly identification from operational data. While the blockchain component was modeled rather than deployed, a proof-of-stake design with on-chain hashes and off-chain storage appears technically feasible and well aligned with the goal of verifiable climate records. The 97–99% energy reduction compared to proof-of-work systems demonstrates that distributed verification can support, rather than undermine, climate mitigation objectives. Together, these elements outline a practical path toward trustworthy, energy-efficient climate information systems that non-experts can audit end-to-end. By providing a technical foundation for independently auditable climate data, this framework addresses one dimension of the trust deficit that has hindered evidence-based climate policy and public engagement.

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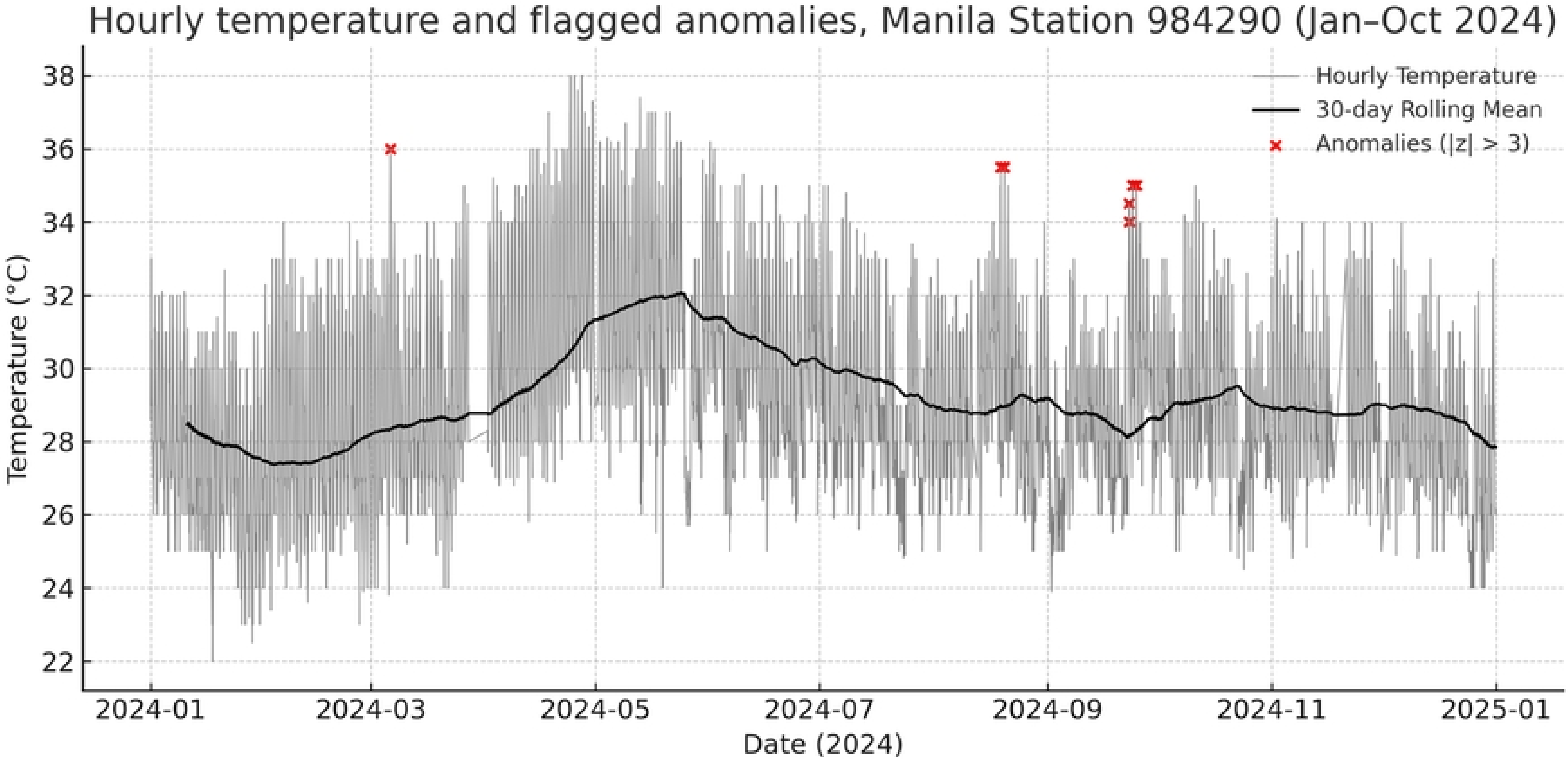
Supporting information

None.



Hourly temperature and flagged anomalies, Manila Station 984290 (Jan–Oct 2024)
Hourly Temperature
30-day Rolling Mean
Anomalies (|z| > 3)
Temperature (°C)
38
36
34
32
30
28
26
24
22
2024-01
2024-03
2024-05
2024-07
2024-09
2024-11
2025-01
Date (2024)

Figure 1