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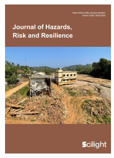

Article

Democratizing Climate Action & Enhancing Climate Literacy: An AI-Assisted Geospatial Analysis of Historical Trends and Future Projections for Urban Resilience Using Kolkata as a Case Study

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Abstract: Climate science has generated unprecedented data and curated complex scientific tools for its analysis, yet this study addresses the persistent gap stemming from poor science communication and public disengagement. It validates a novel, readily accessible framework using Generative AI (GAI) as a supportive and facilitative tool to synthesize code for Google Earth Engine (GEE) data extraction and R statistical analysis, democratizing climate inquiry for non-experts. The methodology was applied to Kolkata, India, an exposed and vulnerable metropolitan area exhibiting notable policy deficits. Historical analysis (1990–2024) revealed a significant, long-term warming trend, particularly the Land Surface Temperature (LST) (0.0752 °C/year) strongly associated with rapid urban expansion (19.02 km^2/year), which intensified the nocturnal Urban Heat Island (UHI) effect (Night-time UHII rose by +0.60 °C). This data quantifies the public's lived experience of warmer winters, diminishing nocturnal cooling and accelerated flood risk from concentrated rainfall intensity. Future projections based on CMIP6/CanESM5 and derivative illustrations suggest that mean annual temperature may rise by up to 3 °C and project a critical 55.8% probability of late-monsoon months becoming an extreme rainfall month by 2030. The study re-affirms that translating scientific data into clear, validated, citizen-centric narratives is essential for transforming passive beneficiaries into proactive enablers. The proposed scalable framework offers a replicable model for developing community-informed, anticipatory climate action and driving structural improvements in urban disaster risk reduction (DRR).

Keywords: generative AI; climate data; lived experience; science communication

1. Introduction: Bridging the Climate Science-Action Divide

1.1. Addressing the Paradox: Scientific Progress Versus Public Disengagement

The global effort in climate science has generated a formidable quantum of data, allowing researchers to move leaps and bounds in developing highly refined inferences and interpretations regarding historical changes and future scenarios [1,2]. Despite this scientific progress, the scale and technical complexity of the underlying data structure, often involving intricate modeling, statistical processing and advanced programming, create a significant barrier to public comprehension and engagement [3]. This situation results in a knowledge-action dissonance—the general public tends to keep away from the science, deferring the responsibility for analysis and action solely to scientists and policymakers [4–6]. This deferral is problematic because a lack of public interest curtails the spirit of inquiry necessary for widespread behavior change and the political support needed for effective preventive (climate change mitigation) and anticipatory action (climate change adaptation). When scientific research adopts a deficit perspective, assuming the public simply lacks knowledge, it often fails to engage in the necessary dialogue required for inclusive and effective communication practices [7]. The core challenge, therefore, is not the inadequacy of the data itself, but rather the failure to establish relevance. Unless complex data is successfully connected to non-scientific audiences in a way that resonates with their lives and everyday experiences, the potential to inspire collective action remains limited [8,9].

1.2. The Imperative of Lived Experience and Foresight Communication

Effective climate communication requires two distinct, yet interconnected, bridges: communicating foresight information (future risk) [10] and correlating past data with current lived experiences [11]. The public requires not just a forecast of abstract temperature anomalies but a clear translation of scientific metrics into tangible impacts on health, productivity, local infrastructure and life-as-usual. The process of bridging climate science and anecdotal evidence hinges on translating technical concepts into relatable public consequences. For instance, when individuals observe that summers feel hotter, this anecdotal experience gains power when verified and quantified by robust scientific data showing the same [12]. This coupling, the verification of subjective reality by empirical evidence, is essential for creating the political and social mandate required for structural policy changes. Framing climate change impacts, such as extreme heat as immediate public health crises, or establishing the narration of extreme rainfall to be synonymous to urban floods, rather than solely abstract environmental threats, is critical for achieving this integration.

1.3. Kolkata: A Case Study in Institutional Thinness and Urban Vulnerability

Kolkata, a prominent metropolitan city in India, serves as a compelling case study for the failure of proactive climate governance. Despite being exposed and vulnerable to climate hazards [13], including intense heat and extreme rainfall events, the city lacks fundamental adaptive policies, a robust Heat Action Plan (HAP) for example. The Kolkata Climate Action Plan (K-CAP) is understood to be launched but it is not a public facing document, which underscores the need of a study like this—lack of public engagement in key climate policies that should ideally govern strategic development in the forthcoming decades. Administrative and political interest is often reactive, limited primarily to responding after extreme events have occurred. Academics, meanwhile, frequently confine their valuable discussions to insular circles, reinforcing the fragmentation of knowledge. Analysis of climate governance in Indian cities confirms that policies often suffer from institutional thinness [14,15]—non-inclusive of the general populace—and reflect a persistent inclination towards relief-oriented approaches (managing disasters). Usually, the administrative posture views the general public merely as beneficiaries to be integrated in minimal preparedness activities, response and relief efforts, rather than potential enablers of transformational change. By democratizing the tools of climate inquiry, this research seeks to transform civil society into an informed constituency capable of applying sustained pressure for community-driven local climate action.

1.4. Outline of the Proposed GAI-Assisted Research Framework

This paper introduces and validates a Generative AI (GAI) assisted methodology designed specifically to lower the entry barrier for complex climate analysis using only freely available, open-source resources—Google Earth Engine (GEE) for accessing global climate data and R for statistical processing and visualization.

The study proceeds in two primary analytical sections:

(1) Past Data (1991–till available date): Analysis of historical trends for temperature, precipitation and humidity, combined with an examination of anthropogenic factors (LULC change) driving local impacts.

(2) Future Data (near future 2030 or till 2070): Accessing Coupled Model Intercomparison project 6 (CMIP6) Global Climate Model (GCM) data via GEE to project mid-century climate hazard risks under various Shared Socioeconomic Pathways (SSPs). Studies [16] emphasise the necessity of using multi-model ensembles (like CMIP6) to understand future climate uncertainty, confirming that access to these models is the critical starting point. It is necessary to understand at this point that definitive future outlooks and projections cannot be based on a single such ensemble but such ensembles, accessible through open platforms like Google Earth Engine, makes it the practical starting point for many users [17].

In both sections, the data extracted and analysed using GAI-generated code is translated explicitly for public communication, correlating technical findings with lived experience to foster a new generation of climate action advocates amongst the general populace.

2. The Democratization Framework: Generative AI, Open Science and Ethical Protocol

2.1. Theoretical Foundations of Open-Source Climate Informatics

The foundation of democratizing climate knowledge, in this body of work, rests on leveraging open-source environments. Open-source software and platforms, such as Google Earth Engine (GEE) and R, have been playing a crucial role in democratizing analytic tools that were previously inaccessible due to expensive licenses, fostering innovation and localized research capacity, particularly in the Global South [18]. GEE provides cloud-based access to petabytes of satellite imagery and global climate data archives, including observed historical datasets and future projections (CMIP6 GCM ensembles) [19]. R provides a powerful, open-source statistical computing environment essential for time-series analysis, correlation and high-quality data visualization. The use of these platforms ensures that the methodology remains globally accessible and replicable, adhering to the principles of open science.

2.2. Generative AI as a Catalyst for Non-Expert Data Access

The integration of Generative Artificial Intelligence (GAI) is the essential catalyst for lowering the technical barrier inherent in using GEE and R. GAI, exemplified by Generative Pretrained Transformers (GPT) models, is utilized here not here as a facilitative tool for code synthesis, rather than an independent analytical method. It generates specialized code—GEE JavaScript/Python scripts for cloud-based data extraction and R scripts for statistical analysis and visualization—based on high-level natural language prompts—Large Language Model (LLM) prompts. The ability of GAI to automate complex and often repetitive coding tasks accelerates the software development lifecycle, allowing users to rapidly generate scripts for minimum viable products or advanced functionalities [20]. This capability fundamentally transforms the required skill set—the barrier shifts from needing advanced proficiency in multiple programming languages (JavaScript for GEE, R for stats) to needing critical proficiency in prompt engineering and code verification. This democratization should enable young professionals and interested citizens, who may lack traditional coding backgrounds, to access and analyse high-resolution climate data directly, thereby empowering them to engage deeply in climate science.

2.3. Ethical Considerations and the Protocol for Transparency in GAI-Assisted Research

While GAI offers unparalleled speed and accessibility, its integration into scientific research introduces ethical complexities, particularly concerning transparency, reproducibility, bias and accountability. When GAI is used for core scientific processes, such as generating code—'to collect, analyse, interpret, or visualize data (quantitative or qualitative)'—disclosure is mandatory to maintain research integrity. Failure to adhere to transparency standards risks corrupting the research record and degrading the quality and reproducibility of analytical methods [21].

To ensure academic rigor and responsible integration of the GAI-assisted framework, a strict protocol was established:

(1) Verification and Audit: All GAI-generated GEE and R scripts are subject to manual audit and verification by the research team. This step ensures that the code accurately reflects scientific good practices and adheres to the intended logic, mitigating the risk of GAI-generated errors (often termed "hallucinations") or inadvertently skewed logic.
(2) Transparency: The specific GAI model used and the precise core prompts utilized to generate the key scripts for data extraction and statistical plotting are disclosed in the Supplementary Materials. This measure addresses the "transparency paradox" [22] in AI-assisted research and ensures the replicability of the methodological framework.
(3) Bias Mitigation: The researchers remained vigilant for potential biases in GAI outputs, particularly concerning script logic that might selectively filter or interpret data in a non-neutral manner.

Table 1 below contrasts the technical demands of the traditional geospatial workflow against the GAI-assisted approach, highlighting the implications for climate knowledge democratization.

Table 1. Comparative analysis of GAI-assisted vs. traditional workflow.

	Traditional Geospatial Workflow	GAI-Assisted (LLM-Generated) Workflow	Implication for Democratization
GEE Script Generation	Manual proficiency in JavaScript/Python API required	Automated generation via LLM prompts	Drastically lowers coding barrier; enables rapid access to data archives

Table 1. *Cont.*

	Traditional Geospatial Workflow	GAI-Assisted (LLM-Generated) Workflow	Implication for Democratization
R Data Processing	Requires advanced statistical coding expertise and debugging	Automated syntax generation; rapid prototyping of visualizations	Accelerates analysis time; shifts focus from syntax to scientific interpretation
Reproducibility & Integrity	High, if code is shared	High, contingent upon full disclosure of LLM source and prompt engineering	Establishes a new standard for responsible open science using AI

3. The GAI-Driven Analytical Protocol: Case Study Kolkata

3.1. Study Area Delineation and Data Selection

The study area was delineated as the Kolkata Metropolitan Area (KMA) in Eastern India. The analysis focuses on three Essential Climate Variables (ECVs) which is most commonly known to the general populace and also deemed most critical for public health and urban planning in the region—Temperature, Humidity and Precipitation. As already mentioned, the temporal scope covers two periods—Historical Baseline, spanning across 1990 till available date, aligned with standard climatological reference periods and Future Projections, spanning from near future period (2030) up until 2070.

3.2. Historical Data Sources (1990–Present)

Historical data extraction relied on high-resolution reanalysis and satellite products available through Google Earth Engine (GEE). The specific datasets were chosen for their consistency, temporal coverage and spatial resolution, enabling fine-scale urban climate analysis. Table 2 illustrates the sources used for historical data extraction.

Table 2. Sources used for historical data extraction.

Climate Variable	GEE Dataset ID	Time Period	Key Variables/Bands	Reason for Selection
Mean Temperature & Humidity (Absolute & Relative)	ECMWF/ERA5_LAND/ MONTHLY	1990–2030 (Time series analysis)	temperature_2m (for Mean Temp); dewpoint_temperature_2m (for Humidity calculation)	**Consistency and High Resolution:** ERA5-LAND provides continuous, high-resolution (0.1°) reanalysis data, suitable for establishing monthly climate means and humidity trends.
Maximum/Minimum Temperature & Diurnal Temperature Range (DTR)	ECMWF/ERA5_LAND/ HOURLY or DAILY_AGGR	1990–Present (current year)	temperature_2m (hourly for Max/Min derivation); temperature_2m_max, temperature_2m_min (daily aggregated)	**Diurnal Cycle Analysis:** Hourly or Daily aggregated data is essential to accurately derive maximum and minimum temperatures, which are necessary for calculating DTR, a crucial metric for nocturnal heat stress and UHI effect.
Land Surface Temperature (LST) & Urban Heat Island (UHI)	LANDSAT/LT05/C02/T1 _L2 (L5) and LANDSAT/LC08/C02/T1 _L2 (L8)	Comparison periods: 1990–2000 (L5) and 2015–2025 (L8)	ST_B6 (L5 LST); ST_B10 (L8 LST)	**Localized Intra-Urban Detail:** Landsat provides high spatial resolution (30m) thermal data, which is necessary to analyse and map the localized, intra-urban Land Surface Temperature change and quantify the Urban Heat Island intensity driven by Land Use/Land Cover (LULC) dynamics.
Precipitation (Annual Total & Monthly Mean Daily)	UCSB-CHG/CHIRPS/DAILY	1990–2025 (Present)	precipitation	**Rainfall Intensity:** The CHIRPS dataset offers high spatial resolution ~5.5 km) daily precipitation estimates, enabling accurate analysis of shifts in rainfall intensity and the frequency of extreme precipitation events.

3.3. Future Projection Data Sources

Future climate scenarios utilized the CMIP6 multi-model data, accessed via the GEE repository. Table 3 illustrates the sources used for future projections. A single GCM was selected for consistency across all ECVs and the full range of Shared Socioeconomic Pathways (SSPs) was used to capture the envelope of uncertainty and policy impacts.

While CMIP6 could be ambiguous for complex future climate scenarios and should be considered in conjunction to other ensembles and climate data like Coordinated Regional Downscaling Experiment (CORDEX), the GDDP dataset can provide high-resolution data for local and regional impact studies [23]. In fact, an evaluation of CMIP6 performance in the Indian context [24], highlighted how bias correction improves the reliability of temperature and precipitation projections for Indian cities.

While a single GCM (CanESM5) was selected for consistency across all ECVs to ensure the workflow remains user-friendly for first-time users, the resulting projections are intended as scientific illustrations of potential pathways rather than definitive, policy-defining forecasts. They provide a practical entry point for the public to engage with climate foresight without the technical overhead of multi-model ensembles.

Table 3. Sources used for future scenario data extraction.

Data Source (GEE ID)	Global Climate Model (GCM)	SSP Scenarios Included	Time Period	Key Variables	Reason for Selection
NASA/GDDP-CMIP6	CanESM5	SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5	1985–2070	tas (Mean Temperature); huss (Specific Humidity); pr (Precipitation)	CMIP6 GDDP provides bias-corrected, downscaled GCM data suitable for regional analysis [16,23,24]. The CanESM5 model was selected for consistency across key ECVs (T, H, P) and the inclusion of all four primary SSPs ensures a comprehensive assessment of future risk, ranging from low-emission (SSP1-2.6) to fossil-fueled development (SSP5-8.5) scenarios.

3.4. GAI-Assisted Data Extraction and Analysis Procedure Framework

The analytical process relied entirely on GAI for code generation and subsequent execution on open-source platforms. This structured approach ensures accessibility for non-expert users while maintaining analytical rigor. The proposed methodology, as a framework, is illustrated in Figure 1.

- Step 1: Using Generative AI Prompts for Google Earth Engine (GEE) Code Synthesis Generative AI (GAI) was employed to synthesize the necessary geospatial processing scripts, enabling users without advanced proficiency in JavaScript or Python APIs to access complex data. GAI was prompted to generate GEE code that defined the Kolkata Metropolitan Area (KMA) boundary, filtered the required datasets (ERA5-LAND, Landsat, CHIRPS, CMIP6 etc.) and defined the complex functions necessary for spatial and temporal aggregation (e.g., calculating annual, monthly and seasonal means across the 1990–Present and 1985–2070 periods).
- Step 2: GEE Execution for Data Extraction and Map Generation The GAI-generated GEE scripts were executed in the cloud-based platform. This execution filtered, processed and aggregated the petabytes of data into manageable, localized outputs.
- Step 3: The data extracted in Step 2 (mostly in CSV format) was then prepared for sophisticated trend analysis. GAI was prompted to generate R scripts specifically tailored for statistical computation.
- Step 4: R The GAI-generated R code was executed to perform analytical and visualization tasks. These scripts performed time-series analysis (e.g., linear regression, trend-line fitting etc.) and calculated derived variables (e.g., Diurnal Temperature Range, probabilities of extreme rainfall events etc.). R was also used to generate high-impact plots optimized for clarity and public communication, ensuring the scientific data is easily correlated with lived experiences.

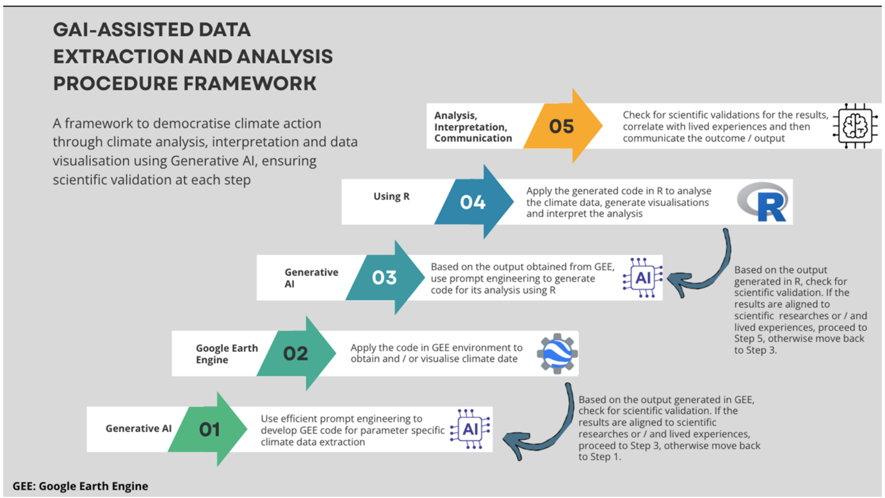

Figure 1. GAI assisted data extraction and analysis process.

4. Extraction and Analysis of Historical Climate Trends and Anthropogenic Drivers in Kolkata

4.1. Temperature Dynamics & Humidity

The first step in demystifying climate data for the general public is to quantify their subjective observations, such as "This January is hotter or cooler than the previous January," or, "This June is the hottest I've felt in the last 10 years". To rigorously test these observations, the GAI-driven framework extracted monthly Maximum, Minimum and Mean 2m Air Temperatures from the ERA5-LAND reanalysis dataset, spanning 1990 to the latest available date. Each monthly time series was fitted with a second-degree polynomial trendline (as seen in Figures 2–6). This choice is scientifically justified because local climate signals, particularly within urban environments, are rarely governed by simple linear change. Factors like non-linear feedback mechanisms from Urban Heat Island (UHI) intensification and abrupt shifts in Land Use/Land Cover (LULC) introduce acceleration, which the polynomial curve is better equipped to capture for trend identification and accessible foresight. The trendline was further extrapolated to 2030, offering a near-term projection to help the public anticipate expected thermal shifts.

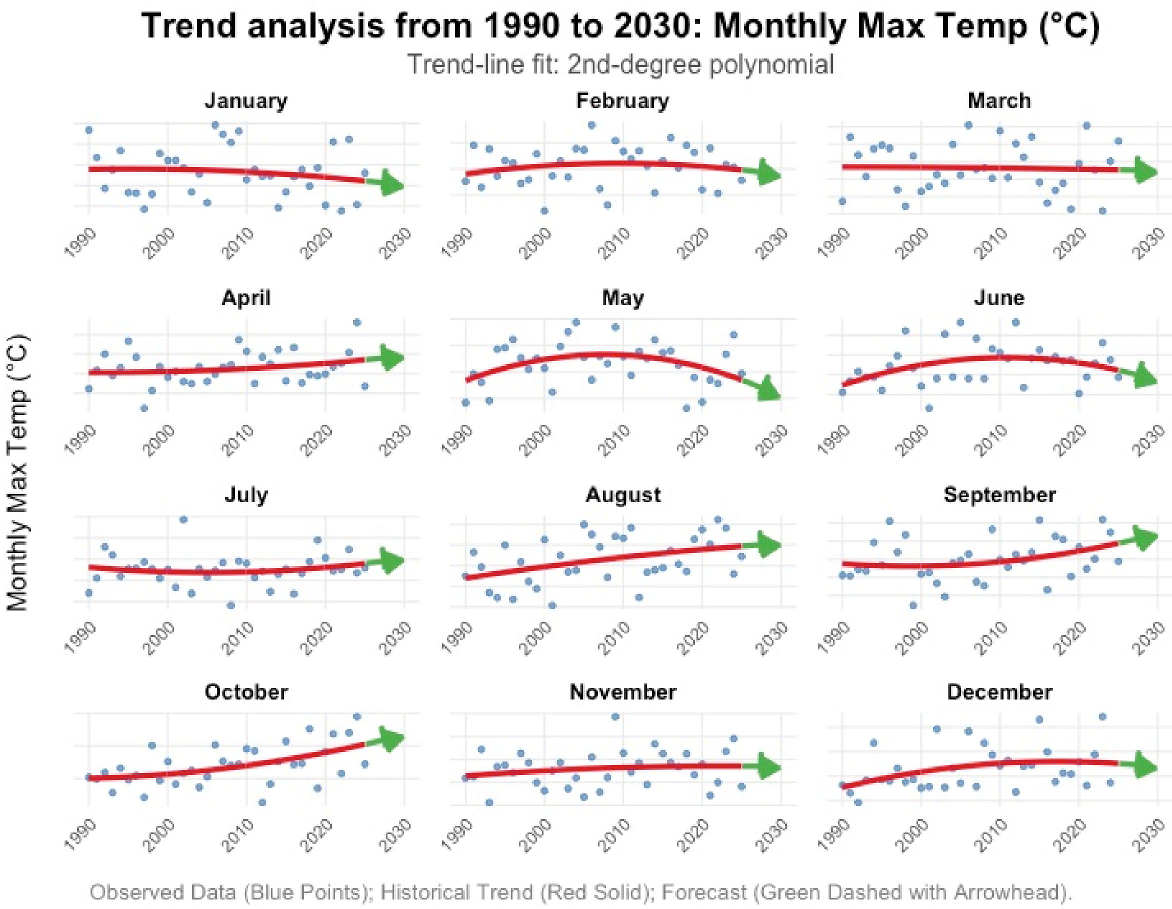

Figure 2. Trend analysis of each month's maximum temperature till date, extrapolated till 2030.

The core issue of nocturnal thermal stress was quantified through the monthly Diurnal Temperature Range (DTR) analysis (Figure 5). A decline in DTR, where minimum (night-time) temperatures rise faster than maximum (daytime) temperatures, is a hallmark of urban warming and translates directly to the public experience of loss of nocturnal cooling, exacerbating health risks. A visual representation of the summary of long-term monthly temperature change was prepared and can be seen as Figure 6.

For atmospheric moisture analysis, both Relative Humidity (RH) (Figure 7) and Absolute Humidity (AH) (Figure 8) were employed. While RH is the standard metric for perceived discomfort (muggy vs. dry) reported in weather forecasts, AH, measured in g/m^3, is the necessary physical constraint.22 Scientific Justification: AH is the direct measure of the atmospheric moisture load that governs the thermodynamic potential for evaporative cooling. When AH is high, the air's capacity to absorb sweat is limited, making the heat danger real regardless of minor temperature variations, making it essential for accurate thermal stress calculation.

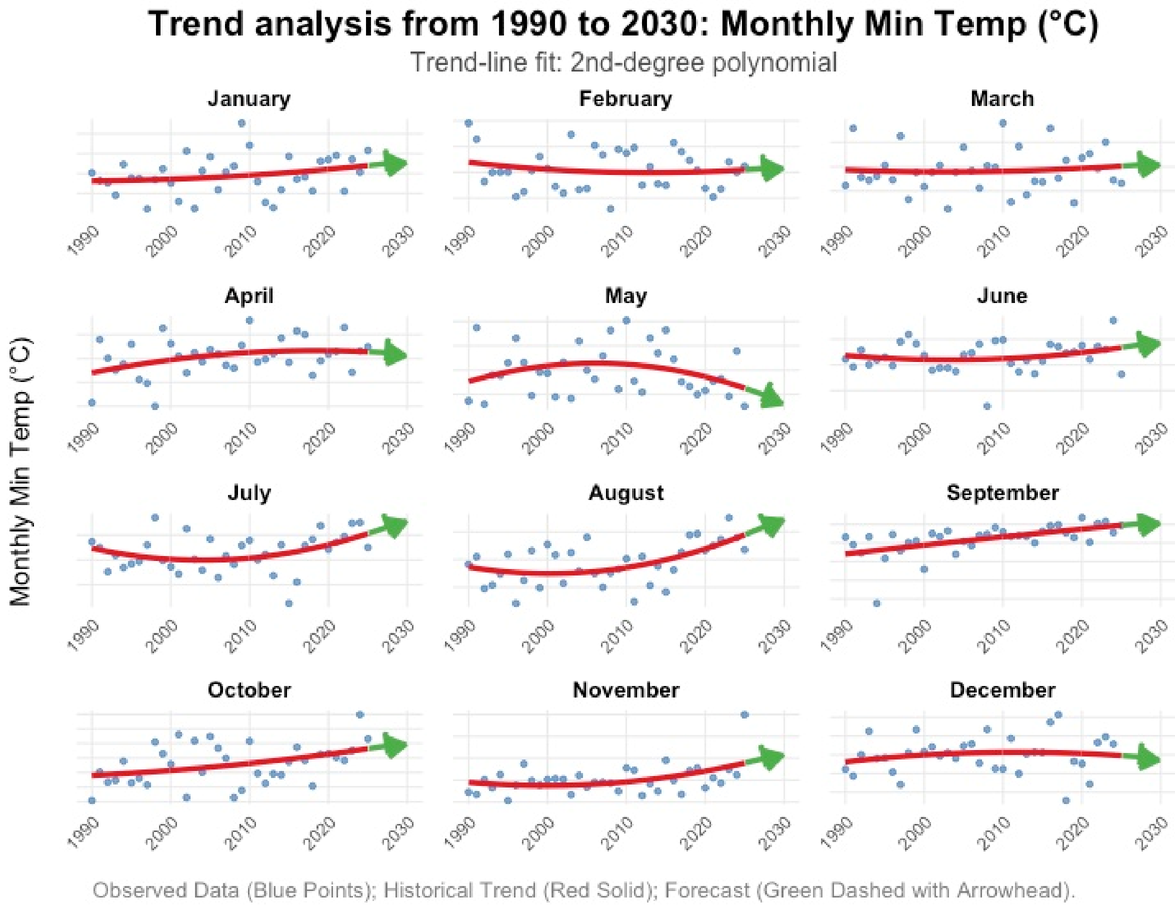

Figure 3. Trend analysis of each month's minimum temperature till date, extrapolated till 2030.

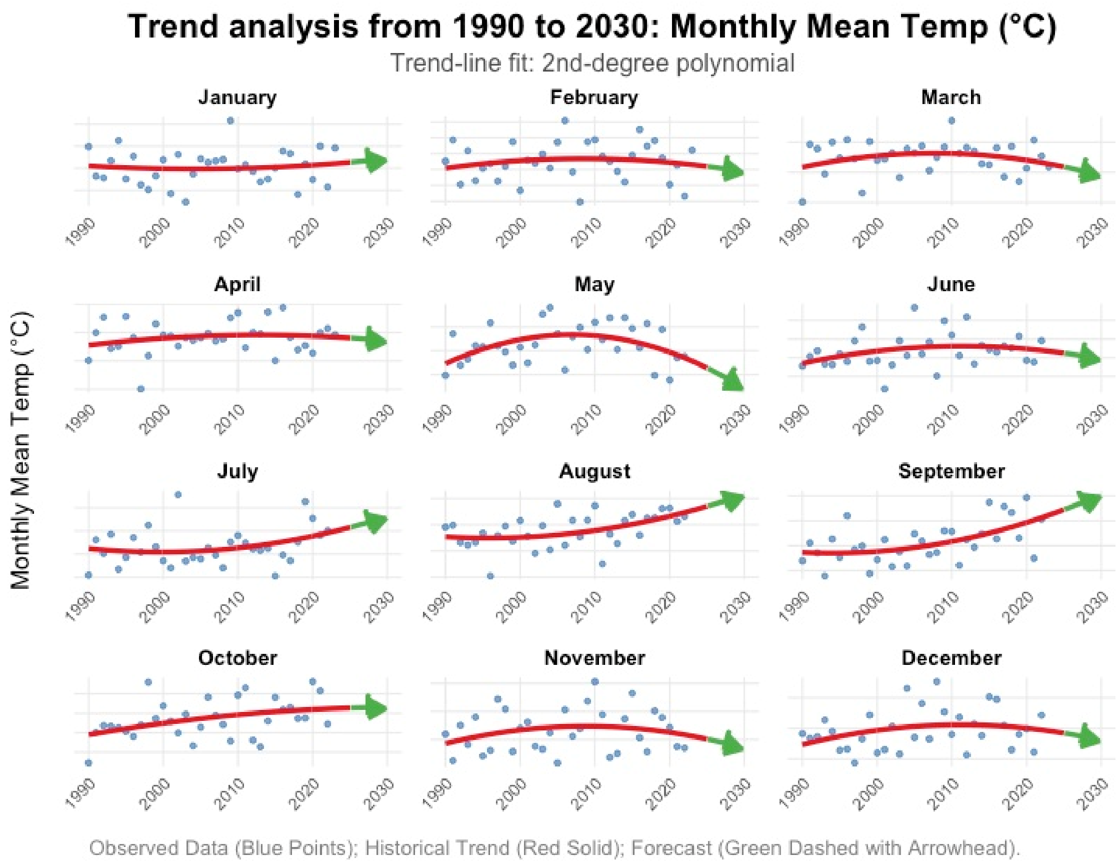

Figure 4. Trend analysis of each month's mean temperature till date, extrapolated till 2030.

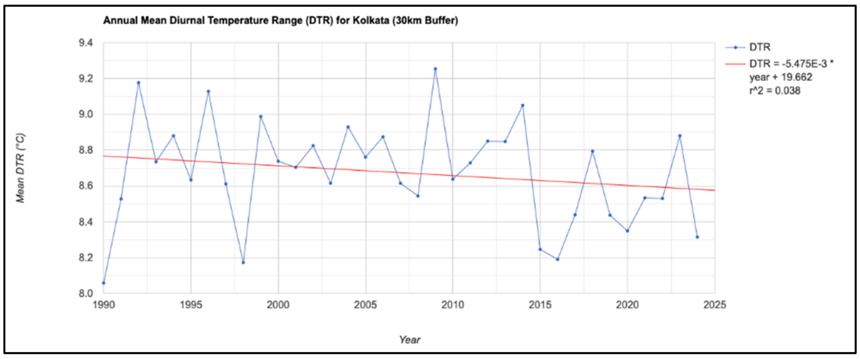

Figure 5. Understanding the trend of annual mean diurnal temperature range.

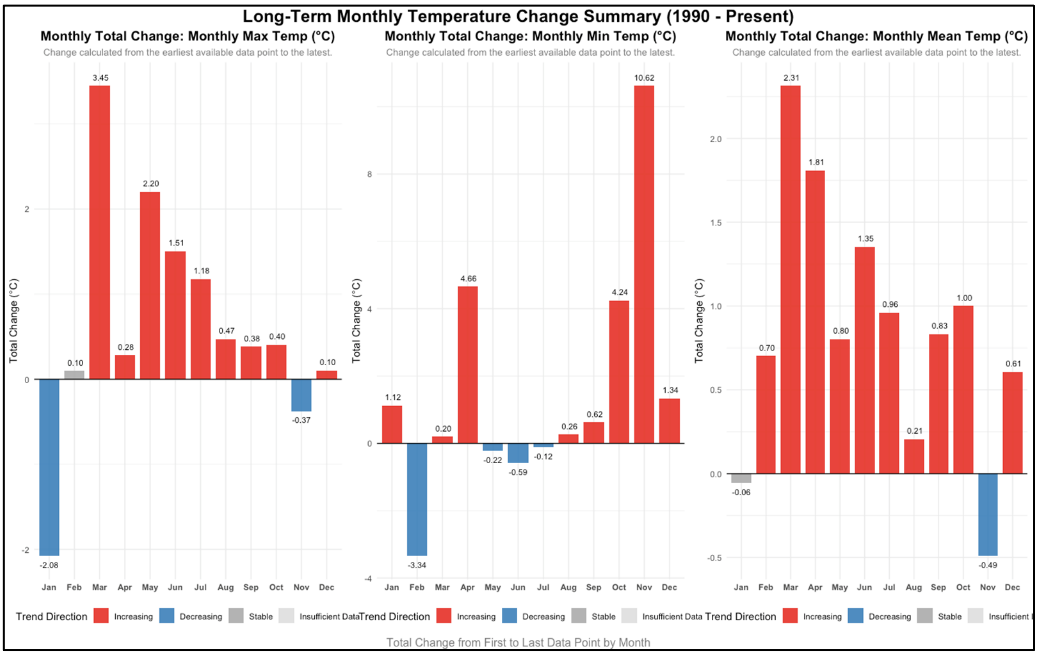

Figure 6. Understanding the long-term monthly trends of temperature (max, min and mean).

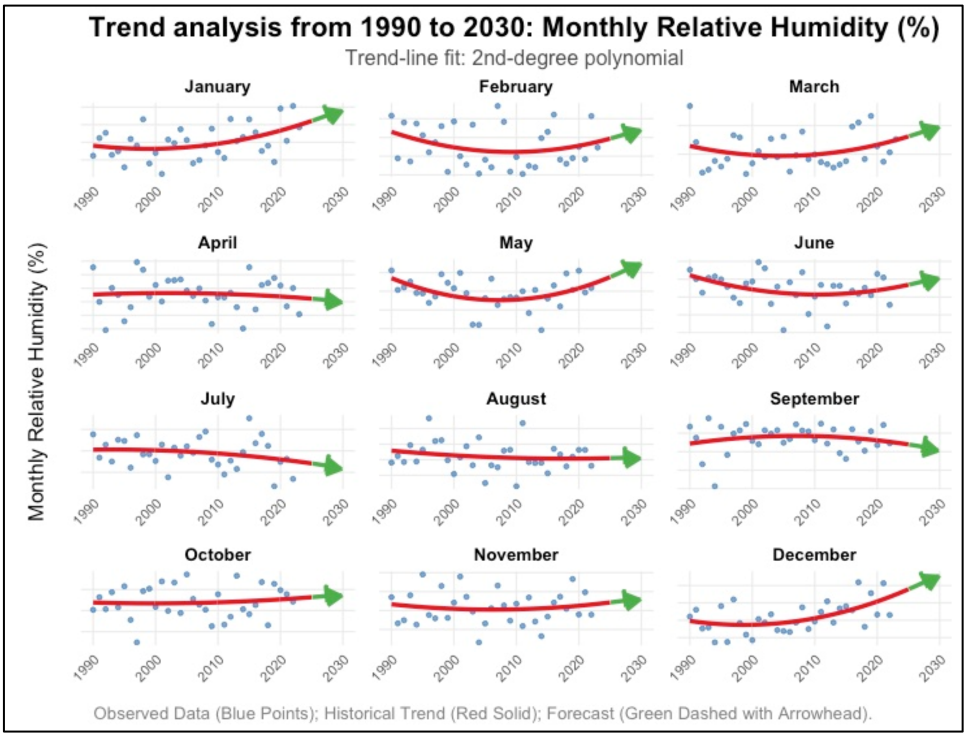

Figure 7. Understanding the long-term monthly trend of Relative Humidity (RH).

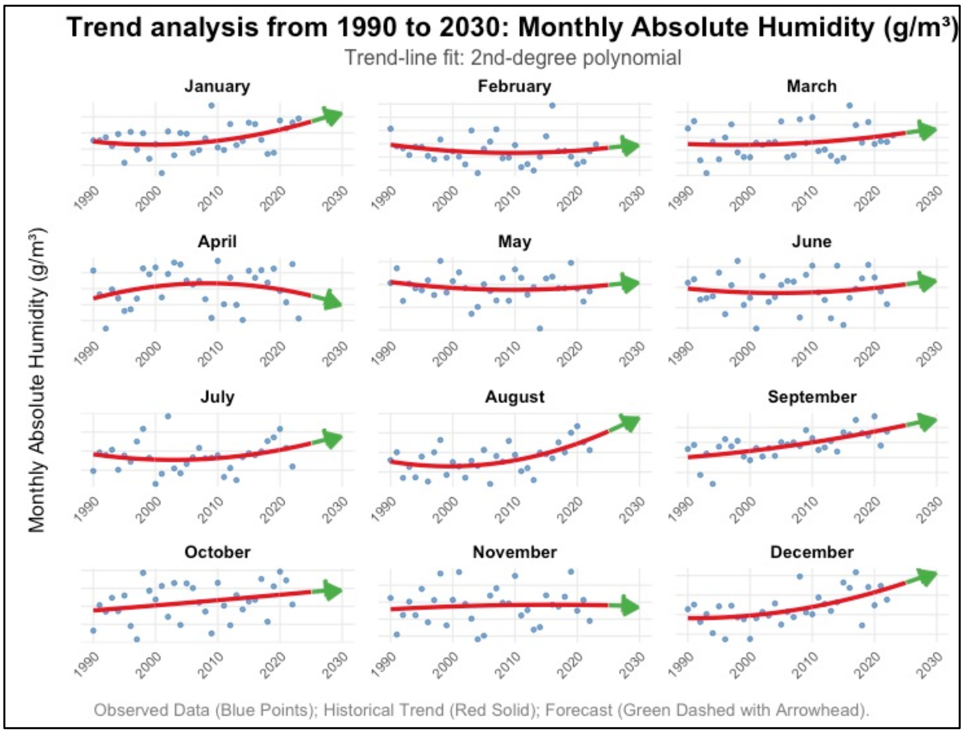

Figure 8. Understanding the long-term monthly trend of Absolute Humidity (AH).

4.2. Precipitation Variability and Extreme Events

To analyze the shift in precipitation dynamics, the GAI-generated R scripts performed a comprehensive multi-metric trend assessment using the CHIRPS daily precipitation data (1990–2024). This analytical depth addresses the reality that climate change often alters the nature of rainfall more severely than the total annual volume, leading to increased flood risk.

Linear modeling was applied to the annual total rainfall to quantify the overall, long-term change in accumulated precipitation volume (Figure 9). Linear regression models were run independently for each of the 12 calendar months to pinpoint seasonal contributions to variability (Figure 10). To understand the influence of ENSO on rainfall events, past extreme rainfall events (particularly the months and years) were found out (Figure 11) and a comparative tend of annual rainfall metrics was performed (Figure 12). Similarly, linear modeling on the Annual Mean Daily Rainfall data quantified the change in average intensity over time (Figure 13). To isolate the growth in high-intensity potential, a Logistic General Linear Model (GLM) was used to calculate the predicted probability of a given month exceeding the 90th percentile rainfall threshold by 2030 (Figure 14).

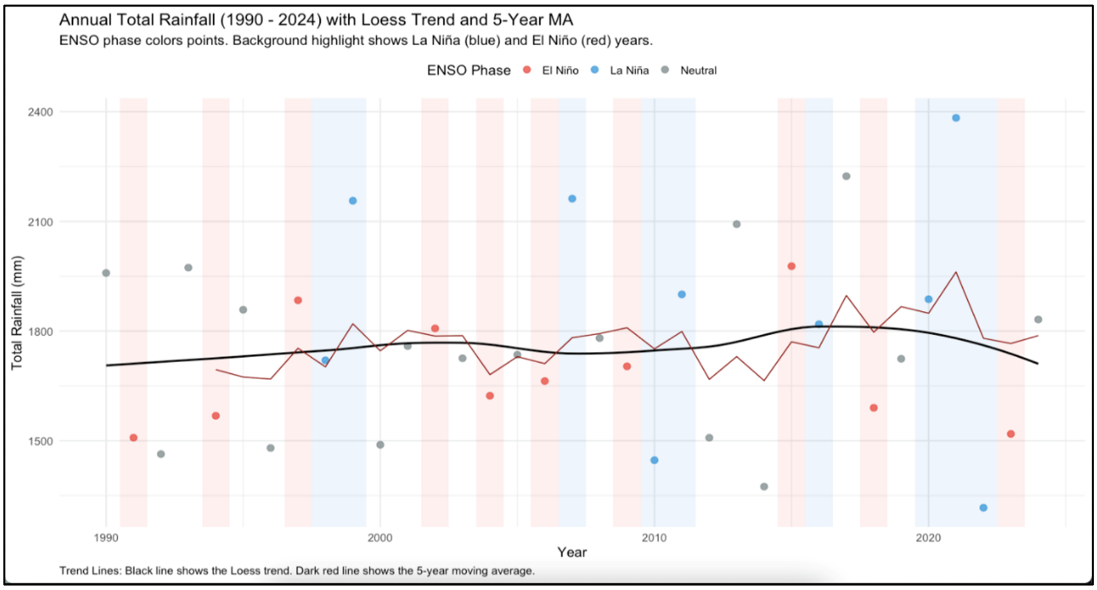

Figure 9. Understanding the long-term trend of total rainfall in Kolkata.

Figure 10. Understanding the long-term trend of monthly mean daily rainfall in Kolkata.

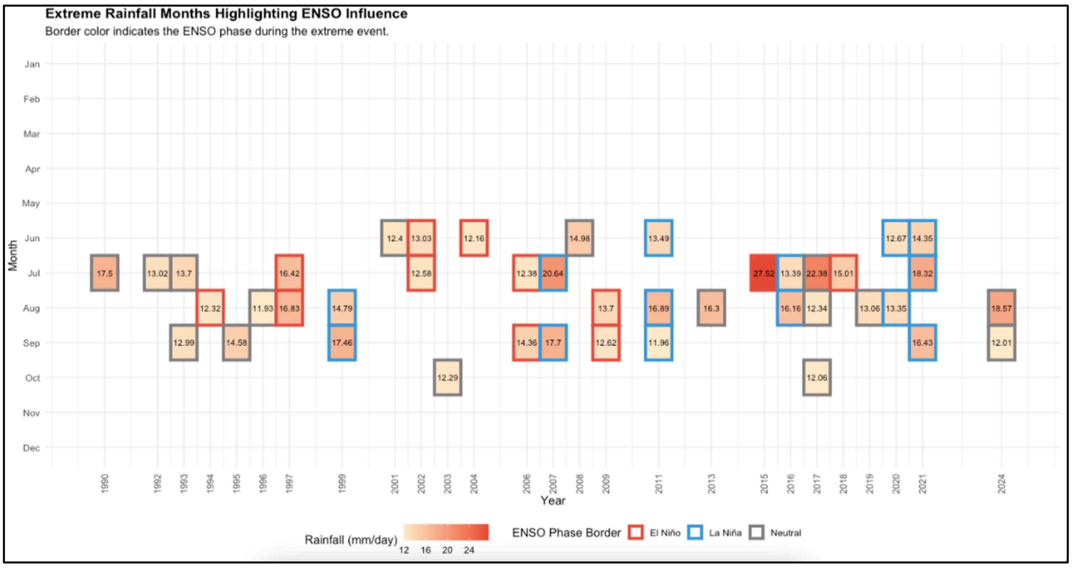

Figure 11. Extreme rainfall months and years.

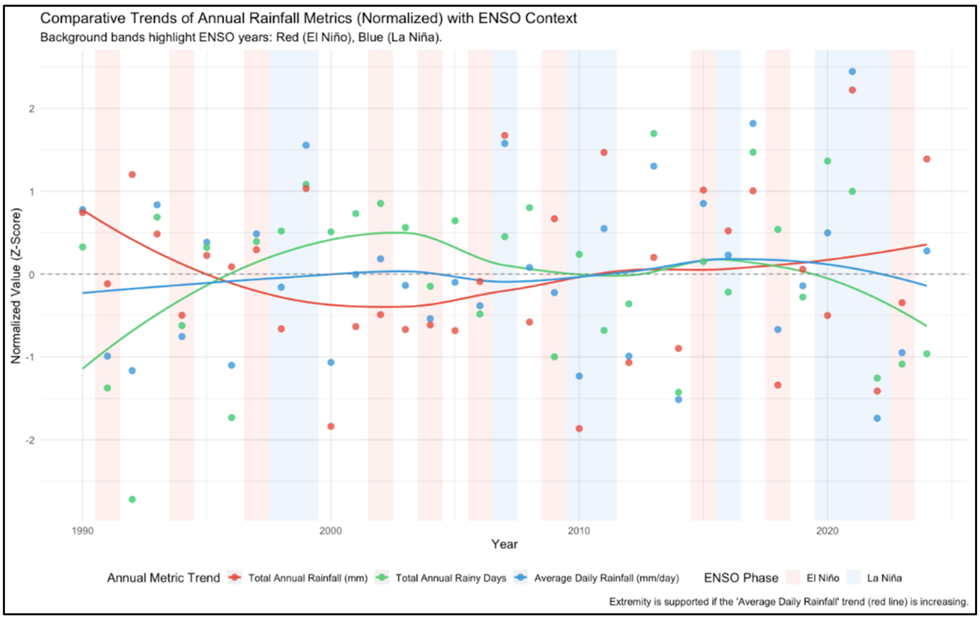

Figure 12. Comparative trend of annual rainfall metrics.

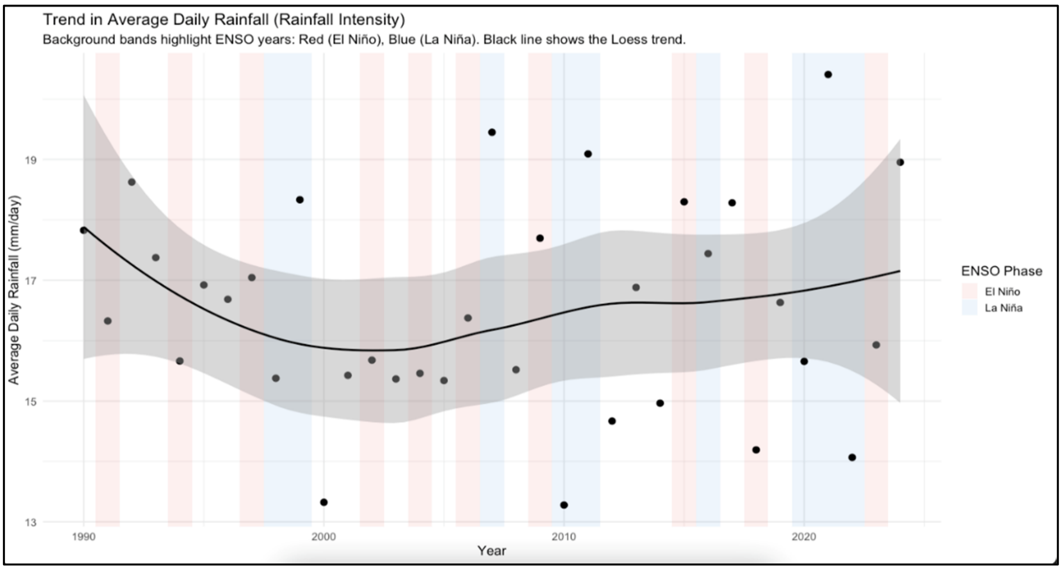

Figure 13. Trend in average daily rainfall.

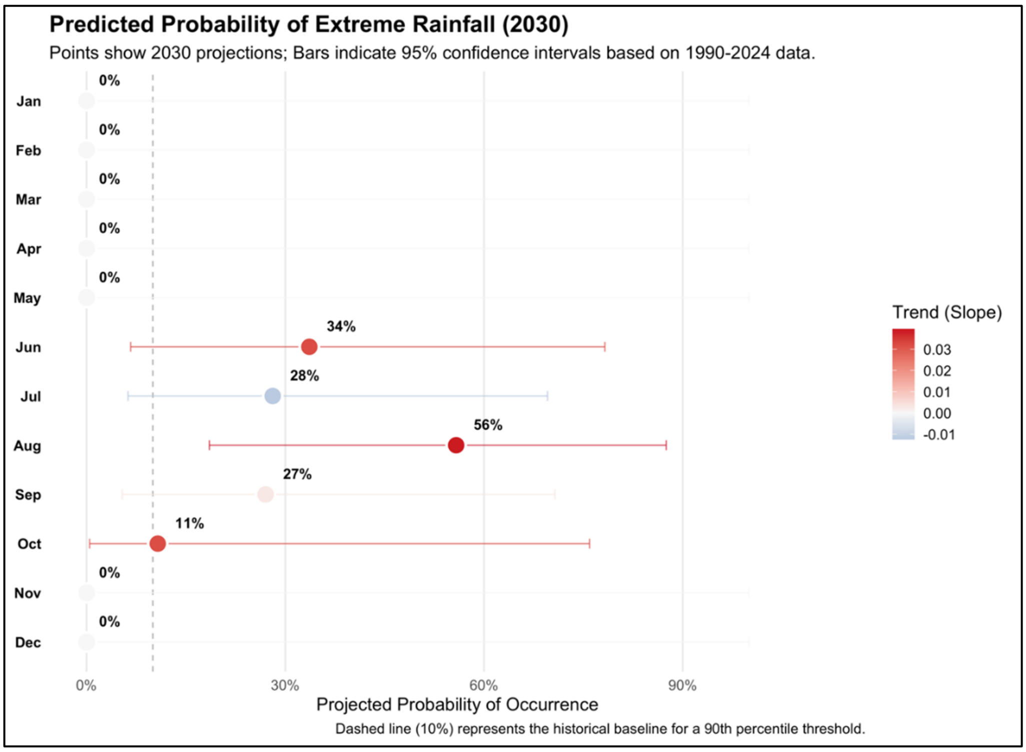

Figure 14. Probability of extreme rainfall, by months, in the near future.

4.3. Anthropogenic Drivers

Anthropogenic factors provide the key link between human decision-making and localized climate riskscape. The core analysis focused on quantifying the structural changes in the city's built environment and the resulting thermal response.

Analysis of the MODIS Land Cover product (2003–2023) confirmed severe, statistically significant expansion of the urban footprint. The total urban and built-up area increased at a rapid, relentless linear rate of 19.02 km^2/year ($R^2 = 0.927$) (Figure 15). This expansion, primarily at the expense of natural buffers like sparse vegetation and wetlands, is highly associated with the intensification of localized thermal stress. The long-term LST trend derived from Landsat analysis (1990–2024) revealed a significant overall linear warming slope of 0.0752 °C/year. This continuous rise lucidly translates to a cumulative warming of approximately 2.6 °C over the 35-year study period, validating the perceived long-term increase in heat. Furthermore, the seasonal LST analysis (Figure 16) highlights the high volatility of June, characterized by the widest spread in LST values, linked to the erratic onset of the monsoon.

The critical impact of LULC was confirmed by the analysis of Urban Heat Island Intensity (UHII), using the temperature difference between the urban core and the rural background (Figure 17). Regression analysis (2001–2023) showed a statistically significant strengthening trend of +0.0495 °C/year (p = 0.00051), suggesting a strong association between urban expansion and the increasing thermal contrast between the city and its periphery over time. A comparative analysis over two decades (2000/2001 vs. 2022/2023) revealed a crucial diurnal shift. Daytime UHII decreased from 3.21 °C to 0.91 °C. Night-time UHII increased from 2.79 °C to 3.39 °C. This strengthening of the night-time UHI by +0.6 °C is a signature characteristic of a mature, dense UHI caused by heat retention in built-up infrastructure and is closely linked to the public's observed loss of nocturnal cooling.

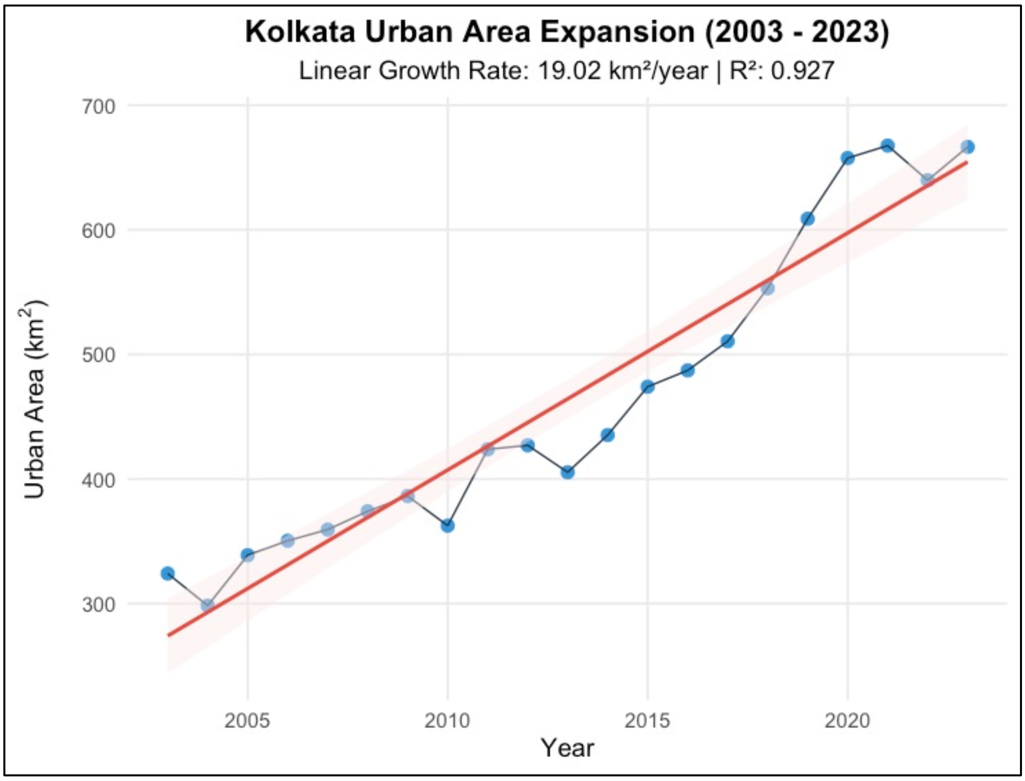

Figure 15. Urban area expansion in Kolkata.

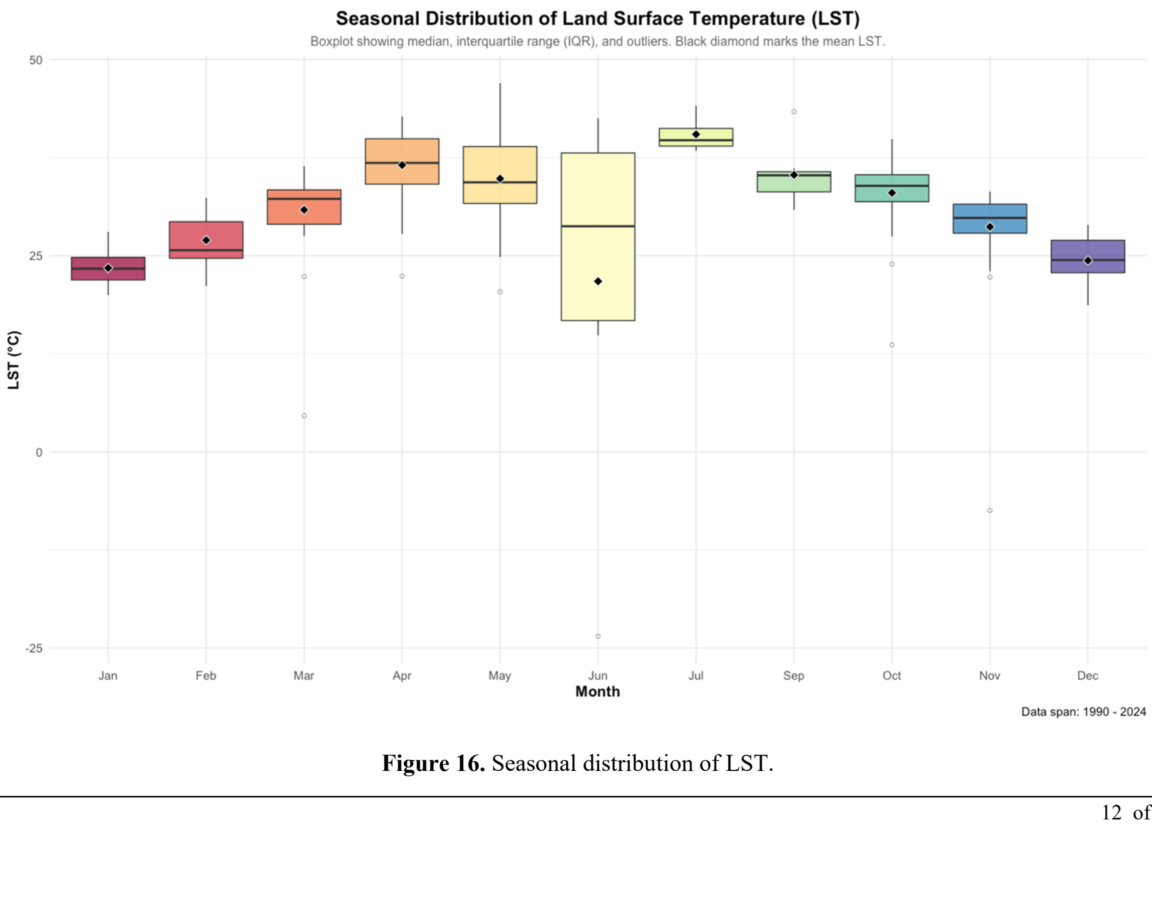

Figure 16. Seasonal distribution of LST.

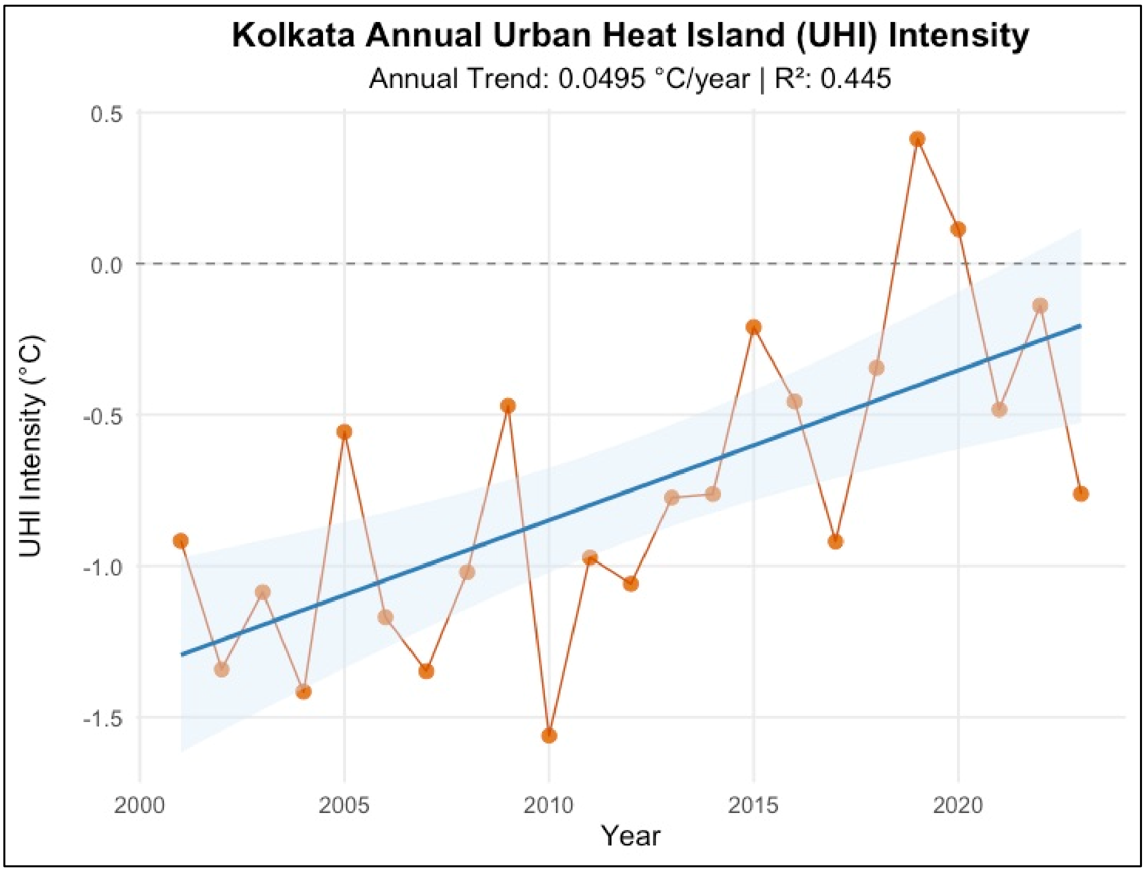

Figure 17. Kolkata Urban Heat Island (UHI) analysis.

5. Synthesis: Data Analysis, Interpretation and Correlation with Lived Experiences

5.1. Translating Science into Citizen-Centric Narratives: Temperature & Humidity

The rigorous data analysis from Section 4 must be synthesized and interpreted within the context of the public's daily life to inspire climate action. The GAI-driven framework allows quick transition from complex statistical output (R scripts) to visualizations optimized for public consumption. Effective climate visualization must uphold the principles of clarity, accuracy and impact [25]. The R analysis and plots generated were specifically tailored to convey a singular, unambiguous message without relying on high levels of scientific complexity, which can confuse non-expert users. However, some degree of scientific rigour was essential—for example use of regression for trend-line fitting, or, probabilistic estimation of extreme rainfall events etc.—to ensure that in the pursuit of clarity of communication, criticality of science is not lost.

The analysis of monthly historical data (from 1990 till available date) generated a series of interesting plots (Figures 2–8), each of which has been discussed concisely in the following paragraphs.

From the above plot, it is easy to understand that most of the months have been experiencing a rise in tis maximum temperature. The most interesting observation is that those months which are usually correlated with being temperature-wise amicable, like October or November, have been seeing rise in maximum temperatures.

April has been experiencing a rise in its maximum temperature, which is expected to continue at least till 2030 and this is evidenced by the fact that Kolkata is witnessing heatwaves in April [26]. Similarly, Septembers are hotter than usual, which is also an impediment to the run-up of the most celebrated occasion in Kolkata—Durga Puja [27]. Octobers are warmer [28] and Decembers are also significantly hotter and the same has been experienced and reported [29].

The maximum temperature trend also needs to be seen in conjunction with the minimum temperature trend (Figure 3) and hence the monthly mean temperature trends (Figure 4) too.

We observe, for many months, the minimum temperatures have also risen significantly. This can be verified through various reports available on the internet [30]. But what is practically significant is to observe how the diurnal temperature range (DTR) has emerged for Kolkata (Figure 5).

Over the years, the DTR is decreasing which means that the maximum and minimum temperature in a day have come closer, thereby reducing the gap. This is a health issue and can also lead to morbidity and mortality as seen in Delhi [31]. Interestingly, lowered diurnal temperature range, whether resulting from increased minimum temperature or substantial rise in both the maximum and minimum temperatures, leads to more dependence on mechanical cooling (HVAC) systems, if accessible, or more woes for the urban poor.

While the annual DTR trend is good to gather an overall sense, it is practically not usable for the general public. What would be more useful is to see how the temperature metrics (maximum, minimum and mean) have changed over the period, for each month. The GAI guided R code for this purpose, identifies the metric's value (say, maximum or minimum temperature) from the earliest recorded year and the latest recorded year. It then calculates the total change by subtracting the earliest value from the latest value. Finally, it assigns a direction (say, increasing, decreasing or stable) based on the sign and whether the change exceeds a (+/−) 0.1° threshold. The resultant plot can be seen as Figure 6.

As already discussed, but henceforth visually confirmed, Kolkata has been experiencing an overall rise in its maximum, minimum and hence mean temperatures in most cases. What is absolutely important is to see that summers are arriving earlier (see, February and March) and winters are also not that cooler as it used to be.

To be concise, the overall long-term decrease in DTR (Figure 5), which can be due to the rise in minimum temperatures (Figure 6) is arguably the most visceral piece of data for the urban resident. The loss of nocturnal cooling, caused by the amplified night-time Urban Heat Island effect, which would be discussed in the Section 5.3), results in continuous thermal stress and poor sleep, which directly impacts health and increases dependence on mechanical cooling systems, if accessible. The science confirms the anecdotal observation—nights are simply no longer providing adequate thermal respite.

Kolkata is also known for its humid weather and hence, it makes sense to analyse humidity as well. While what is usually reported is Relative Humidity (RH), we also take account of Absolute Humidity (AH). While Relative Humidity is what's used in weather reports, absolute moisture content (often measured as water vapor pressure, which correlates directly with AH) is the physical driver of the evaporation process. In extremely hot and humid environments, the high Absolute Humidity (the sheer amount of water vapor) causes the problem, as the air simply has too many water molecules already, regardless of the temperature. Even if the air is cooled a little, the absolute moisture content (AH) can remain dangerously high, still limiting sweat evaporation and causing thermal strain. While Relative Humidity is the key indicator of thermal comfort and perceived stress, as it represents the saturation level that dictates cooling efficiency through sweat, high Absolute Humidity is the underlying physical constraint that makes the heat danger real.

The temperature issue combined with the matter of humidity has brough Kolkata very close to unlive-ability [32]—this has been experienced and reported. Even the science makes sense—when the temperature is high, the air has the capacity to hold more water vapour and hence the humidity rises, which in turn, is a big health issue. In fact, the combined effect of high temperatures (say, heatwave condition) and humidity increases the thermal stress for residents in Kolkata more than many metropolitan cities in India [33]. The worrying part is that this is set to continue in the future, at least till 2030, all conditions holding same.

5.2. Translating Science into Citizen-Centric Narratives: Rainfall

Kolkata recently experienced an extreme rainfall event (ERE) [34] and hence, it is also relevant to discuss the rainfall pattern in Kolkata. The most fundamental discourse of investigation would be to start by analysing the annual total rainfall over the years. However, it is important to also understand that rainfall (precipitation) is also influenced by local (convection rains or orographic rains) as well as regional phenomenon like El Nino, La Nina & Southern Oscillation (ENSO).

In Figure 9, the red line depicts the 5-year moving average, while the black line is the Loess trend. No confirmation can be drawn from the trend-lines, except the fact that the 5-year moving average slows a slight upward trend. This plot, however very clearly depicts, the effect of ENSO on rainfall; whenever there is El Nino, the total rainfall shows a dip, while in the La Nina years, the total rainfall is usually higher. Since nothing definitive could be said about the total rainfall trend, we take the next step to look at monthly mean daily rainfall trends.

The multi-month plots in Figure 10 uses 5-year moving average, which tends to give a better visual representation of the trend than a linear regression. For example, the ERE in September [32] is corroborated with the rising moving average line. However, statistically this is still not a good fit. To understand better, a plot is generated to see which months in which years recorded heavy rainfall. In this case, the extreme rainfall threshold is calculated based on the 90th percentile of all monthly mean daily rainfall values across the entire dataset (1990–2024).

In the above plot, July 2015 stands out and indeed, Kolkata experienced above average rainfall during that period [35]. Similarly, July 2017 and July 2007 stands out, which has also been reported and experienced by the residents of Kolkata [36]. It is also interesting to note that in many cases, the extreme rainfall threshold (as conceptualised in this study) is breached during El Nino period. When seen in conjugation with Figure 9—while the total annual rainfall saw a dip but there have been extreme rainfall events—it means that larger periods of the year remained dry but specific smaller periods witnessed heavy rainfall. To understand this better, two plots were generated, which have been shown in Figures 12 and 13.

This analysis provided compelling visual evidence regarding the shifting nature of rainfall in Kolkata over the 1990–2024 period. The results strongly support the fact that the area is experiencing a trend toward fewer but more intense rain events.

The plot in Figure 12 compares the normalized trends of the three-core metrics using the smoothed Loess lines as shown in Table 4.

Table 4. Rainfall metrics, trends and interpretation.

Metric (Colour)	Trend Analysis (Loess Line)	Interpretation
Total Annual Rainfall (Blue)	Relatively Flat. The line stays very close to the zero (average) line, only dipping slightly in the mid-2000s and ending near the average.	The total amount of rain received annually has remained largely stable over the 35-year period.
Total Annual Rainy Days (Green)	Clear Decreasing Trend. The line starts above the average (0 Z-Score) in the early 1990s, drops significantly below average around 2005 and continues to trend downward, ending well below the long-term average.	The region is experiencing a significant reduction in the overall number of days with precipitation above the 1mm threshold.
Average Daily Rainfall/Intensity (Red)	Clear Increasing Trend. The line starts near the average, dips slightly below in the mid-2000s, but then shows a distinct and steady upward curve from around 2010 onwards, ending notably above the long-term average.	Rain events, when they occur, are becoming significantly more intense.

The stability of the Blue line (Total Rain) combined with the sharp decline of the Green line (Rainy Days) forces the Red line (Intensity) upward. The data confirms this, providing strong evidence of a shift in rainfall distribution toward high-intensity events. This finding is crucial for public understanding—the problem is not necessarily getting more rain overall, but rather receiving the same amount of rain in fewer, more catastrophic bursts. This directly links the phenomenon of high-impact urban flooding in Kolkata to a structural change in the hydrological cycle.

The plot in Figure 13 visualizes the raw data for the Average Daily Rainfall (Intensity), confirming the trend seen in the normalized plot (Figure 12). The plot clearly demonstrates that the intensity is now consistently higher than it was in the middle of the study period, reinforcing the finding from the normalized chart. The background bands provide important context for inter-annual variability. The El Niño (Red Bands) years often, though not always, coincide with data points (for all three metrics) that are below the average line (0 Z-score) in Figure 12. This suggests El Niño typically leads to a drier year. The La Niña (Blue Bands) years often coincide with data points above the average line, especially in the 2010s, suggesting higher total rainfall and more rainy days. Crucially, the long-term upward trend in Intensity (Red Line) continues regardless of the ENSO cycle, suggesting the increasing intensity is driven by a broader climate factor rather than just year-to-year ENSO variations.
Following the established line of query, the next analysis focused on an attempt to predict the likelihood of an extreme rainfall event in the near future, by 2030, by using a Logistic General Linear Model (GLM). Table 5 gives a lucid explanation of the plot in Figure 14 and the plot is to be read as follows:

(1) Predicted 2030 Probability (X-axis/Value): The calculated likelihood (as a percentage) that a given month will experience an extreme rainfall event (defined as a mean daily rainfall exceeding the 11.83 mm/day threshold, 90th percentile).
(2) Trend Direction (Colour/Log Odds Slope): Whether the probability of this event occurring is increasing (Red) or decreasing (Blue) over the 1990–2024 period.

Historically, the risk might have been more evenly distributed across the four core monsoon months (June–September) but the model suggests a concentration of the extreme event risk in June and August, while July's probability is slightly diminishing. August is the primary concern, with a predicted 55.8% chance of being an extreme month by 2030. Additionally, the rising risk in October (post-monsoon) suggests the high-intensity phase of rainfall is extending later into the year.

The dashed vertical line in the Caterpillar Plot represents the Long-Term Average probability (1/12 or 8.3%) for any random month to be an extreme month. Every core monsoon month (June–October) has a predicted 2030 probability that is significantly higher than this 8.3% average, confirming that the problem of extreme rainfall is concentrated heavily within the rainy season. The analysis, in conjunction with the plot in Figure 14 points to a future where high-impact rainfall events are becoming more frequent and more focused within the rainy season, peaking aggressively in August and extending into October. However, this would be confirmed in the later section where scenario-based projections are unpacked and analysed.

Table 5. Dominant trends of the LGM.

Month	Log Odds Slope (Trend)	Predicted 2030 Probability	Interpretation
August	Strongly Increasing (Red, Slope ~ 0.0395)	55.8%	This is the highest risk month. The probability of an extreme event is predicted to be over 50% by 2030, with the strongest upward trend.
June	Increasing (Red, Slope ~ 0.0321)	33.6%	The risk is also significantly increasing in June, potentially marking a more intense start to the monsoon season.
October	Increasing (Red, Slope ~ 0.0318)	10.7%	While the absolute risk is lower, the probability in this post-monsoon month is increasing, suggesting a lengthening of the high-intensity rainfall period.
September	Increasing (Red, Slope ~ 0.0029)	27.0%	The risk remains high, but the rate of increase (slope) is much flatter compared to June or August.
July	Slightly Decreasing (Blue, Slope ~ 0.0125)	28.1%	This is the only core monsoon month showing a slightly decreasing trend in the probability of being an extreme event, though the overall risk remains high.
Dry Months (Jan, Feb, Mar, Apr, May, Nov, Dec)	Neutral (Slope ~ 0)	~ 0\%	The probability of an extreme event in the dry season remains effectively zero, with no detectable trend.

5.3. Anthropogenic Drivers: The Human-Coded Layer of Complexity

In the context of climate-related extremes—hazards like warm nights, heatwaves or extreme rainfall, anthropogenic factors play a crucial role. In this regard, one must note that within the period of 2003—2023, Kolkata has witnessed a linear growth rate (change per year) of 19.02 km²/year and the expansion, if plotted, would look like Figure 15.

This, invariably, means that the land surface temperature has gone up and it would give rise to serious problems of Urban Heat Island (UHI) effect. The subsequent sections deal with this. Using a GEE code, we calculated the mean LST for an early period (1990–2000) and the recent period (2015–2025) and observed an overall warming trend of 0.075 °C/year, which lucidly translates to a cumulative warming of roughly 2.6 °C over the 35 years. This is on conformation with previous studies [37,38].

We use the extracted data from GEE to understand the seasonal cycle and variability of LST also. The following observations from Figure 16 are noteworthy. April, May and June exhibit the highest LST medians and means. June shows the widest box indicating the highest variability in LST for the entire year. This high variability in June could be linked to the highly erratic onset of the monsoon (some years start hot and dry, others start cloudy and wet). The mean LST (black diamond) for June is notably pulled down compared to the April and May means, suggesting the LST drops sharply when the monsoon arrives. January and December have the lowest LST values, with relatively tight boxes, indicating low temperature variability in winter. LST drops significantly in July as the monsoon establishes itself (more clouds, more rain). Temperatures remain stable through October before declining into winter.

This plot gives a clear indication of how volatile the LST is, in terms of seasonal variation, in Kolkata.

Another important aspect is to understand why the diurnal temperature range is decreasing due to anthropogenic factors. The primary reason, among many other things, is the Urban heat Island (UHI) phenomenon, as has been reported on various occasions [39]. The UHI intensity for Kolkata was analysed over the peak summer months (1 April to 31 May) from 2001 to 2023. The UHI intensity was calculated as the temperature difference between the Urban Area (a 30 km buffer around the city centre) and a designated rural reference area.

Regression analysis performed on the annual UHI intensity time series showed that the UHI intensity exhibited a statistically significant strengthening trend with an annual rate of +0.0495 °C/year (*p*-value: 0.00051) (Figure 17). This indicates that the thermal contrast between the urban core and the rural surroundings is consistently increasing over time. The model explained 44.5% of the variability in the annual UHI intensity, suggesting a moderate but reliable long-term relationship. The UHI intensity changed from an initial value of -0.92 °C in 2001 to 0.76 °C in 2023. Although the intensity remained technically negative (indicating the specific rural reference area was slightly warmer than the urban area on average during the analysed peak summer periods), the +0.16 °C shift in the intensity value confirms a significant warming of the urban centre relative to the rural reference over the 23-year span.

A second analysis, using a different methodology (Urban Core vs. GHSL-masked Rural), demonstrates a crucial diurnal difference. GHSL marked rural refers to an area that has been defined as non-urban based on data from the Global Human Settlement Layer (GHSL) dataset. The Daytime UHII significantly decreased by 2.3 °C, suggesting the overall Rural area is experiencing more daytime LST increase or the urban heat mitigation efforts are more effective during the day. Conversely, the Night-time UHII increased by +0.6 °C. This strengthening of the night-time UHI is a critical finding, indicating that the urban area is increasingly retaining heat after sunset relative to the rural area, a signature characteristic of exacerbated UHI effects due to built-up infrastructure (as confirmed in Figure 15) and reduced radiative cooling. In summary, despite a complex diurnal pattern, the highly significant long-term trend of +0.0495 °C/year confirms a statistically robust strengthening of the Urban Heat Island effect in Kolkata between 2001 and 2023.

6. Synthesis: Data Analysis, Interpretation of Future Climate Projections for Kolkata

In the above section, historical data was extracted from GEE, analysed and visualised through R and interpreted for common understanding. The resultant plots were evidenced through lived experiences—newspapers articles, reports etc.—to exemplify that GAI codes can indeed be used to analyse climate data and even infer information to establish trust. While understanding historical precedence is important, it is more important to understand what can happen in the future in the realm of climate change effect and impact. In the following subsections, we maintain the same strategy of extracting information from GEE and then processing it via R and we continue to study the most commonly known climate variables—temperature, humidity and rainfall (precipitation).

6.1. Projected Changes in Temperature & Humidity under Selected SSP Scenarios

We analysed the climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) dataset, specifically employing the CanESM5 Global Climate Model (GCM), which provides daily, downscaled predictions. The study region, as in all cases, is a 30 km buffer around the centre of Kolkata. The time series extends from a historical baseline (1985) through the end of the 21st century's climate period (2070). Crucially, the analysis covers two out of the four distinct Shared Socioeconomic Pathways (SSPs)—SSP2-4.5: Middle-of-the-road path (intermediate emissions) and SSP5-8.5: Fossil-fuelled development path (very high emissions, extreme warming).

The climate projections, through the obtained illustrations**,** demonstrate how the severity is associated with different future emissions pathways. indicate a clear and accelerating trend of annual mean temperature increase in Kolkata (Figure 18), with the severity directly dependent on the future emissions pathway. All scenarios begin converging at similar temperatures near the historical baseline but diverge significantly after approximately 2030. Under SSP2, the mean annual temperature is projected to increase steadily, levelling off near 29.5 °C by 2070. Under the SSP5-8.5 scenario, the highest emissions scenario, the temperature rise is substantially more aggressive. The mean annual temperature is projected to exceed 31 °C by 2070. The analysis strongly suggests that unless global emissions follow the lower SSPs (like SSP1-2.6, which is implicitly the lower bound of the projected trends), Kolkata is committed to experiencing a mean annual warming of at least ∼1.5 °C to 3 °C relative to the 1985–2010 baseline by 2070.

The projections for Specific Humidity (Figure 19), which quantifies the actual mass of water vapor in the air (g/kg), mirror the temperature trends, indicating a substantial increase in atmospheric moisture content across all future scenarios. The increase in specific humidity aligns with the Clausius-Clapeyron relationship, where warmer air can hold significantly more moisture. The specific humidity is projected to rise from a baseline around 16.7 g/kg in the historical period to approximately 17.9 g/kg by 2070 (SSP2) and exceeding 19 g/kg by 2070 (SSP5-8.5).

The combined increase in both temperature and specific humidity is critical. Higher specific humidity significantly elevates the Wet-Bulb Temperature, leading to a disproportionately greater increase in physiological heat stress and compounding the risks of morbidity and mortality for the city's population.

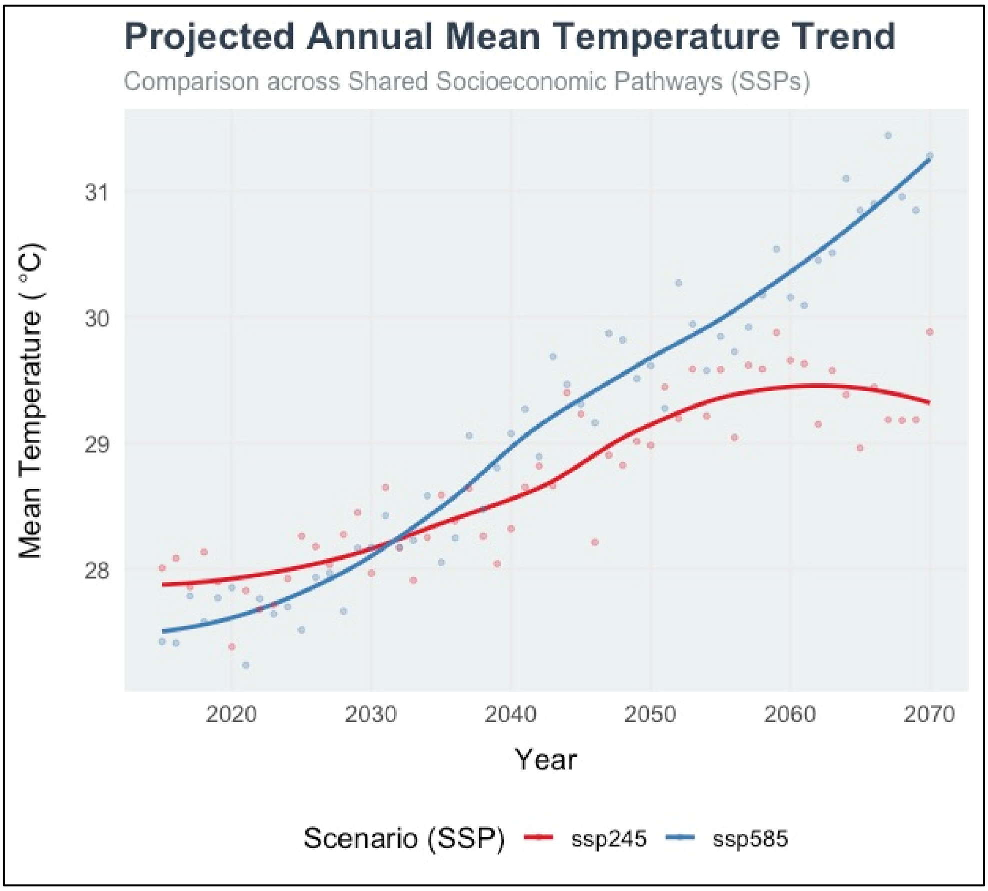

Figure 18. Projected annual mean temperature trend.

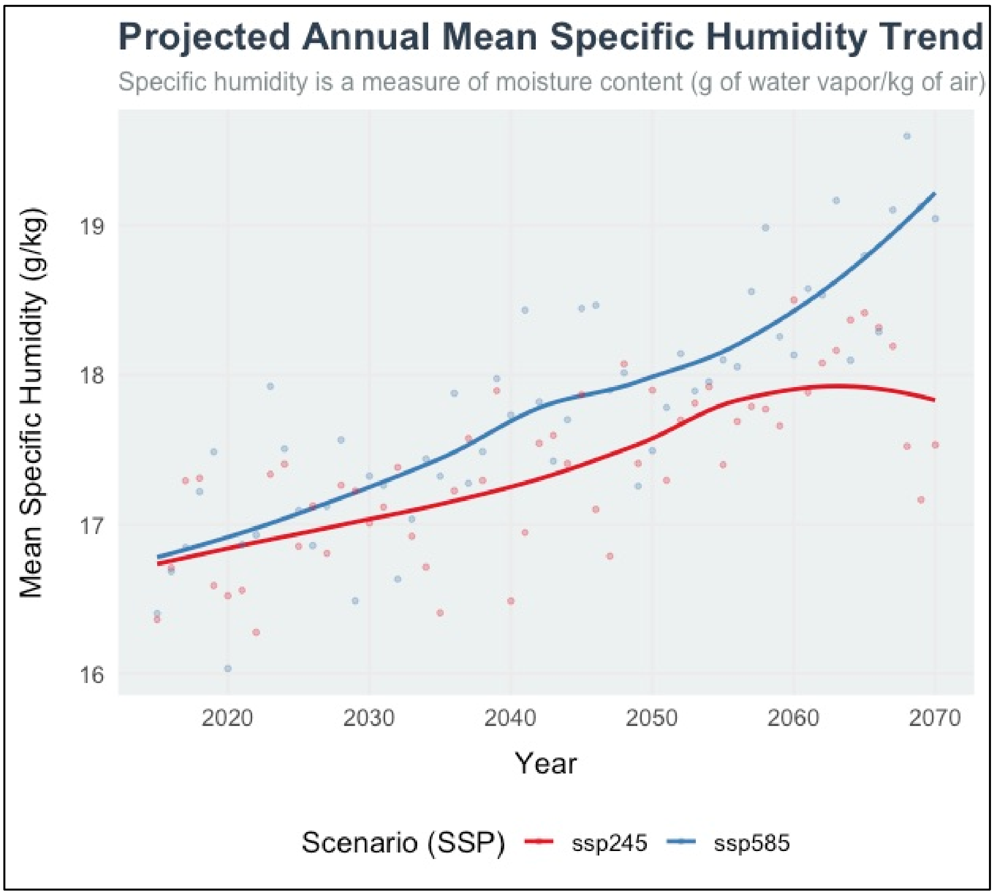

Figure 19. Projected annual mean specific humidity trend.

6.2. Forecasted Monsoon and Extreme Rainfall Events

The analysis undertaken use the CanESM5 Global Climate Model (GCM) within the CMIP6 framework, spanning two out of four SSPs. The analysis (Figure 20) revealed that, unlike the monotonic increase observed in temperature, the long-term trend in mean annual rainfall exhibits high inter-annual variability but a generally stable or slightly increasing long-term average, with scenario-dependent differences. For SSP2, the trend line shows an initial slight decrease or stabilization around 1400 mm, followed by a gradual increase, reaching approximately 1650 mm by 2070. This suggests a relatively modest long-term increase in total annual accumulation under an intermediate mitigation pathway. However, the SSP5 scenario projects a consistently higher mean annual rainfall, starting near 1550 mm and stabilizing around 1700 mm. The higher accumulation under the SSP5 scenario aligns with the increased atmospheric moisture capacity associated with the greater warming projected under this pathway (as confirmed by the previous humidity analysis).

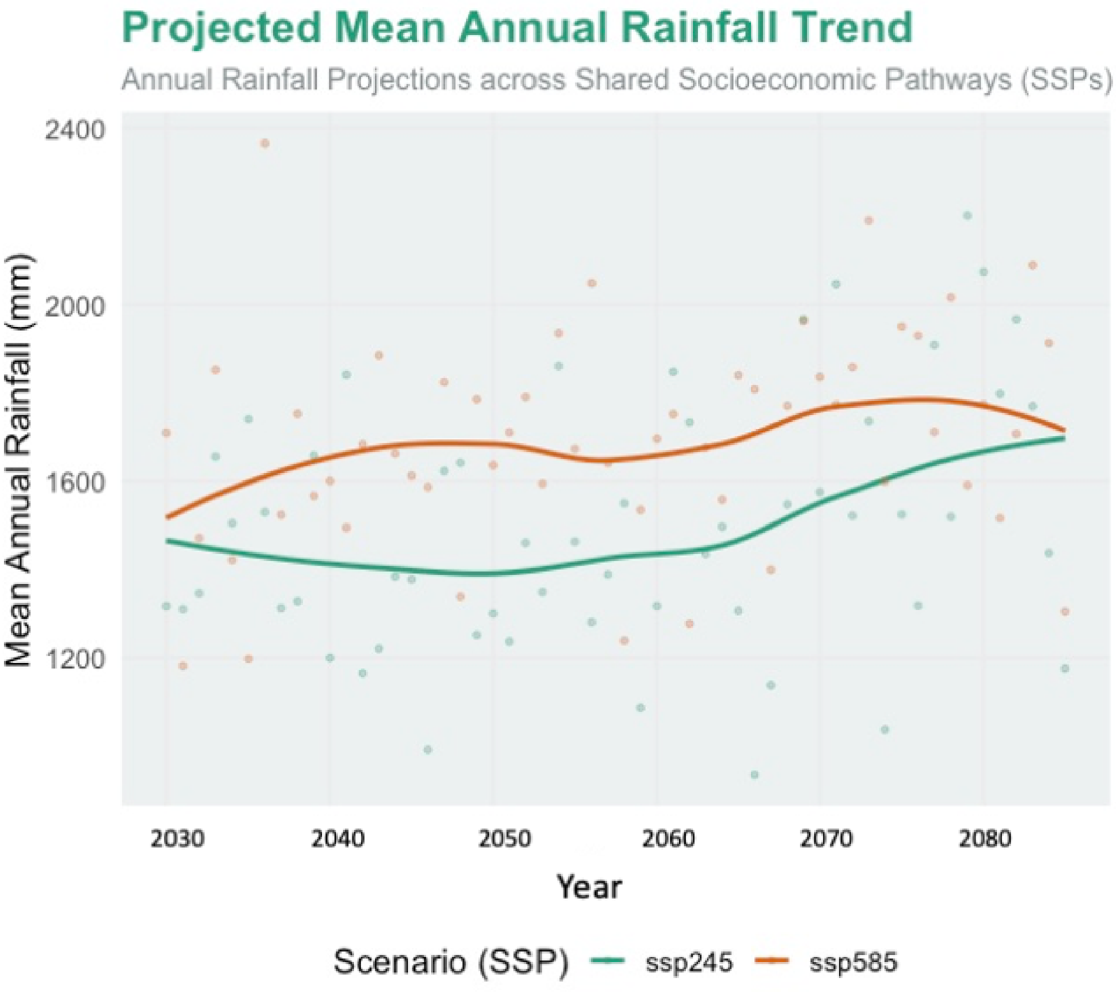

Figure 20. Long-term trend in mean annual rainfall for SSP2 and SSP5 pathways.

While both scenarios show a rising trend toward the end of the century, the absolute difference in mean annual precipitation between the two scenarios remains relatively narrow (~50 mm difference by 2070).

Additionally, to assess the potential for extreme events, a boxplot analysis (Figure 21) comparing the full distribution of annual rainfall across the two key scenarios (SSP2 and SSP5) was performed. The median (the central line within the box) for SSP5 is higher than that of SSP2, confirming the general increase in average annual rainfall under the higher warming scenario. The most critical finding relates to the spread (variance) and the maximum projected values. The interquartile range (the box itself) is notably larger for the SSP5 scenario (~1550 mm to 1800 mm) compared to SSP2 (~1450 mm to 1700 mm). This indicates that the variability and uncertainty in annual rainfall are significantly greater under the high-emissions path. The SSP5-8.5 scenario also displays a distinct positive outlier (around 2350 mm), representing an annual total far outside the typical distribution. This is a robust indicator of a substantially elevated risk of extreme annual rainfall events—a direct consequence of increased atmospheric energy and moisture content.

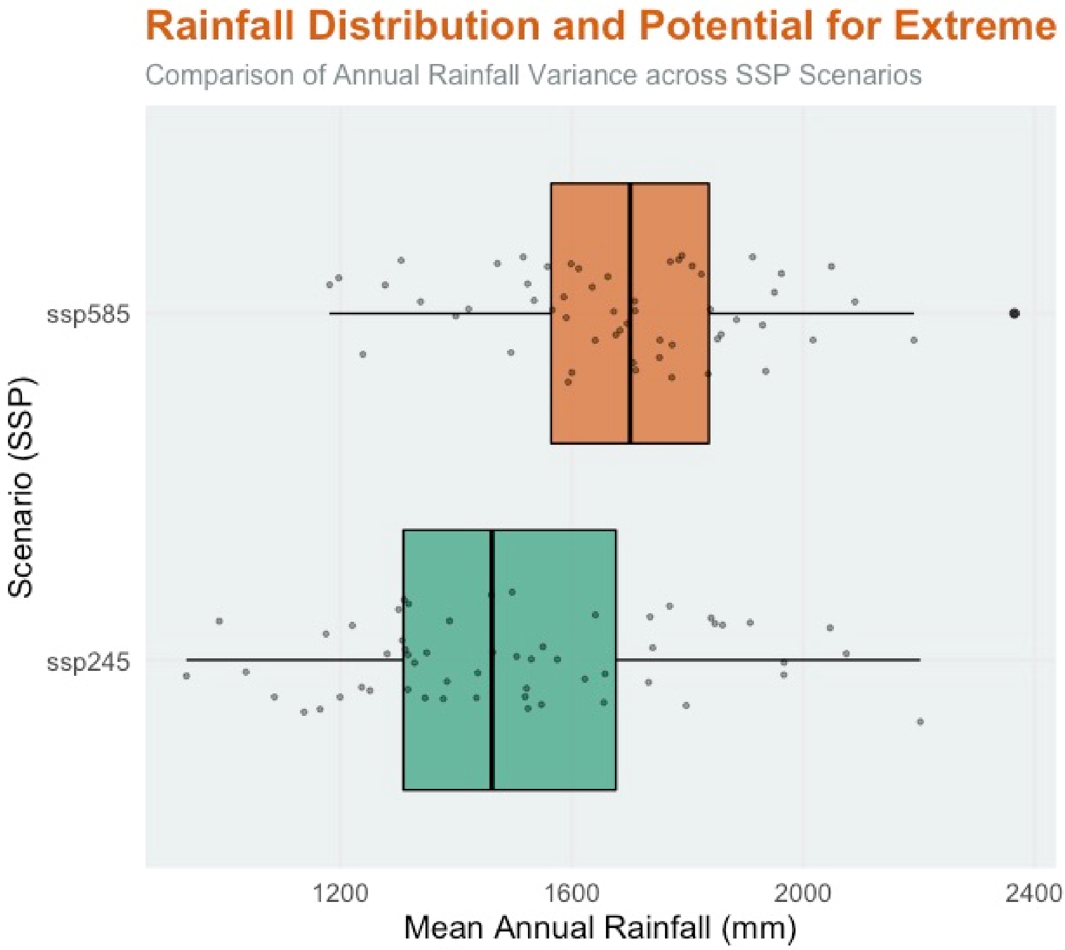

Figure 21. Long-term trend in mean annual rainfall for SSP2 and SSP5 pathways.

To be very concise, the projections suggest that while Kolkata may only see a small increase in its long-term average annual rainfall, the greater concern lies in the intensification of the hydrological cycle.

7. Discussion: Climate Resilience through Democratized Climate Literacy

The central purpose of this study was to move climate discourse beyond the domain of highly specialized science and into the civic arena, empowering the general populace to become informed agents of change. In the first part of the study, the results strongly validate the efficacy of this approach by establishing a direct, undeniable link between complex geospatial data and localized, lived experiences. In the later parts, the study assumes that the user would be genuinely interested to explore the climate futures of an area of interest and assisted by the proposed GAI-driven framework (Figure 1), would be able to start playing around with data and different forms of analysis and interpretations. Practically, this body of work hands out a do-it-yourself playbook for citizens to become climate literate, taking a step towards climate action.

7.1. Reaffirming the Framework for Citizen-Driven Inquiry

The methodology unequivocally confirms that complex climate data can be accessed and rigorously analysed using readily available GAI to synthesize code for Google Earth Engine (GEE) and R. This framework successfully transforms the core barrier to climate literacy—the need for specialized programming proficiency, as illustrated in Table 1. By shifting the intellectual burden from writing low-level code to mastering critical prompt engineering and analysis verification, the framework empowers non-experts, especially youth and young professionals, to interrogate and probe public domain data. This ability to self-verify trends (such as the warming trends or the extreme rainfall probabilities) or challenge local policy narratives using empirical evidence, is fundamental to establishing a powerful, bottom-up demand for accountability in climate governance, leading to effective and efficient climate action.

At this point, it is also necessary to underscore the fact that climate science is complex and there are embedded uncertainties associated with different processes of analysis, which one tends to understand as one starts practising and gaining more and more practical knowledge. However, it is essential to begin one's journey in climate science research, analysis and communication and it is only that far that the proposed framework can take an applicant. If the applicant is persistent with their interest and inquisition for knowledge, the applicant will realize that the framework is just the first stepping stone towards a vast ocean of knowledge and work. The limited usability in terms of complexity and uncertainty of climate science but powerful influencing capacity has been captured in Figure 22.

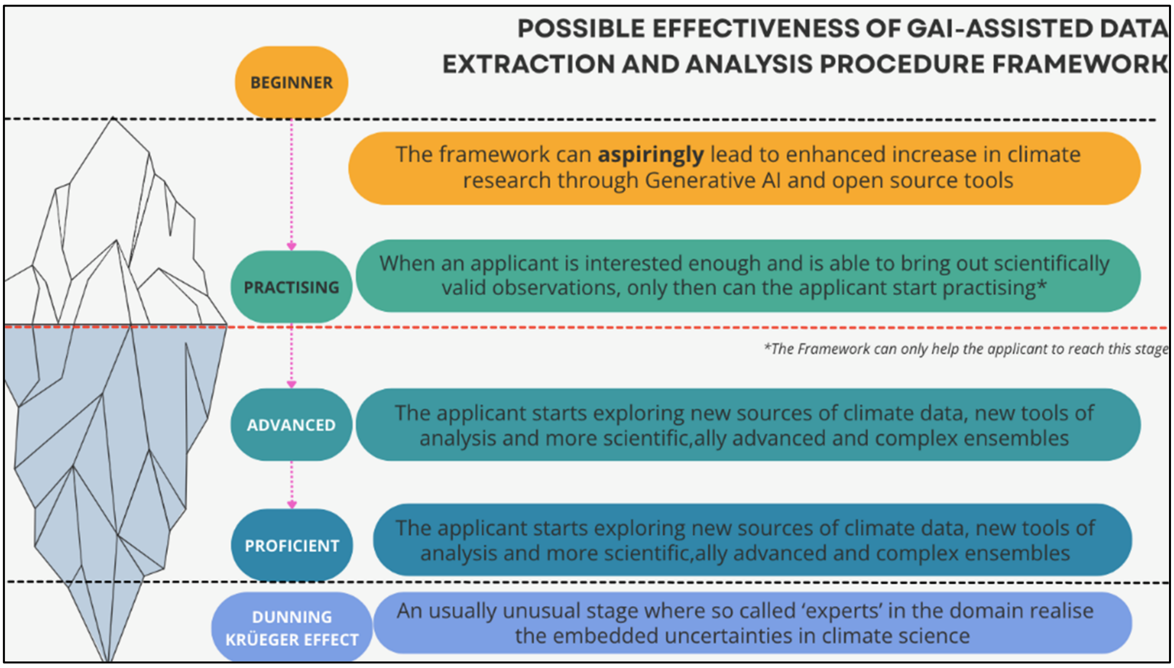

Figure 22. Possible effectiveness of the proposed framework.

7.2. Science Communication as a Tool for Transformative Governance

The clarity obtained by correlating historical climate data with lived experiences is not merely an academic exercise, rather it is a necessity for achieving adaptive and transformative governance. When scientific findings—such as the decline in Diurnal Temperature Range (DTR) and the dramatic 3.39 °C night-time Urban Heat Island Intensity (UHII)—are successfully translated into understandable public discomfort, say the "nights are now warmer", either the political mandate or the community consensus or the individual urge for structural reform strengthens. Similarly, the data-driven interpretation of flood risk, which demonstrates a stable total rainfall volume but an increasing intensity (Figures 12 and 13), refocuses public discourse away from abstract climate variability toward concrete, addressable urban drainage and Land Use/Land Cover (LULC) policy failures. This attractive and lucid visualization of science must be aggressively fostered to shift the city's posture from reactive disaster relief toward proactive, long-term Disaster Risk Reduction (DRR) and climate action.

7.3. Driving Anticipatory Action and Key Recommendations

The analysis of future projections (Section 6) serves two vital purposes. First, to arouse the spirit of inquiry, particularly amongst the youth and key decision-makers, emphasizing the urgency of anticipatory action. The projected exponential temperature and specific humidity increases (Figures 18 and 19) and the 55.8% predicted probability of being marked for late-monsoon months like August extreme rainfall event by 2030 (Figure 14) provide quantifiable foresight of severe risks that cannot be ignored.

Second, this body of work, through the evidences and foresights generated can serve out some recommendations. For example, the strengthening nocturnal UHII and the projected Wet-Bulb Temperature (WBT) risk necessitate moving beyond incremental actions (like water kiosks) toward transformational interventions. This includes mandating climate intelligent and energy efficient building codes and adopting widespread passive cooling infrastructure. Secondly, the LULC analysis confirming urban expansion at 19.02 km^2/year and the resulting LST increase must immediately inform policy that protects and expands blue-green and even grey assets. These are vital for cooling and crucial for managing the forecasted increase in high-intensity precipitation events, leading to major flood events. Thirdly, authorities must foster interdisciplinary collaboration and standardize data structures to integrate climate forecasts with public health surveillance, ensuring equitable, data-driven preparedness and response—this is too optimistic to be achieved in the near or even mid-term future.

7.4. Methodological Limitations and Framework Boundaries

While the introduced framework successfully democratizes access to complex climate data, it is important to acknowledge its inherent limitations. First, the future climate analysis relies on a single GCM (CanESM5) to maintain a simplified, user-friendly workflow for non-experts. While this serves as an effective illustrative pathway, it does not capture the full range of uncertainty provided by multi-model ensembles, which are required for robust policy definition. Second, the statistical analyses presented are primarily associative; while they identify significant trends and correlations between urban growth and temperature rise, they do not account for all complex, non-linear atmospheric feedback mechanisms. Finally, the GAI component is strictly a facilitative tool for code generation; the accuracy of the output remains dependent on the user's ability to perform manual verification and scientific audit of the synthesized scripts to mitigate potential AI hallucinations. The framework is intended as a foundational stepping stone for climate literacy rather than a replacement for high-level specialized modeling.

8. Conclusions and Way Forward

This study successfully established the efficacy and utility of the GAI-driven framework, demonstrating a practical and low-barrier pathway for non-experts to access and analyse complex geospatial climate data. By leveraging freely available GEE and R environments, mediated by LLM-generated code, the framework successfully democratizes the means of climate inquiry, validating the central hypothesis of this paper—can climate literacy be made interest-driven rather than leaving it at skill-driven discipline?

Effective **science communication** is made easier through this framework because it mandates the translation of dense technical data (e.g., LST, UHII, specific humidity) into relatable, visualized, citizen-centric narratives validated by local lived experience (Figures 6 and 12). This shift from abstract numbers to local relevance is the essential bridge that creates public ownership and promotes sustained engagement.

This effective communication directly leads to **better risk governance, preparedness and anticipatory action**. By arming the public and young professionals with verifiable, local evidence of rising nocturnal heat and accelerating extreme flood risk, the framework creates the civic mandate necessary to pressure policymakers toward long-term, structural interventions rather than maintaining the status quo of relief-oriented disaster management [22].

Finally, since the underlying framework relies exclusively on freely available platforms (GEE, R) and replicable GAI codes that can be easily modified by non-experts, this work is inherently highly scalable and replicable. This model can be immediately applied to other vulnerable urban centers across the Global South that face similar institutional and knowledge capacity deficits, enabling a wider movement toward community-informed climate resilience.

Supplementary Materials

The additional data and information can be downloaded at: https://media.sciltp.com/articles/others/2601161351336963/JHRR-25110076-Supplementary-Materials.pdf.

Author Contributions

R.K.: conceived the idea and developed it; S.S.: assisted in ensuring that the language of the paper and the visualisations are understandable to youth and interested readers. Both authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study utilized publicly available data and therefore did not require ethical review or consent.

Informed Consent Statement

Not applicable.

Data Availability Statement

All the data used and analyzed in this study are publicly available. Specific links to datasets would be provided on request.

Conflicts of Interest

The authors have no relevant financial or non-financial interests to disclose. The authors have no conflicts of interest to declare that are relevant to the content of this article. Both authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

Use of AI and AI-Assisted Technologies

In this work, the authors used Google Gemini to generate the code and scripts for extracting climate data from Google Earth Engine and for performing analysis and developing visualizations in RStudio. This methodology was subsequently developed into a framework upon which this study is based. The authors have reviewed and edited the framework as needed and take full responsibility for the analysis and visualizations in this article. No AI or AI-assisted technologies were used to generate the written content.

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