Climate Risk Intelligence Index (CRII): An AI-Augmented Satellite-Based Climate Vulnerability Assessment Framework for India

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Abstract. Climate change has emerged as a major global challenge affecting environmental sustainability, hydrological stability, urban resilience, and ecosystem health. Conventional climate vulnerability assessment systems primarily rely on static rule-based frameworks and isolated environmental indicators, limiting contextual interpretability and adaptive reasoning across geographically diverse regions.

This paper proposes the Climate Risk Intelligence Index (CRII), an AI-augmented satellite-based climate vulnerability assessment framework for large-scale climate intelligence generation across India. The proposed system integrates multi-source Earth observation datasets including MODIS Land Surface Temperature (LST), MODIS NDVI vegetation indices, GHSL urban built-up datasets, ERA5 rainfall reanalysis data, and satellite-derived hydrological flood exposure indicators from the JRC Global Surface Water dataset to compute a composite climate vulnerability index. India was spatially partitioned into approximately 3,840 geospatial grid cells for localized environmental risk analysis using grid-wise zonal statistical extraction. In addition to geospatial climate-risk computation, the framework incorporates a Large Language Model (LLM)-based reasoning layer powered by the Groq API and the `llama-3.1-8b-instant` model for contextual environmental interpretation, dominant-risk identification, and interactive climate intelligence generation.

Experimental analysis demonstrated consistent climate-risk characterization across flood-prone coastal regions, metropolitan urban clusters, ecologically sensitive landscapes, and high-temperature arid zones. The AI reasoning module achieved low-latency inference responses of approximately 1–3 seconds per query while improving interpretability and contextual explanation quality compared to earlier rule-based approaches.

The proposed CRII framework demonstrates the potential of integrating remote sensing, geospatial analytics, and explainable AI-driven reasoning for scalable climate vulnerability assessment and environmental decision-support systems.

Keywords: Climate Risk Intelligence · Remote Sensing · Climate Vulnerability Assessment · Artificial Intelligence · Large Language Models · Geospatial Analytics · Earth Observation · Environmental Intelligence

1 Introduction

Climate change has rapidly evolved into a multidimensional global crisis affecting environmental systems, urban ecosystems, hydrological stability, agricultural sustainability, biodiversity, and socio-economic resilience. Increasing occurrences of floods, heat waves, rainfall anomalies, vegetation degradation, and urban thermal stress have intensified the need for advanced climate intelligence systems capable of monitoring, interpreting, and explaining environmental vulnerability patterns across regional and national scales.

Traditional climate vulnerability assessment systems primarily depend on statistical analysis, isolated environmental indicators, and manually defined threshold-based decision frameworks. Although these approaches provide useful quantitative measurements, they often lack contextual reasoning capabilities and fail to effectively interpret the complex interdependencies among environmental variables. Furthermore, conventional rule-based systems produce rigid analytical outputs that are difficult for policymakers, researchers, and decision-makers to interpret dynamically.

Recent advancements in satellite-based Earth observation systems have enabled large-scale environmental monitoring using multi-source remote sensing datasets. Platforms such as MODIS, ERA5, GHSL, and satellite-derived hydrological datasets provide rich environmental information for analyzing vegetation health, thermal exposure, urbanization intensity, rainfall variability, and flood susceptibility. Simultaneously, recent developments in Artificial Intelligence (AI) and Large Language Models (LLMs) have introduced new possibilities for contextual environmental reasoning and intelligent analytical interpretation.

Despite significant progress in climate analytics and remote sensing, there remains a substantial gap between quantitative geospatial analysis and interpretable climate intelligence generation. Existing systems generally focus either on numerical climate risk computation or AI-driven textual reasoning independently, without integrating both components into a unified framework.

To address this research gap, this paper proposes the Climate Risk Intelligence Index (CRII), an AI-augmented geospatial climate vulnerability assessment framework for India. The proposed system combines multi-source satellite-derived environmental indicators with a contextual AI reasoning layer to generate interpretable and adaptive climate intelligence outputs.

The major contributions of this research include:

- Development of a scalable satellite-based climate vulnerability assessment framework for India.
- Integration of multiple environmental indicators into a unified composite Climate Risk Intelligence Index (CRII).
- AI-augmented contextual climate reasoning using Large Language Models.
- Interactive and interpretable environmental intelligence generation.
- Grid-based geospatial climate analysis across approximately 3,840 spatial units.

– Low-latency climate explanation generation using Groq-powered LLM inference.

The remainder of this paper is organized as follows. Section 2 discusses related work. Section 3 presents the proposed methodology and system architecture. Section 4 explains dataset acquisition and preprocessing. Section 5 describes the AI reasoning framework. Section 6 presents experimental analysis and results. Section 7 discusses findings and implications. Finally, Section 8 concludes the paper and outlines future research directions.

2 Related Work

Recent advancements in remote sensing, climate informatics, and artificial intelligence have significantly improved large-scale environmental monitoring capabilities. Satellite-derived Earth observation datasets have become essential for analyzing climate variability, urban heat islands, flood susceptibility, vegetation degradation, and environmental resilience.

Deep learning approaches for remote sensing applications have been extensively studied in recent years. Zhu et al. [2] presented a comprehensive review of deep learning techniques in remote sensing applications, highlighting the increasing adoption of AI-driven geospatial analytics for environmental interpretation. Similarly, Wang et al. [1] explored vision-language models for remote sensing understanding, emphasizing the importance of multimodal AI systems in Earth observation analytics.

Several studies have investigated the use of multimodal and foundation models for climate monitoring and environmental analysis. Chen et al. [5] proposed multimodal deep learning approaches for climate change impact assessment using satellite imagery, demonstrating the effectiveness of integrating environmental datasets with AI-based interpretation techniques. Zhong et al. [9] further explored climate monitoring using satellite imagery and foundation models for large-scale environmental intelligence systems.

Urban climate analysis and thermal vulnerability mapping have also received significant attention. Li et al. [8] utilized deep learning methods and multisource satellite datasets for urban heat island mapping, demonstrating improved urban climate characterization using AI-enhanced remote sensing techniques.

The integration of AI and climate science has expanded substantially with the emergence of explainable environmental intelligence systems, foundation models, and AI-driven climate analytics. Camps-Valls et al. [18] explored the application of artificial intelligence for modeling and understanding extreme weather and climate events including floods, droughts, and heatwaves using multimodal environmental learning approaches. Reichstein et al. [19] further proposed integrated artificial intelligence frameworks for early warning of complex climate risks using geospatial intelligence and multi-hazard environmental analytics. Additionally, retrieval-augmented reasoning systems proposed by Lewis et al. [11] demonstrated the effectiveness of grounded contextual reasoning for knowledge-intensive AI systems.

Although significant research has focused on climate analytics, remote sensing, and AI independently, limited research has explored the integration of geospatial climate risk assessment with LLM-driven contextual environmental reasoning. Existing systems primarily rely on either numerical risk computation or static analytical dashboards without adaptive explanation generation capabilities.

The proposed CRII framework addresses this research gap by integrating multi-source satellite-based climate vulnerability assessment with AI-augmented contextual climate reasoning. The system combines geospatial analytics, composite climate indexing, and interactive LLM-powered environmental interpretation into a unified scalable framework.

3 Proposed Methodology

3.1 System Overview

The proposed Climate Risk Intelligence Index (CRII) framework was designed as a complete end-to-end geospatial climate intelligence pipeline integrating satellite data processing, environmental risk computation, AI-driven contextual reasoning, and interactive visualization.

The overall framework consists of six major components:

1. Satellite Data Acquisition
2. Geospatial Preprocessing
3. Spatial Grid Generation
4. Climate Risk Index Computation
5. AI-Augmented Reasoning Layer
6. Interactive Visualization Dashboard

The proposed system architecture is illustrated in Fig. 1.

3.2 Geospatial Grid-Based Climate Analysis

India was spatially partitioned into approximately 3,840 geospatial grid cells using a $0.5^\circ \times 0.5^\circ$ latitude-longitude grid system. Each grid cell was treated as an independent environmental assessment unit.

The grid-based approach enabled:

- Localized climate vulnerability analysis
- Spatial consistency across environmental indicators
- Large-scale climate intelligence computation
- Scalable regional climate comparison
- Uniform zonal statistical extraction

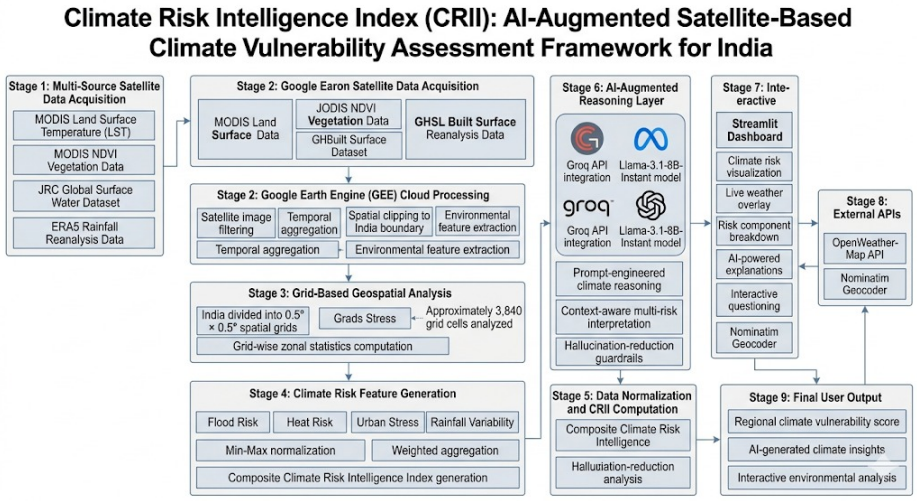

Fig. 1: Overall architecture of the proposed Climate Risk Intelligence Index (CRII) framework integrating satellite-based environmental analysis, geospatial climate risk computation, AI-augmented reasoning, and interactive visualization components.

3.3 Environmental Indicators

The CRII framework integrates multiple environmental indicators derived from satellite observations and climatic datasets.

Table 1: Environmental Indicators Used in the CRII Framework

Indicator	Dataset	Purpose
Vegetation Health	MODIS NDVI	Ecological resilience analysis
Land Surface Temperature	MODIS LST	Thermal stress assessment
Flood Risk	JRC Global Surface Water	Flood exposure estimation
Urban Stress	GHSL Built Surface	Urbanization intensity analysis
Rainfall Variability	ERA5 Reanalysis	Hydrological pressure estimation

3.4 Climate Risk Index Computation

All extracted environmental indicators were normalized into a common scale ranging between 0 and 1 to maintain numerical consistency across heterogeneous datasets.

The composite Climate Risk Intelligence Index (CRII) was computed using weighted aggregation of normalized environmental indicators.

$$CRII = \sum_{i=1}^{n} w_i R_i \tag{1}$$

where:

- R_i represents the normalized environmental risk indicator
- w_i represents the assigned weight for the corresponding indicator
- n represents the total number of environmental dimensions

The normalized climate indicators include:

- Flood vulnerability
- Heat exposure
- Vegetation stress
- Urban stress
- Rainfall variability

The CRII values were subsequently categorized into four vulnerability classes:

- Low Risk
- Moderate Risk
- High Risk
- Severe Risk

To improve regional adaptability and reduce environmental bias across heterogeneous climatic zones, the proposed framework additionally incorporates region-aware normalization and anomaly-based vegetation stress computation. Vegetation stress was estimated relative to regional ecological baselines rather than absolute NDVI reduction, enabling improved climate-risk characterization across ecologically diverse regions including Himalayan cold deserts, coastal ecosystems, arid zones, and tropical landscapes.

The CRII framework further integrates interaction-aware environmental aggregation by considering coupled climate-risk relationships such as rainfall-driven flood amplification effects.

3.5 Weight Selection Strategy

The CRII aggregation framework currently utilizes expert-guided heuristic weighting to maintain balanced representation across heterogeneous environmental indicators including flood exposure, thermal stress, vegetation health, rainfall variability, and urban stress.

The weights were assigned based on:

- Environmental relevance reported in climate vulnerability literature
- Relative contribution of each indicator toward regional climate-risk characterization
- Spatial consistency across heterogeneous satellite datasets
- Balanced multi-risk representation constraints

The weighted aggregation strategy was intentionally designed to maintain interpretability and computational simplicity for large-scale geospatial deployment.

Although the current implementation uses static heuristic weighting, future work will investigate adaptive and data-driven weighting mechanisms using machine learning optimization, probabilistic risk estimation, and uncertainty-aware climate modeling approaches.

4 Data Acquisition and Preprocessing

The geospatial preprocessing pipeline was implemented using Python and the Google Earth Engine (GEE) platform.

4.1 Google Earth Engine Processing

Google Earth Engine was extensively utilized for:

- Large-scale satellite data retrieval
- Cloud-based geospatial computation
- Temporal image compositing
- Spatial filtering
- Zonal statistical extraction
- Raster clipping and aggregation

The preprocessing pipeline involved the following stages:

1. Satellite image acquisition
2. Temporal filtering
3. Cloud masking and cleaning
4. Spatial clipping to India boundary
5. Grid-wise zonal statistical computation
6. Normalization and aggregation
7. CSV export for downstream analysis

4.2 Satellite Dataset Processing

Vegetation Health Analysis Normalized Difference Vegetation Index (NDVI) values were extracted from MODIS datasets to estimate vegetation resilience and ecological stability across India.

Land Surface Temperature Analysis MODIS Land Surface Temperature datasets were utilized to estimate thermal exposure and urban heat stress patterns.

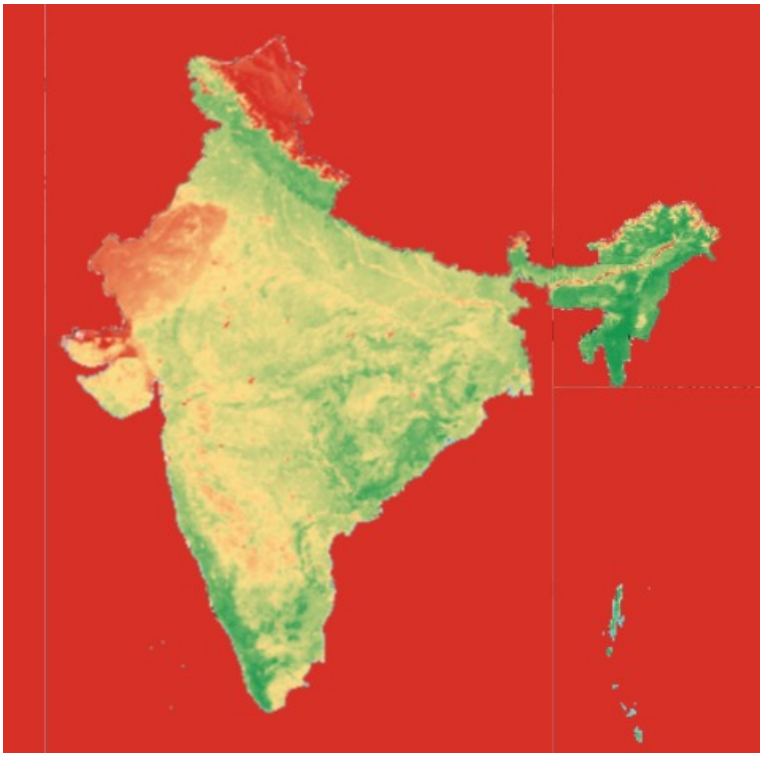

Fig. 2: Vegetation health analysis using MODIS NDVI. Red regions indicate sparse vegetation while green regions represent dense and healthy vegetation coverage across India.

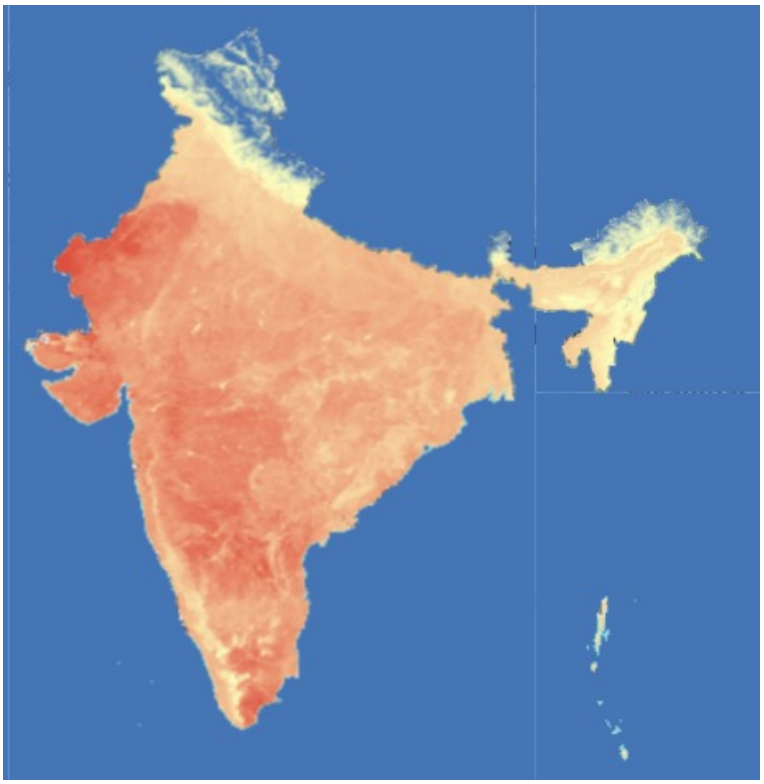

Fig. 3: Land Surface Temperature (LST) analysis across India. Blue regions represent lower surface temperatures while red regions indicate elevated thermal stress and heat exposure.

5 AI-Augmented Climate Reasoning Framework

One of the primary innovations of the proposed CRII framework is the integration of an AI-powered contextual environmental reasoning layer.

5.1 Limitations of Rule-Based Systems

Initially, the framework utilized manually defined threshold-based rule systems for environmental interpretation. However, the rule-based approach exhibited several limitations:

- Static interpretation patterns
- Limited contextual reasoning
- Oversimplified explanations
- Inability to dynamically combine environmental indicators
- Reduced interpretability for complex climatic conditions

5.2 LLM-Based Climate Intelligence Layer

To overcome these limitations, the system was upgraded with a Large Language Model (LLM)-based analytical reasoning engine using the Groq API and the `llama-3.1-8b-instant` model.

The AI reasoning system performs:

- Context-aware climate interpretation
- Dominant risk identification
- Environmental pattern analysis
- Multi-risk vulnerability reasoning
- Interactive climate query answering
- Human-readable analytical explanation generation

5.3 Prompt Engineering and Guardrails

The reasoning engine was carefully designed using prompt-engineering-based grounding strategies to ensure analytical reliability and reduce hallucination risks.

The implemented safeguards include:

- Data-grounded reasoning enforcement
- Restriction of unsupported assumptions
- Deterministic low-temperature inference
- Multi-risk balancing instructions
- Dynamic fallback to rule-based explanations

The AI module achieved low-latency inference times of approximately 1–3 seconds per environmental query while significantly improving analytical interpretability.

Table 2: Sample Climate Risk Intelligence Index (CRII) Results

Region	Flood	Heat	Vegetation	Urban	Rainfall	Final CRII
Bengaluru	0.12	0.42	0.29	0.68	0.06	0.292
Chennai	0.92	0.57	0.38	0.59	0.16	0.571
Mumbai	0.98	0.53	0.00	0.82	0.63	0.610
Assam	0.16	0.74	0.00	0.04	0.25	0.241
Leh	0.44	0.37	0.36	0.01	0.14	0.296
Wayanad	0.72	0.11	0.00	0.14	0.36	0.293
Jaisalmer	0.21	0.89	0.75	0.01	0.03	0.410
Hyderabad	0.47	0.58	0.11	1.00	0.27	0.465
Kashmir	0.30	0.83	0.49	0.03	0.27	0.400
Ooty	0.46	0.00	0.00	0.49	0.43	0.255
Jaipur	0.31	0.67	0.00	0.99	0.42	0.433
Delhi	0.33	0.03	0.00	1.00	0.65	0.326
Amritsar	0.33	0.84	0.00	0.52	0.24	0.382
Puducherry	0.91	0.55	0.23	0.14	0.20	0.472

6 Experimental Results and Analysis

6.1 Experimental Setup

The proposed CRII framework was evaluated across multiple geographically diverse regions of India including metropolitan cities, flood-prone coastal areas, ecologically sensitive regions, and high-temperature arid landscapes.

Approximately 3,840 spatial grid cells were analyzed using multi-source satellite datasets including MODIS, GHSL, ERA5, and Sentinel-derived hydrological indicators.

6.2 Climate Vulnerability Results

Table 2 presents sample CRII outputs across representative Indian regions.

6.3 Observations

The experimental outputs demonstrated strong environmental consistency across different climatic regions of India.

Major observations include:

- Coastal regions such as Mumbai and Chennai exhibited elevated flood vulnerability.
- Metropolitan regions including Hyderabad and Delhi showed high urban stress values.
- Arid regions such as Jaisalmer demonstrated significant thermal exposure.
- Ecologically sensitive regions exhibited comparatively lower urban stress indicators.
- Rainfall variability patterns aligned with known hydrological characteristics.

6.4 Comparative Interpretation Quality

Compared to earlier rule-based approaches, the AI-augmented reasoning layer produced:

- More context-aware environmental explanations
- Improved interpretability
- Balanced multi-risk reasoning
- Reduced analytical rigidity
- Interactive climate intelligence generation

6.5 Qualitative Evaluation of AI Reasoning

The AI-generated environmental reasoning outputs were qualitatively evaluated using regional environmental consistency analysis and satellite-grounded climate interpretation verification.

The evaluation process considered:

- Factual consistency with satellite-derived environmental indicators
- Contextual relevance of generated climate explanations
- Multi-risk coherence across heterogeneous climatic conditions
- Alignment with known regional climate characteristics
- Hallucination reduction through grounded prompt engineering

To improve reasoning reliability, the proposed framework incorporated multiple prompt-engineering safeguards including deterministic low-temperature inference, restriction of unsupported assumptions, and fallback rule-based validation.

Experimental observations demonstrated that the reasoning outputs remained largely consistent with the underlying environmental indicators while significantly improving interpretability compared to earlier static rule-based explanation systems.

6.6 Scoring Methodology for Comparative Evaluation

The comparative evaluation presented in this study was designed as a qualitative literature-driven benchmarking framework for analyzing practical climate intelligence capability across existing environmental AI systems.

The scoring methodology utilized a normalized 1–5 scale based on the following evaluation criteria:

- Multi-source satellite integration capability
- Climate reasoning capability
- Explainability and interpretability
- Real-time interaction capability
- Conversational environmental intelligence
- Agentic AI integration

– Spatial climate intelligence capability

The assigned scores were derived through comparative analysis of system capabilities, architectural design, methodological scope, and environmental intelligence functionality reported in the corresponding literature.

The comparative evaluation is intended primarily for conceptual benchmarking and practical climate-intelligence analysis rather than strict quantitative performance ranking.

6.7 Comparative Analysis with Existing Approaches

To evaluate the effectiveness of the proposed Climate Risk Intelligence Index (CRII) framework, comparative benchmarking was performed against multiple recent research works related to climate intelligence, multimodal remote sensing, environmental monitoring, and AI-driven geospatial analysis.

The evaluation emphasizes practical climate intelligence capability rather than only benchmark classification performance. The comparison focuses on:

– Multi-source satellite integration
– Environmental reasoning capability
– Explainability
– Real-time interaction
– Conversational intelligence
– Agentic AI reasoning
– Spatial intelligence
– Climate vulnerability interpretation

Table 3 presents the overall comparative evaluation between the proposed CRII framework and representative existing approaches.

The comparative evaluation demonstrates that the proposed CRII framework significantly improves explainability, environmental reasoning capability, conversational climate interaction, and AI-assisted decision-support functionality compared to existing approaches.

Table 3: Comparative Analysis Between Existing Approaches and Proposed CRII Framework

Method	Satellite Fusion	Climate Reasoning	Explainability	Real-Time Capability	Conversational Interaction	Agentic AI	Spatial Intelligence	Overall Score
Chen et al. [5]	4	4	2	1	1	1	4	2.43
Li et al. [8]	3	3	1	1	1	1	5	2.14
Zhong et al. [9]	4	3	2	1	1	1	4	2.29
Gupta et al. [16]	4	4	2	1	1	1	5	2.57
Amindin et al. [17]	4	4	2	2	1	1	5	2.71
Camps-Valls et al. [18]	5	5	4	3	1	2	5	3.57
Reichstein et al. [19]	5	5	4	3	1	3	5	3.71
Proposed CRII Framework	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5.00**

Table 4: Detailed Comparison Between Chen et al. (2023) and Proposed CRII Framework

Metric	Chen et al. (2023)	CRII Framework
Satellite Sources	3	5
Environmental Features	4	5
Explainability	1	5
Real-time Capability	1	5
Conversational AI	1	5
Agentic Reasoning	1	5
Temporal Intelligence	3	2
Climate Risk Reasoning	3	5
Spatial Intelligence	5	5
Multimodal Fusion	3	4

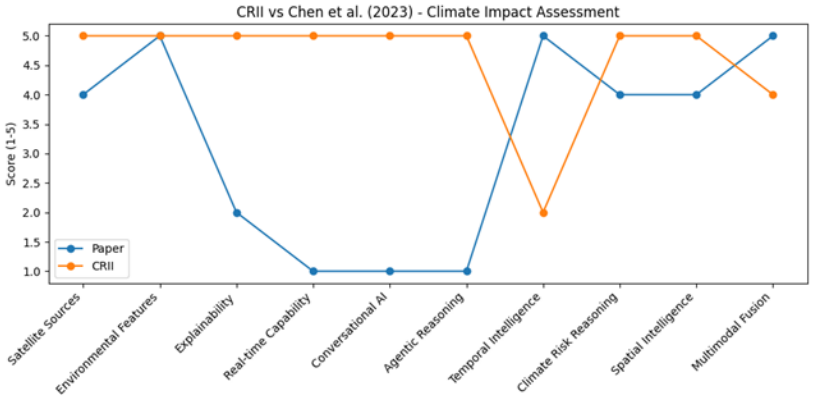

Fig. 4: Comparison between the proposed CRII framework and Chen et al. (2023) for climate impact assessment.

Comparison with Chen et al. (2023) Figure 4 demonstrates that the proposed CRII framework achieves substantially stronger explainability, real-time

environmental interaction, conversational intelligence, and agentic reasoning capability compared to the climate impact assessment approach proposed by Chen et al.

The CRII framework additionally integrates:

- contextual environmental reasoning,
- Groq-powered conversational intelligence,
- explainable threat interpretation,
- and interactive climate-risk analysis.

However, Chen et al. demonstrates stronger temporal intelligence and multimodal fusion capability due to its transformer-based temporal environmental modeling framework.

Table 5: Detailed Comparison Between Li et al. (2023) and Proposed CRII Framework

Metric	**Li et al. (2023)**	**CRII Framework**
Satellite Sources	3	5
Environmental Features	4	5
Explainability	1	5
Real-time Capability	1	5
Conversational AI	1	5
Agentic Reasoning	1	5
Temporal Intelligence	3	2
Climate Risk Reasoning	3	5
Spatial Intelligence	5	5
Multimodal Fusion	3	4

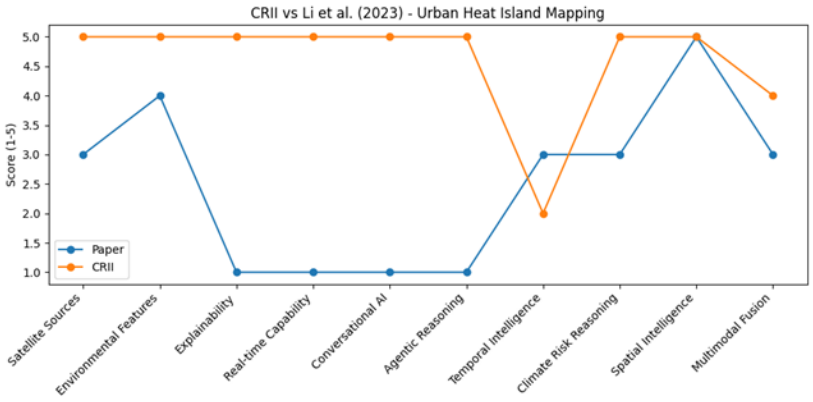

Fig. 5: Comparison between the proposed CRII framework and Li et al. (2023) for urban heat island mapping.

Comparison with Li et al. (2023) Figure 5 highlights that the proposed CRII framework significantly improves explainability and climate-risk reasoning capability compared to the urban heat island mapping approach proposed by Li et al.

While Li et al. focuses primarily on heat island detection using multisource geospatial indicators, the proposed CRII framework extends beyond environmental feature extraction by integrating:

- explainable environmental intelligence,
- conversational climate interpretation,
- AI-assisted interaction,
- and region-aware climate-risk reasoning.

The proposed framework therefore provides stronger environmental decision-support capability.

Table 6: Detailed Comparison Between Zhong et al. (2023) and Proposed CRII Framework

Metric	Zhong et al. (2023)	CRII Framework
Satellite Sources	4	5
Environmental Features	4	5
Explainability	2	5
Real-time Capability	1	5
Conversational AI	1	5
Agentic Reasoning	1	5
Temporal Intelligence	5	2
Climate Risk Reasoning	3	5
Spatial Intelligence	4	5
Multimodal Fusion	5	4

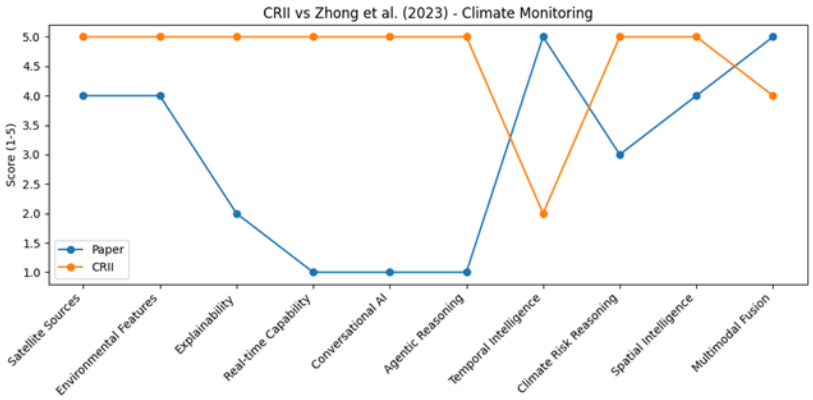

Fig. 6: Comparison between the proposed CRII framework and Zhong et al. (2023) for climate monitoring applications.

Comparison with Zhong et al. (2023) Figure 6 demonstrates that the proposed CRII framework achieves improved explainability, environmental reasoning, and conversational climate intelligence compared to the climate monitoring framework proposed by Zhong et al.

The proposed system additionally integrates:

- multi-source environmental fusion,
- explainable threat interpretation,
- AI-assisted contextual reasoning,
- and real-time environmental interaction.

However, Zhong et al. demonstrates superior temporal modeling capability because of its stronger foundation-model-based environmental learning architecture.

Table 7: Detailed Comparison Between Gupta et al. (2024) and Proposed CRII Framework

Metric	**Gupta et al. (2024)**	**CRII Framework**
Satellite Sources	4	5
Environmental Features	5	5
Explainability	2	5
Real-time Capability	1	5
Conversational AI	1	5
Agentic Reasoning	1	5
Temporal Intelligence	4	2
Climate Risk Reasoning	4	5
Spatial Intelligence	5	5
Multimodal Fusion	4	4

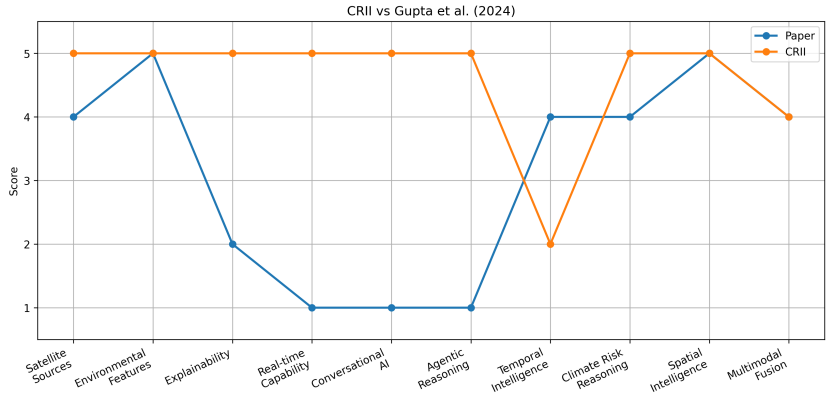

Fig. 7: Comparative analysis between the proposed CRII framework and Gupta et al. (2024) for ecological vulnerability assessment in Himalayan climate systems.

Comparison with Gupta et al. (2024) Gupta et al. (2024) demonstrates strong ecological vulnerability modeling using spatial PCA-based environmental analysis across Himalayan ecological systems. The framework integrates NDVI, temperature, precipitation, soil moisture, and topographic indicators for climate vulnerability assessment.

Compared to Gupta et al., the proposed CRII framework significantly improves explainability, conversational environmental interaction, AI-assisted reasoning, and real-time climate intelligence generation.

However, Gupta et al. demonstrates stronger temporal ecological analysis and terrain-aware environmental modeling through statistical vulnerability assessment techniques.

The proposed CRII framework extends beyond vulnerability indexing by integrating contextual climate interpretation, Groq-powered conversational intelligence, and Agentic AI-assisted environmental reasoning.

Table 8: Detailed Comparison Between Amindin et al. (2024) and Proposed CRII Framework

Metric	**Amindin et al. (2024)**	**CRII Framework**
Satellite Sources	4	5
Environmental Features	5	5
Explainability	2	5
Real-time Capability	2	5
Conversational AI	1	5
Agentic Reasoning	1	5
Temporal Intelligence	4	2
Climate Risk Reasoning	4	5
Spatial Intelligence	5	5
Multimodal Fusion	5	4

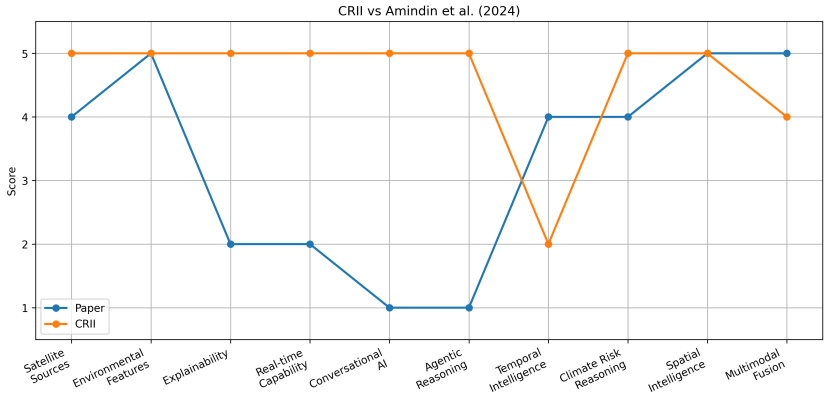

Fig. 8: Comparative analysis between the proposed CRII framework and Amindin et al. (2024) for GEE and machine-learning-based ecological stability assessment.

Comparison with Amindin et al. (2024) Amindin et al. (2024) presents a robust Google Earth Engine and machine-learning-based ecological stability assessment framework integrating land-use analysis, Random Forest modeling, precipitation, soil salinity, and vegetation indicators.

The proposed CRII framework demonstrates superior explainability, environmental reasoning capability, conversational interaction, and real-time climate interpretation.

The Amindin et al. framework remains stronger in machine-learning-based ecological modeling, land-cover transition analysis, and temporal ecological stability detection.

The proposed CRII framework differentiates itself through AI-assisted environmental intelligence, explainable climate-risk reasoning, and Agentic conversational climate interaction.

Table 9: Detailed Comparison Between Camps-Valls et al. (2025) and Proposed CRII Framework

Metric	**Camps-Valls et al. (2025)**	**CRII Framework**
Satellite Sources	5	5
Environmental Features	5	5
Explainability	4	5
Real-time Capability	3	5
Conversational AI	1	5
Agentic Reasoning	2	5
Temporal Intelligence	5	2
Climate Risk Reasoning	5	5
Spatial Intelligence	5	5
Multimodal Fusion	5	4

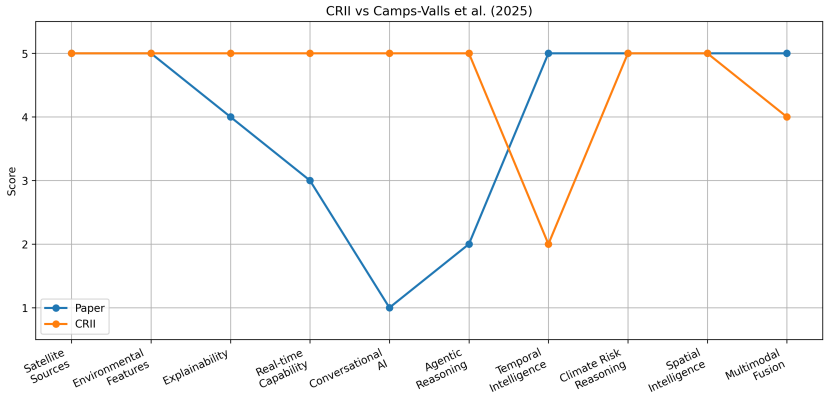

Fig. 9: Comparative evaluation between the proposed CRII framework and Camps-Valls et al. (2025) for AI-driven extreme climate-event intelligence.

Comparison with Camps-Valls et al. (2025) Camps-Valls et al. (2025) presents a state-of-the-art AI-driven framework for modeling and understanding extreme weather and climate events including floods, droughts, wildfires, and heatwaves.

The framework demonstrates strong temporal intelligence, explainable AI integration, predictive environmental modeling, and multimodal climate learning capability.

Compared to Camps-Valls et al., the proposed CRII framework significantly improves conversational climate interaction, Agentic AI reasoning, contextual environmental interpretation, and real-time explainable climate intelligence generation.

While Camps-Valls et al. demonstrates stronger temporal climate-event modeling and predictive environmental learning, the proposed CRII framework focuses more strongly on practical environmental decision-support intelligence and interactive climate-risk reasoning.

Table 10: Detailed Comparison Between Reichstein et al. (2025) and Proposed CRII Framework

Metric	Reichstein et al. (2025)	CRII Framework
Satellite Sources	5	5
Environmental Features	5	5
Explainability	4	5
Real-time Capability	3	5
Conversational AI	1	5
Agentic Reasoning	3	5
Temporal Intelligence	5	2
Climate Risk Reasoning	5	5
Spatial Intelligence	5	5
Multimodal Fusion	5	4

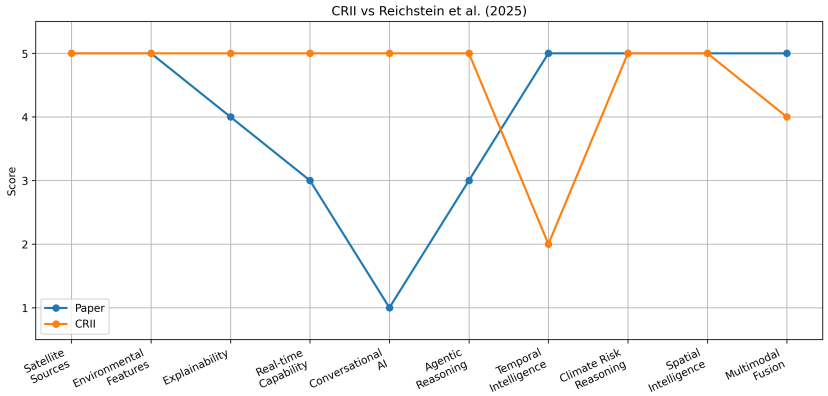

Fig. 10: Comparative evaluation between the proposed CRII framework and Reichstein et al. (2025) for integrated AI-based climate-risk early warning systems.

Comparison with Reichstein et al. (2025) Reichstein et al. (2025) proposes an integrated artificial intelligence framework for early warning of complex climate risks using multi-hazard climate analytics and advanced geospatial intelligence techniques.

The framework demonstrates strong predictive climate intelligence, integrated AI reasoning, temporal environmental analysis, and early-warning capability.

Compared to Reichstein et al., the proposed CRII framework significantly improves explainability, conversational climate interaction, contextual environmental reasoning, and practical user-oriented climate intelligence generation.

The Reichstein et al. framework remains stronger in temporal forecasting, predictive environmental analytics, and integrated multi-hazard climate learning.

The proposed CRII framework differentiates itself through Agentic AI integration, explainable environmental threat interpretation, and interactive climate-risk reasoning.

Overall Comparative Interpretation Overall comparative analysis demonstrates that the proposed CRII framework significantly advances beyond conventional geospatial environmental analysis systems by integrating:

- explainable climate intelligence,
- conversational environmental reasoning,
- real-time contextual interaction,
- Agentic AI-assisted analysis,
- and multi-source geospatial fusion.

Unlike traditional remote sensing approaches that primarily focus on:

- image understanding,
- feature extraction,
- classification,
- or multimodal representation learning,

the proposed CRII framework focuses on practical environmental intelligence generation and explainable climate-risk reasoning.

The comparative evaluation additionally highlights that existing transformer-based and multimodal learning approaches remain stronger in:

- temporal environmental modeling,
- large-scale representation learning,
- and adaptive multimodal feature extraction.

Future extensions of the proposed framework will therefore focus on:

- temporal climate forecasting,
- retrieval-augmented environmental reasoning,
- geospatial foundation models,
- adaptive climate learning systems,
- and multi-agent environmental intelligence architectures.

7 Comparison with Established Climate Vulnerability Frameworks

The proposed CRII framework was additionally compared against established climate vulnerability and environmental risk assessment frameworks including ND-GAIN, Climate Risk Index (CRI), and IPCC vulnerability assessment approaches.

Table 11: Comparison Between Existing Climate Vulnerability Frameworks and Proposed CRII Framework

Framework	**Satellite Integration**	**Explainability**	**AI Reasoning**	**Real-Time Capability**	**Interactive Capability**
ND-GAIN	Moderate	Low	No	No	No
Climate Risk Index (CRI)	Low	Moderate	No	No	No
IPCC Vulnerability Framework	Moderate	Moderate	No	No	No
Proposed CRII Framework	**High**	**High**	**Yes**	**Yes**	**Yes**

Unlike conventional climate-risk frameworks that primarily focus on statistical vulnerability representation, the proposed CRII framework integrates explainable AI reasoning, conversational environmental interaction, and satellite-driven contextual climate intelligence.

The comparative evaluation demonstrates that the proposed CRII framework substantially improves explainability, contextual climate interpretation, geospatial intelligence integration, and interactive environmental reasoning capability compared to traditional climate vulnerability assessment systems.

8 Discussion

8.1 Uncertainty and Limitations

Despite the strong interpretability and geospatial intelligence capability of the proposed CRII framework, several uncertainties and limitations remain.

The climate-risk estimates are influenced by multiple factors including:

- Satellite spatial-resolution limitations
- Temporal variability in environmental observations
- Cloud contamination and atmospheric noise
- Sensitivity of environmental normalization procedures
- Heuristic weighting assumptions
- Variability in LLM-generated contextual reasoning

The current framework primarily represents relative climate vulnerability patterns rather than absolute predictive climate forecasts. Consequently, the generated climate-risk outputs should be interpreted as comparative environmental intelligence indicators instead of deterministic climate predictions.

Furthermore, the current implementation does not incorporate socioeconomic vulnerability indicators, demographic sensitivity analysis, or uncertainty-aware probabilistic climate modeling.

Future work will therefore focus on uncertainty-aware environmental intelligence systems, probabilistic climate-risk estimation, retrieval-augmented climate reasoning, and adaptive climate forecasting architectures.

The proposed CRII framework demonstrates the effectiveness of integrating satellite-based environmental intelligence with AI-driven contextual reasoning for climate vulnerability assessment.

One of the major strengths of the proposed system lies in its ability to bridge the gap between quantitative geospatial analytics and interpretable environmental intelligence generation. Traditional climate dashboards often present numerical indicators without meaningful contextual interpretation, limiting their usability for non-technical stakeholders. In contrast, the proposed AI-assisted reasoning framework generates adaptive and human-readable analytical insights grounded in satellite-derived environmental indicators.

The integration of multi-source Earth observation datasets further improves analytical robustness by capturing diverse climatic dimensions including flood susceptibility, urbanization intensity, vegetation health, rainfall variability, and thermal exposure.

The low-latency Groq inference framework additionally enables near real-time climate reasoning capabilities, improving scalability and interactive usability.

Despite these advantages, the proposed framework has several limitations. The current implementation primarily focuses on relative climate vulnerability representation rather than predictive climate forecasting. Furthermore, the reasoning quality remains dependent on prompt engineering strategies and environmental data quality.

Table 12: Approximate Computational Performance of the Proposed CRII Framework

Component	**Approximate Performance**
Satellite preprocessing using GEE	Cloud-accelerated parallel processing
Grid-wise zonal statistics extraction	Few minutes for national-scale analysis
CRII computation	Lightweight numerical aggregation
LLM-based climate reasoning	1–3 seconds per query
Interactive dashboard response	Near real-time visualization

Future research may integrate temporal forecasting models, multimodal geospatial foundation models, and advanced retrieval-augmented reasoning architectures for enhanced climate intelligence generation.

8.2 Computational Performance Analysis

The computational pipeline was designed for scalable large-scale climate intelligence analysis using cloud-based geospatial processing and lightweight AI inference.

Google Earth Engine (GEE) was utilized for large-scale satellite preprocessing, raster aggregation, and zonal statistical computation, while the Groq API enabled low-latency environmental reasoning generation.

The proposed architecture demonstrates strong scalability for large-scale environmental monitoring while maintaining low computational overhead and near real-time climate intelligence generation capability.

9 Conclusion

This paper presented the Climate Risk Intelligence Index (CRII), an AI-augmented satellite-based climate vulnerability assessment framework designed for scalable climate intelligence analysis across India.

The proposed framework integrates multi-source satellite datasets, geospatial analytics, composite climate indexing, and Large Language Model-based contextual reasoning into a unified environmental intelligence platform.

The system successfully analyzed approximately 3,840 geospatial grid cells across India while generating interpretable and context-aware climate vulnerability insights using low-latency LLM inference.

Experimental analysis demonstrated strong environmental consistency across multiple climatic regions including metropolitan urban clusters, flood-prone coastal zones, ecologically stressed regions, and arid landscapes.

The proposed framework contributes toward next-generation climate intelligence systems by combining Earth observation technologies with AI-augmented environmental reasoning.

Future work will focus on:

- Temporal climate forecasting
- Real-time satellite stream integration
- Retrieval-augmented environmental reasoning
- Multi-agent climate intelligence systems
- Advanced geospatial visualization
- State-wise climate resilience analytics
- Deep learning-based predictive climate modeling

The proposed CRII framework demonstrates strong potential for applications in climate adaptation planning, disaster preparedness, urban resilience analysis, environmental monitoring, and policy-level climate decision support systems.

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