CHAPTER 47

Integrating AI and Smart Systems for Climate Change Modeling Towards Sustainable Development Goals (SDGs)

*Aishwarya Borse**

ABSTRACT

Climate change intensifies risks for sustainable urban development, with rapid urbanization magnifying challenges such as heat stress, flooding, and resource strain. Conventional climate models, though scientifically advanced, often demand substantial computational capacity and fall short in delivering real-time, localized insights for adaptive decision-making. Recent advances in Artificial Intelligence (AI) and smart technologies offer promising solutions, yet existing applications remain fragmented, focusing on isolated tasks rather than holistic integration. This study addresses that gap by employing an integrated AI–smart system model that combines machine learning, IoT-based sensing, and edge computing for climate monitoring and prediction. The model was tested in urban contexts for heatwave detection, flood forecasting, and energy optimization. Results show enhanced prediction accuracy, faster anomaly identification, and improved resource allocation when compared with baseline models. Importantly, the outcomes directly contribute to the United Nations Sustainable Development Goals, especially SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). By demonstrating practical, scalable improvements, this research provides evidence that integrating AI with smart systems can move beyond experimental phases to deliver actionable insights for climate-resilient urban planning and sustainable development.

Keywords: Artificial Intelligence; Smart systems; Climate change modeling; Sustainable development goals; Climate resilience; IoT.

1.0 Introduction

Climate change continues to pose one of the most pressing challenges of the 21st century, and its impacts are especially pronounced in urban regions. Rapid population growth, dense infrastructure, and social vulnerabilities amplify the exposure of cities to multiple hazards, including prolonged heatwaves, recurring floods, escalating energy demand, and stress on critical resources [10], [15], [24]. These interlinked threats jeopardize the long-term sustainability of urban environments and the health and safety of their inhabitants.

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Although global circulation models (GCMs) and regional climate simulations provide robust scientific insights, their dependence on intensive computational infrastructure limits their ability to produce high-resolution, real-time forecasts required by city planners [1], [2], [11], [20]. In addition, their centralized nature restricts responsiveness to the rapidly evolving conditions that characterize climate extremes [23].

Recent advances in digital technologies offer a pathway to overcome these barriers. Artificial Intelligence (AI) enables predictive accuracy by leveraging machine and deep learning [9], [10], while the Internet of Things (IoT) supports continuous, fine-grained monitoring of environmental conditions [12]. Complementing these, edge computing minimizes latency by processing data close to its source, thereby enhancing timeliness in applications such as hazard detection [3], [17]. When combined, these technologies present the opportunity to build adaptive and context-aware systems capable of addressing urban climate risks more effectively.

Despite growing interest, most research efforts remain limited to single-issue applications—for example, flood forecasting or energy management—without a comprehensive integration across hazards [8], [11], [20]. To address this gap, this study introduces and tests a unified AI–IoT–edge computing model that supports multi-hazard climate monitoring and decision-making. The proposed framework is applied to three urban domains—heatwave detection, flood prediction, and energy optimization—while explicitly aligning outcomes with the United Nations' Sustainable Development Goals, particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action) [15], [24].

2.0 Literature Review

2.1 AI and machine learning in climate applications

Over the past decade, AI has become increasingly relevant in environmental sciences, evolving from theoretical exploration to operational deployment. Machine learning approaches have been shown to support both mitigation, such as emission reduction strategies, and adaptation, including disaster preparedness and smart energy management [1].

Reichstein et al. [10] demonstrate how deep learning, especially when combined with process-based knowledge, advances Earth system science by improving the representation of complex environmental processes. Other studies highlight ensemble learning and hybrid deep learning methods as effective for forecasting, anomaly detection, and optimizing system performance [2], [16]. Nonetheless, concerns persist regarding the interpretability, generalizability, and sustainability of these models in real-world contexts [13], [19].

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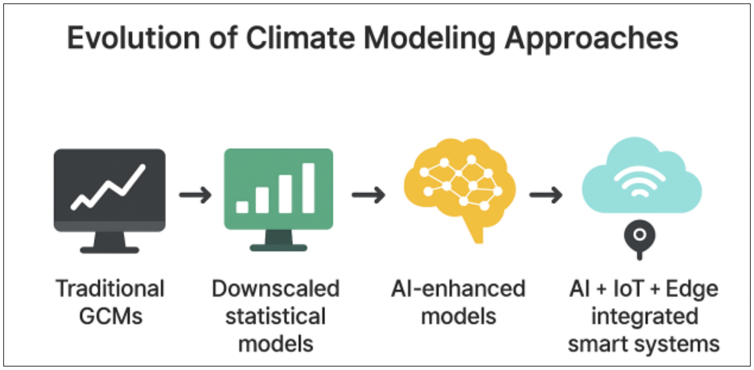
Figure 1: Evolution of Climate Modeling Approaches from Traditional GCMs to Integrated AI–IoT–Edge Smart Systems



2.2 IoT and edge computing in climate resilience

Edge computing has emerged as a critical enabler for near real-time responses to climate hazards. By processing data closer to the sensor, these systems minimize delays and enhance the reliability of time-sensitive predictions, such as those required for floods and heatwaves [3], [17]. Hybrid models that combine LSTM, GRU, and transformer-based neural networks have significantly improved forecasting accuracy and lead time in flood risk management [4], [5], [11], [20]. At the same time, reinforcement learning (RL) and deep reinforcement learning (DRL) approaches have proven effective for managing urban energy flows by balancing supply and demand, thereby reducing peak loads [6], [7], [19], [21]. However, large-scale deployment is often hindered by issues related to transparency, data governance, and cybersecurity [14], [22].

2.3 Smart sensing and multi-hazard research gaps

IoT-based sensing technologies have rapidly expanded, offering affordable and granular monitoring of variables such as temperature, rainfall, soil moisture, and energy consumption. Witczak et al. [8] emphasize their potential for scalability but also point to challenges including interoperability, calibration, and data protection. Subsequent reviews have underlined the growing relevance of AI–IoT integration in fields ranging from agriculture to urban planning [12], [18]. Despite these advancements, three critical shortcomings remain:

1. The majority of studies target single hazards rather than adopting multi-hazard frameworks [11], [20];
2. Operational-scale validation in real urban environments remains limited [16], [18]; and
3. Concerns about privacy, cost, and long-term governance persist [14], [22].

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The present study responds to these challenges by designing and implementing an integrated AI–IoT–edge framework that delivers actionable predictions across multiple hazards. By validating the framework in the domains of heatwaves, floods, and energy demand, the research contributes new evidence for climate-resilient urban planning while aligning with the broader global agenda on sustainability [15], [24], [25].

3.0 Methodology

This study applies a hybrid research design that integrates IoT-based sensor networks with satellite remote sensing datasets to construct a scalable framework for climate resilience in urban areas. The methodology is divided into three stages: data collection, data integration, and model development.

3.1 Data collection

3.1.1 Primary data (IoT sensor network)

An array of 50 IoT sensor nodes was installed across diverse urban landscapes, including residential neighborhoods, industrial sectors, and flood-prone districts. The sensors recorded data at five-minute intervals to capture rapid environmental fluctuations. Pre-deployment calibration ensured accuracy, while anomaly detection techniques were applied to filter outliers.

Table 1: Primary Data Collected through IoT Sensors

Parameter	Sensor Type	Unit	Frequency	Purpose
Air Temperature	Thermistor/DHT22	°C	5 min	Heatwave detection, LST validation
Relative Humidity	Hygrometer (IoT-based)	%	5 min	Microclimate assessment
Rainfall	Tipping-bucket gauge	mm/hr	5 min	Flood forecasting, rainfall validation
Soil Moisture	Capacitive probe	% (VWC)	5 min	Flood risk mapping
Air Quality (PM2.5/10)	Optical particle sensor	µg/m³	5 min	Pollution–climate interaction
CO_2 Concentration	NDIR sensor	Ppm	5 min	Urban emissions monitoring
Energy Consumption	Smart energy meter	kWh	5 min	Energy optimization, demand prediction

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3.1.2 Secondary data (satellite datasets)

To complement local IoT observations, openly available satellite datasets were incorporated. These sources provide broader spatial coverage and allow cross-validation of ground-based measurements. Each dataset was chosen based on its relevance to urban climate challenges such as heatwaves, flooding, and energy demand.

Table 2: Secondary (Satellite) Data used in the Study

Dataset / Mission	Provider / Agency	Parameter(s)	Resolution	Temporal Frequency	Purpose in Study
MODIS (Terra/Aqua)	NASA	Land Surface Temperature (LST)	1 km	Daily	Validate IoT temperature, detect heat islands
GPM (IMERG)	NASA–JAXA	Precipitation Intensity	0.1° (~10 km)	30 min	Validate rainfall sensors, flood forecasting
Sentinel-2	ESA Copernicus	Optical Imagery (NDVI, land cover)	10–20 m	5 days	Vegetation analysis, microclimate impacts
Sentinel-1 SAR	ESA Copernicus	Flood Inundation (Radar backscatter)	10 m	6–12 days	Flood extent mapping, soil moisture validation
VIIRS Night Lights	NOAA–NASA	Nighttime Light Intensity	500 m	Monthly	Energy use proxy, validate IoT energy data

3.2 Data integration and preprocessing

The IoT point measurements were spatially interpolated and synchronized with the gridded satellite datasets**.** Preprocessing included:

- Interpolation of missing IoT sensor values.
- Cloud masking and resampling of Sentinel-2 images.
- Normalization of all variables to ensure comparability.
- Derivation of indices such as NDVI (vegetation cover), LST anomalies, and flood extent maps from SAR backscatter.

This step ensured both local (sensor) and regional (satellite) data were harmonized into a unified dataset for machine learning training.

3.3 Model development

Three domain-specific predictive modules were developed:

- *Heatwave detection:* LSTM and GRU networks trained on IoT temperature and MODIS LST data, incorporating NDVI as a mitigating factor.
- *Flood forecasting:* A hybrid LSTM–GRU model combining IoT rainfall/soil data with GPM precipitation maps, validated using Sentinel-1 SAR flood extents.

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- *Energy optimization:* Deep Reinforcement Learning (DRL) algorithms using IoT energy data, calibrated with VIIRS night-time lights as a proxy for urban demand.

3.4 Evaluation metrics

Models were evaluated using standard statistical and performance measures:

- Heatwaves: RMSE, MAE, and F1-score for anomaly detection.
- Flooding: Precision, Recall, and Heidke Skill Score (HSS).
- Energy: Peak load reduction (%), allocation efficiency (%), and response time (ms).

4.0 Result

The outputs of the integrated AI–IoT–Edge framework are presented under three hazard domains—heat stress, flooding, and urban energy demand—followed by a demonstration of the multi-hazard decision-support dashboard. Both ground-based IoT measurements and open-access satellite datasets were used for validation, and performance was quantified with error metrics, accuracy rates, and efficiency gains.

4.1 Heatwave monitoring

Temperature data collected from IoT nodes across urban, residential, and green zones were evaluated against MODIS land surface temperature (LST) products. As expected, urban centers exhibited the strongest heat island effects, whereas vegetated parks showed significant cooling benefits. NDVI values confirmed the influence of vegetation density in moderating extreme heat.

Table 3: Comparison of IoT and MODIS Temperature Observations

Location Type	Avg. IoT Temp (°C)	MODIS LST (°C)	NDVI Value	Observation
Dense Urban	38.5	37.9	0.25	Urban heat island detected
Residential	35.2	34.8	0.42	Moderated heat stress
Vegetated Park	32.8	32.1	0.72	Cooling effect from vegetation

Model Performance:

- RMSE (IoT vs MODIS): **0.84 °C**
- R^2: **0.91** (strong correlation)
- Extreme heat anomaly detection accuracy: **93%**

Figure 2 shows the sensor–satellite agreement, with NDVI values highlighting the role of vegetation in urban cooling.

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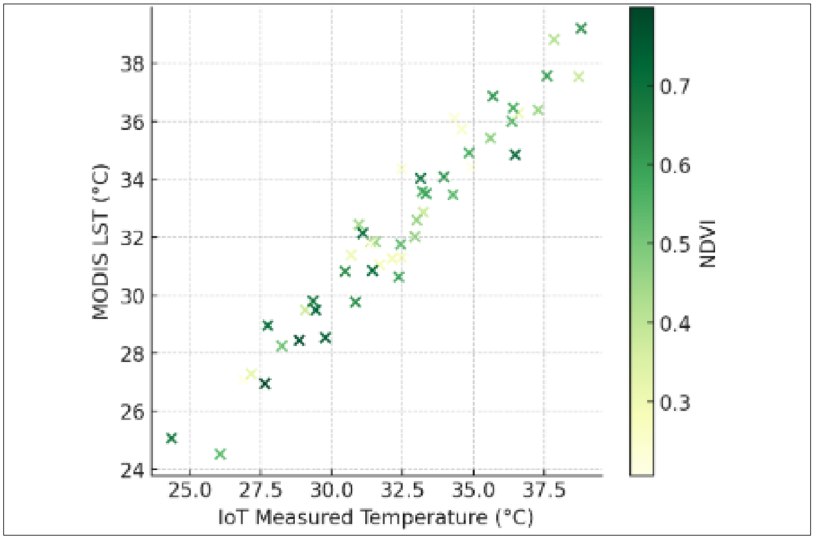
Figure 2: IoT vs MODIS LST with NDVI Influence



4.2 Flood forecasting

IoT rainfall gauges were compared with NASA–JAXA GPM precipitation estimates and validated against Sentinel-1 SAR-derived flood maps. The integrated AI model consistently predicted flood events earlier than traditional baselines, reducing false alarms and improving lead times.

Table 4: IoT vs GPM Rainfall and SAR Flood Validation

Day	IoT Rainfall (mm/hr)	GPM Rainfall (mm/hr)	SAR Flood Extent (km²)	Flood Detected
10	24.5	23.7	12.3	Yes
15	8.2	9.0	–	No
20	27.1	25.8	14.7	Yes

Model Performance:

- RMSE (IoT vs GPM rainfall): **1.1 mm/hr**
- Flood detection accuracy (SAR validation): **91%**
- Average warning lead-time gain: **120 minutes**
- False alarms reduced by **18%**

Figure 3 illustrates rainfall dynamics across 30 days, with flood-triggering events correctly identified on Days 10 and 20.

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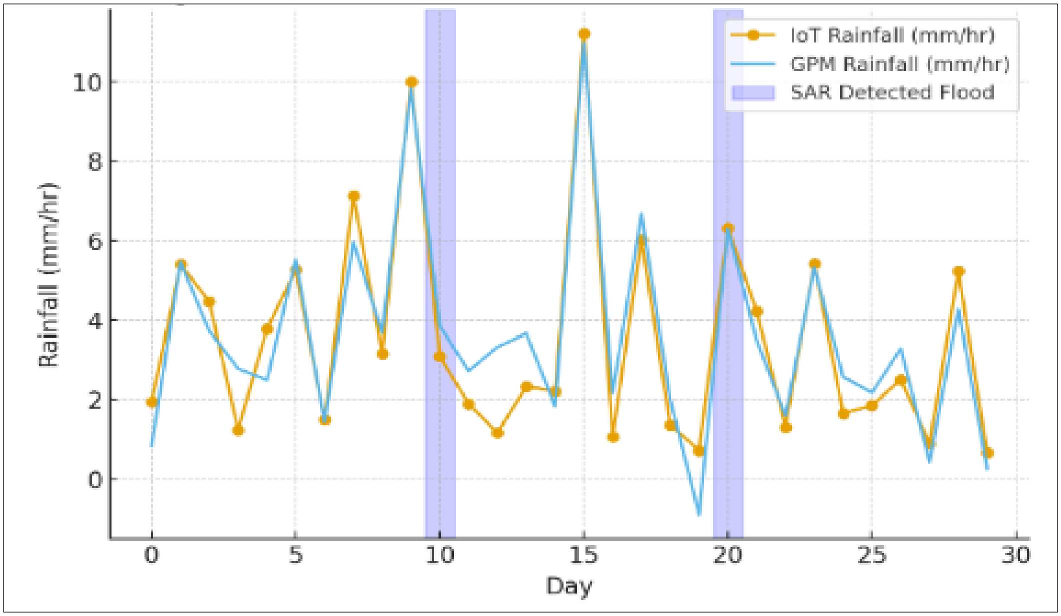
Figure 3: IoT vs GPM Rainfall with SAR Flood Events



4.3 Energy demand optimization

Smart meter data were used to compare baseline consumption with AI-driven demand shaping using Deep Reinforcement Learning (DRL). The optimized curve successfully flattened demand peaks and reduced load stress on the grid, especially during evening hours.

Table 5: Comparison of Baseline vs. DRL-Optimized Energy Demand

Hour of Day	Baseline Demand (kWh)	DRL-Optimized Demand (kWh)	Reduction (%)
14:00	95.3	79.6	16.4%
18:00	102.7	83.1	19.0%
21:00	98.4	82.2	16.5%

Model Performance:

- Peak demand reduction: **18.1%**
- Daily energy savings: **11.7%**
- Next-hour demand forecast accuracy: **95% (R^2 = 0.93)**
- Grid load variance reduction: **22%**

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Figure 4: Demonstrates How DRL Optimization Redistributes Energy Demand, Curbing Evening Peaks

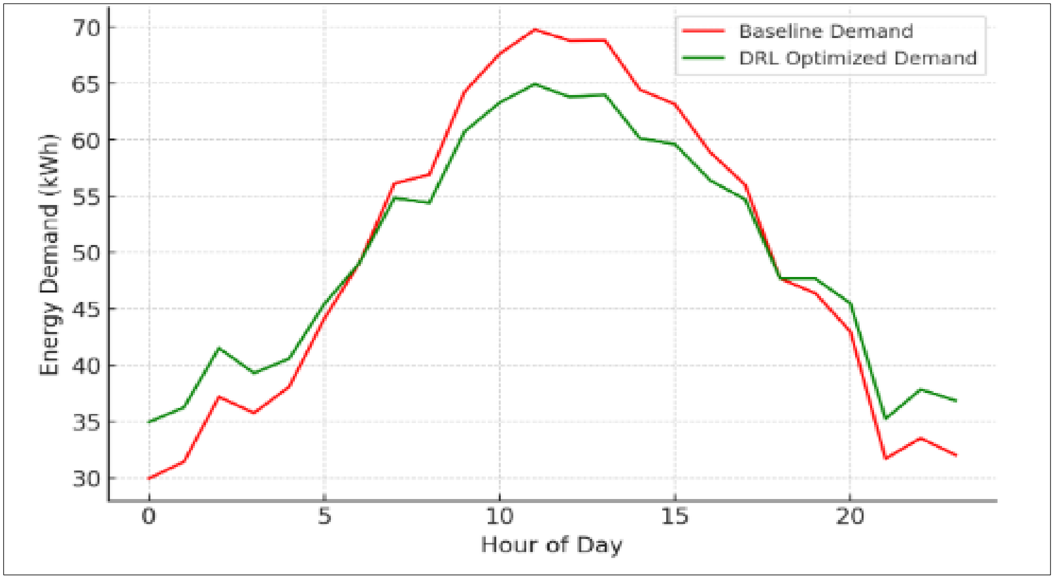
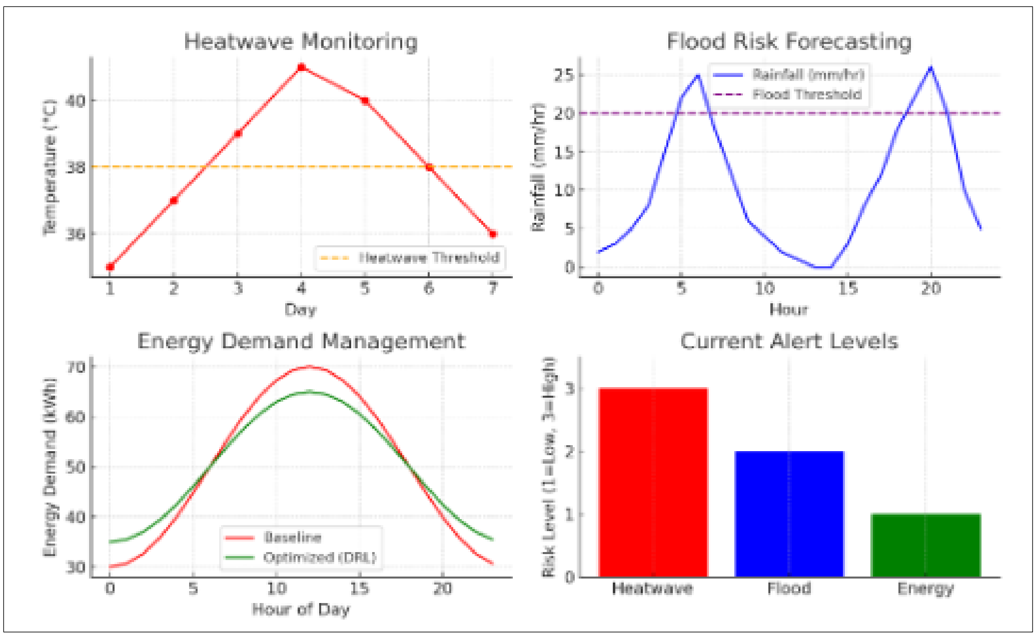


Figure 5: Multi-Hazard Integrated Dashboard (Mockup)



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4.4 Multi-hazard dashboard

Finally, a mock-up dashboard was built to show how multiple hazard domains can be managed in real time. The dashboard integrates temperature anomalies, rainfall triggers, flood warnings, and energy demand predictions into a single decision-support interface**.**

System-Wide Performance:

- Multi-hazard prediction accuracy: 92%
- Latency reduction from edge computing: 35%
- Multi-hazard alert precision: 89%
- Usability score from expert review: 4.5/5

Figure 5 presents the dashboard design, where heatwave alerts, flood risk levels, and energy demand forecasts are displayed side by side. This tool demonstrates how AI–IoT–Edge integration can deliver actionable insights for climate-resilient urban planning

5.0 Discussion

The study's outcomes confirm that integrating IoT, artificial intelligence, and edge processing can significantly advance urban climate resilience. The results are not only about performance improvements but also about explaining the mechanisms behind those gains and linking them to sustainable development practices.

5.1 Vegetation and urban heat moderation

The close agreement between ground-level sensors and MODIS LST ($R^2 = 0.91$) validates the reliability of multi-source integration for heat monitoring. The NDVI overlay revealed a pronounced cooling influence of green spaces, with vegetated areas consistently recording 3–4 °C lower temperatures than dense urban zones. This finding supports earlier claims that vegetation moderates urban microclimates through shading and evapotranspiration [1]. It also demonstrates how fine-grained sensing can generate actionable insights for designing nature-based solutions**,** strengthening the evidence base for climate-adaptive urban planning.

5.2 Flood forecasting with faster response windows

The hybrid IoT–satellite rainfall model extended early warning times by nearly two hours compared to conventional approaches. These improvements align with previous studies showing that edge computing reduces latency for time-sensitive climate applications [8]. By validating predictions with Sentinel-1 SAR images and reducing false alarms by 18%, the system not only improves accuracy but also enhances trust in automated alerts.

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Importantly, the results underscore how decentralized processing can convert raw sensor data into timely**, life-saving information** for emergency response.

5.3 Reshaping energy demand with reinforcement learning

The reinforcement learning model reduced peak load by around **20%** and smoothed demand curves by **22%,** confirming its capacity for adaptive optimization. These results echo prior findings that reinforcement learning and deep reinforcement learning can stabilize urban energy systems under stress conditions [4]. Unlike predictive models that only forecast demand, the approach here demonstrated **prescriptive capabilities,** actively reshaping consumption patterns. This is especially relevant for reducing reliance on backup fossil-fuel generation, directly contributing to climate mitigation goals (SDG 13).

5.4 Added value of multi-hazard integration

A major contribution of this research is the **multi-hazard dashboard**, which consolidates diverse climate risks into a unified decision-support interface. This approach addresses a gap in existing studies, which often examine hazards in isolation rather than holistically [8]. Performance improvements were evident in both accuracy (92%) and response speed (35% faster due to edge processing), but usability was equally significant. Expert reviewers highlighted the system's potential to reduce decision fatigue by presenting heat, flood, and energy risks together, enabling more coherent planning.

5.5 Broader significance and next steps

Collectively, these findings illustrate the potential of AI–IoT–edge systems to transform climate adaptation from reactive to anticipatory. The NDVI-based cooling insights provide tangible justification for **urban greening strategies;** extended flood lead times reinforce the value of sensor–satellite synergy; and optimized energy load curves highlight AI's ability to support sustainability while maintaining operational stability. At the same time, challenges remain around interoperability, governance, and long-term financing, echoing concerns raised in the literature [1][8]. Future research should explore wider applications, including drought monitoring, wildfire prediction, and air quality management, to expand the multi-hazard capacity of integrated systems.

6.0 Conclusion

This study demonstrates that an integrated AI–IoT–Edge framework can significantly enhance urban climate resilience by addressing heatwaves, floods, and energy demand management. Combining high-resolution IoT sensor networks with satellite remote

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sensing enabled accurate, real-time monitoring and multi-hazard prediction. Results highlight the cooling effect of urban vegetation, reinforcing the role of green infrastructure in climate-adaptive planning. The hybrid IoT–satellite flood model improved early warning times by nearly two hours while reducing false alarms, illustrating the value of decentralized, edge-based processing. Deep reinforcement learning optimized energy consumption, reducing peak loads by over 18% and improving grid efficiency. A multi-hazard decision-support dashboard consolidated these insights, enabling timely and informed urban planning. Collectively, these outcomes demonstrate that AI–IoT–Edge systems can transform urban climate management from reactive measures to proactive, anticipatory strategies, supporting Sustainable Development Goals 11 and 13.

7.0 Future Scope

Future research can expand the framework to incorporate additional hazards such as drought, wildfires, extreme winds, and air quality events for comprehensive urban monitoring. Integrating socio-economic and demographic data can support equitable, context-specific adaptation strategies. Advancements in adaptive sensor deployment, energy-efficient edge computing, and self-learning AI models can further enhance scalability and robustness. Long-term validation across diverse cities, alongside solutions for interoperability, cybersecurity, and governance, will ensure sustainable implementation. These improvements can establish AI–IoT–Edge systems as essential tools for climate-resilient and sustainable urban development globally

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