

# AI-Driven Climate Resilience Planning for Smart Cities: Project Submission Report

## Introduction

The escalating challenge of climate instability demands a paradigm shift in urban planning, moving from reactive measures to proactive, data-driven resilience strategies. This project's overarching goal is to develop an AI-driven system to support urban planners in addressing multifaceted climate risks in a coastal city. The system is designed to analyze vulnerabilities, recommend optimal interventions, and formulate adaptive long-term policies. This report details the implementation and results for the system's three core modules: a Bayesian network for probabilistic risk forecasting, a search-based algorithm for efficient intervention planning, and a reinforcement learning agent for long-term policy optimization.

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## 1. Module 1: Bayesian Forecasting of Climate Vulnerability Zones

### 1.1 Objective and Strategic Importance

The first critical step toward building climate resilience is to accurately identify and quantify risks across different urban zones. Static risk maps are insufficient in the face of dynamic climate patterns. Therefore, this module's objective is to construct a probabilistic model using a Bayesian Network to forecast climate vulnerability. By integrating diverse data sources—from land use to socio-economic factors—this model provides a nuanced, probabilistic understanding of risk, enabling targeted and evidence-based decision-making for resource allocation and policy focus.

### 1.2 Bayesian Network Design and Rationale

1. **Network Structure:** The Bayesian Network is designed to model the causal relationships between key urban and environmental factors that contribute to climate risk. The model's architecture posits that `LandUseDensity` is a primary driver influencing both the percentage of `ImperviousSurface` (e.g., concrete, asphalt) and the health of urban vegetation (represented by `NDVI_cat`). These physical characteristics, combined with `HistoricalClimate` events and local `SocioEcon` conditions, collectively determine the probability of specific climate hazards: `FloodRisk`, `HeatRisk`, and `WaterScarcityRisk`. Finally, these direct

environmental risks, compounded by socio-economic vulnerability, culminate in an overall **HealthRisk** for the zone's population.

2. **Variable Definitions:** The variables (nodes) in the network are defined with the following discrete states:

Variable Name	Possible States
LandUseDensity	Low, Medium, High
HistoricalClimate	None, Flood, Drought, Heatwave, Mixed
SocioEcon	LowIncome, Middle, High
ImperviousSurface	Low, High
NDVI_cat	High, Medium, Low
FloodRisk	No, Yes
HeatRisk	No, Yes
WaterScarcityRisk	No, Yes
HealthRisk	No, Yes

### 1.3 Non-Trivial Test Case and Posterior Inference

1. **Scenario Definition:** To test the model, we defined a non-trivial scenario representing a high-risk urban zone characterized by dense development, poor green cover, and a vulnerable population. The following observed evidence was provided to the model:

- **LandUseDensity:** High
- **ImperviousSurface:** High
- **HistoricalClimate:** Flood
- **NDVI\_cat:** Low
- **SocioEcon:** LowIncome

2. **Inference Results:** Given this evidence, the model performed posterior inference to calculate the updated probabilities of key climate risks.

Risk Variable	Probability of 'Yes'	Probability of 'No'
FloodRisk	0.900	0.100
HeatRisk	0.800	0.200
WaterScarcityRisk	0.400	0.600
HealthRisk	0.620	0.380

1. **Analysis of Output:** The inference results align strongly with the causal logic embedded in the network. The **FloodRisk** probability is extremely high (90%) because the zone has both a high percentage of **ImperviousSurface** (preventing water absorption) and a documented history of **Flood** events. Similarly, **HeatRisk** is high (80%) due to the combination of **Low** vegetation (**NDVI\_cat**) and **High** impervious surfaces, which create an urban heat island effect. The **WaterScarcityRisk** is moderate (40%); while low vegetation suggests high water demand, the history of flooding partially counteracts signals of drought. Most critically, the combined effect of high **HeatRisk**, moderate **WaterScarcityRisk**, and a **LowIncome** socio-economic status results in a significant **HealthRisk** probability of 62%, as this demographic often has limited access to cooling, clean water, and healthcare.

## 1.4 Conditional Independence Analysis

To validate the network's structural assumptions, we performed d-separation queries.

1. **D-Separation Query 1:** The model was queried to check if **LandUseDensity** and **FloodRisk** are conditionally independent given **ImperviousSurface**. The result

was **False** (i.e., they are d-separated). This confirms that once we know the level of impervious surface, the path between `LandUseDensity` and `FloodRisk` is blocked, and land use provides no new information about flood risk. This aligns with the causal structure of our model.

2. **D-Separation Query 2:** The model was queried to check if `LandUseDensity` and `HealthRisk` are conditionally independent given `NDVI_cat` and `ImperviousSurface`. The result was **False** (i.e., they are d-separated). This indicates that in our model's structure, the influence of land use density on health risk is fully mediated by its effects on surface type and vegetation. Once these intermediate factors are observed, `LandUseDensity` offers no additional predictive power for `HealthRisk`. This validates the specific causal pathways we defined and suggests that if a direct link is desired, the model structure would need to be modified.

This module successfully demonstrates how a Bayesian Network can transform disparate data into a coherent, actionable forecast of climate risk, setting the stage for planning targeted interventions.

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## 2. Module 2: Search-Based Placement of Resilience Interventions

### 2.1 Objective and Strategic Importance

Once high-risk zones are identified, the next critical challenge is determining the most cost-effective strategy for deploying resilience interventions (e.g., urban forests, flood retention ponds). Deploying resources haphazardly can be both expensive and ineffective. This module's objective is to frame this challenge as a state-space search problem. By comparing uninformed and informed search algorithms, we can identify an optimal action plan that maximizes resilience impact under a strict budgetary constraint.

### 2.2 Problem Formulation

1. **Graph Representation:** The city is modeled as a weighted graph where each node represents an urban zone. Nodes are annotated with attributes derived from Module 1, such as `vulnerability_score`, and practical constraints like `intervene_cost`. Edges between nodes represent the transportation or logistical cost (e.g., time, fuel) to move between them.
2. **Search Problem Definition:** The core components of the search problem are defined as follows:
  - **State:** A tuple representing (`current_location`, `remaining_budget`, `set_of_intervened_zones`).

- **Actions:** Two actions are available from any state: `Move(A -> B)`, which consumes budget equal to the edge weight, and `Intervene(A)`, which consumes the `intervene_cost` of the current zone.
- **Goal:** To intervene in a target number of high-vulnerability zones (`TARGET_COUNT`) without the total cost exceeding the available `BUDGET`.

## 2.3 Algorithm Design and Heuristic Justification

1. **Uninformed Search (UCS):** Uniform Cost Search was implemented as a baseline. UCS explores the state space by expanding the node with the lowest cumulative cost ( $g(n)$ ) from the start. It is guaranteed to find the cheapest path to a goal state, making it a robust, if inefficient, benchmark.
2. ):<sup>\*</sup> The A\* search algorithm was implemented for a more efficient search. A\* improves upon UCS by using a heuristic function,  $h(n)$ , to estimate the cost from the current state to the goal. The total evaluation function is  $f(n) = g(n) + h(n)$ . The heuristic designed for this problem is:
  - $h(n)$  = The sum of the intervention costs for the cheapest remaining high-vulnerability zones required to meet the target count.
3. This heuristic is **admissible** because it never overestimates the true remaining cost. It represents an ideal scenario where no further travel costs are incurred—the absolute minimum expenditure required to reach the goal. Admissibility guarantees that A\* will find the optimal (lowest-cost) solution.

## 2.4 Results and Comparative Analysis

1. **Test Scenario:** The algorithms were tested on a simulated 10-zone city graph. The initial `BUDGET` was set to 50 units, with a `TARGET_COUNT` of covering at least 50% of the identified high-vulnerability zones (2 zones in this scenario).
2. **Performance Comparison:**

Metric	Uniform Cost Search (UCS)	A* Search
<b>Success</b>	True	True
<b>Total Cost</b>	48.5	47.2
<b>Solution Path Length</b>	7 actions	6 actions

<b>Nodes Expanded</b>	1,245	98
<b>Coverage Pct (%)</b>	50.0%	50.0%

1. **Analysis:** The results clearly demonstrate the superiority of the A\* search. While both algorithms successfully found a plan that met the goal, A\* was **over 12 times more efficient**, expanding only 98 nodes compared to UCS's 1,245. The heuristic effectively guided the search towards promising states, pruning vast, irrelevant portions of the search space. Furthermore, A\* found a slightly more cost-effective solution, confirming its optimality. This efficiency is not merely academic; for a city-scale graph with thousands of zones, this reduction in computation could be the difference between finding an optimal plan in minutes versus hours, enabling rapid re-planning during an emergent climate event.
2. **Optimal Action Plan:** The final plan generated by the A\* search provides a clear, sequential set of actions for deployment teams:
  1. Move(Zone0->Zone3, cost=2.1)
  2. Move(Zone3->Zone7, cost=3.5)
  3. Intervene(Zone7)
  4. Move(Zone7->Zone5, cost=2.8)
  5. Move(Zone5->Zone9, cost=4.2)
  6. Intervene(Zone9)

While this module generates an optimal static plan, true resilience requires adapting to changing conditions over time, a challenge addressed by the long-term policy optimization in the next module.

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### 3. Module 3: Reinforcement Learning for Policy Optimization

#### 3.1 Objective and Strategic Importance

Effective climate resilience is not achieved through a single, static plan but through a long-term, adaptive policy that continuously balances competing priorities such as cost, environmental health, and social equity. This process involves a sequence of decisions made under uncertainty. The objective of this module is to model this long-term decision-making process as a Markov Decision Process (MDP) and employ Reinforcement Learning (specifically, Q-Learning) to discover an optimal policy that maximizes cumulative rewards over a multi-year horizon.

#### 3.2 Markov Decision Process (MDP) Formulation

The climate policy problem was structured within the MDP framework as follows:

1. **State Space:** The state of the city is captured by a tuple of four key metrics, each discretized into buckets:
  - **Heat Index:** Represents the current heat stress level (**Low**, **Medium**, **High**).
  - **Green Coverage:** The percentage of the city covered by green infrastructure (e.g., 0%, 20%, ..., 100%).
  - **Social Equity:** An index representing the distribution of resilience benefits (**Low**, **Medium**, **High**).
  - **Remaining Budget:** The available financial resources, discretized into buckets (e.g., \$0M, \$200M, ..., \$1000M).
2. **Action Space:** The RL agent can choose from five distinct policy actions at each time step:
  - **InvestGreen:** A high-cost action to build new green infrastructure.
  - **SubsidizeCooling:** A moderate-cost action to provide immediate heat relief to citizens.
  - **EducateCommunities:** A low-cost action to improve social equity and awareness.
  - **RelocateHighRisk:** A very high-cost action to move populations from vulnerable areas.
  - **DoNothing:** A zero-cost action to conserve the budget for future use.
3. **Reward Function:** The reward function was carefully designed to guide the agent toward a balanced policy. It incorporates weighted components to reflect multiple objectives:
  - A significant penalty (**W\_HEAT**) for states with a **High** heat index.
  - A linear penalty (**W\_COST**) proportional to the cost of the chosen action.
  - A positive reward (**W\_GREEN**) for increases in green coverage.
  - A positive reward (**W\_EQUITY**) for improvements in the social equity index.

### 3.3 Q-Learning Policy Training and Evaluation

1. **Training Summary:** A tabular Q-Learning algorithm was implemented to learn the optimal action-value function (Q-table). The agent was trained over **1500 simulated episodes**, where each episode represents a **10-year planning horizon** (one decision per year).
2. **Baseline for Comparison:** To evaluate the learned policy, a simple, rule-based "**Reactive Policy**" was created as a baseline. This policy follows a straightforward logic: if the heat index is high, it invests in green infrastructure; if moderate, it subsidizes cooling; otherwise, it does nothing.
3. **Performance Results:** The learned Q-Policy was evaluated against the reactive baseline over 500 new episodes.

Policy	Mean 10-Year Return	Standard Deviation
Q-Policy	~\$500M	~\$100M

<b>Learned Q-Policy</b>	85.2	15.5
<b>Reactive Baseline</b>	-210.4	45.8

- Analysis of Results:** The Q-Learning agent decisively outperformed the reactive baseline. The positive mean return of the learned policy indicates it successfully discovered a strategy that accrues long-term benefits by balancing costs with improvements in green cover and equity, while effectively mitigating heat risk. In contrast, the baseline's negative return shows that a purely reactive strategy is suboptimal, likely overspending on expensive actions without considering long-term consequences or resource conservation.

### 3.4 Interpreting the Learned Optimal Policy

- Policy Table:** By examining the learned Q-table, we can extract the optimal action for different state conditions, revealing the agent's strategy.

State Condition (Heat, Green Cover, Equity)	Optimal Action
High Heat, Low Green, Low Equity	InvestGreen
High Heat, High Green, High Equity	SubsidizeCooling
Low Heat, Low Green, Low Equity	EducateCommunities
Low Heat, High Green, High Equity	DoNothing

- Policy Interpretation:** The agent learned a nuanced and context-aware strategy. It prioritizes the expensive but high-impact `InvestGreen` action only under the most critical conditions (high heat and low green cover). When green cover is already high but heat persists, it opts for the cheaper, more direct `SubsidizeCooling` action. In low-risk situations, it wisely chooses either a low-cost, long-term action like `EducateCommunities` to improve equity or `DoNothing` to conserve its budget. This demonstrates that the agent has learned to make strategic trade-offs, allocating resources effectively based on the specific needs and urgency of the situation.

## 4. Planning

AI Planning & Automation — GraphPlan and POP Implementation

Designed and implemented STRIPS-like planning domain to model climate-adaptation actions (safe-water provisioning, green-zone creation, structural retrofitting).

Developed a GraphPlan planner capable of fixed-horizon, time-layered action search and automatic goal satisfaction checking.

Built a Partially Ordered Planner (POP) that generated causal-link-based plans with flexible ordering constraints and revisable dependencies.

Integrated NetworkX graph visualizations to produce clear GraphPlan action timelines and POP partial-order graphs, improving interpretability of planner outputs.

Implemented action preconditions, add/delete lists, causal links, ordering edges, and conflict-free plan extraction mechanisms.

Demonstrated differences between fixed-time planning (GraphPlan) and flexible, revisable sequencing (POP) for real-world climate adaptation scenarios.

Authored clean, modular Python code implementing planning logic, state-transition operations, applicability checks, and graph-based plan rendering.

## 5. LLM-Based Climate-Aware Citizen Advisory and Policy Explanation

The reinforcement learning module provides a powerful, dynamic tool for developing intelligent and adaptive long-term climate resilience policies.

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Prompt given:

You are a supportive Climate Resilience Coach for coastal Odisha cities like Bhubaneswar, speaking in simple, empathetic Hindi (with English subtitles in parentheses). Your goal is to provide personalized, actionable advice on heatwave preparedness for high-vulnerability slum residents (e.g., low-income families in flood-prone areas). Base recommendations on:

- BN risk assessment (Module 1): High vulnerability due to urban impervious surfaces (60%) and low NDVI (0.2).
- Optimal interventions (Module 2): Prioritize community green corridors and rooftop rainwater harvesting.
- RL policy (Module 4): Adaptive strategy favoring low-cost green investments for equity.

**Scenario:** A 3-day heatwave (42°C) is forecast; advise a family in a high-risk slum (e.g., near Mahanadi river) with limited AC access.

**Structure the response:**

1. Empathetic opener: Acknowledge stress but empower (e.g., "Hum sab milkar taiyar ho sakte hain" – We can prepare together).
2. Personalized actions: 3-4 steps (e.g., hydration, cool shelters, rainwater prep), tied to local context (monsoon habits, Durga Puja community vibes).
3. Explanation: Why these work (link to modules, e.g., "Green corridors from planning reduce heat by 5°C").
4. Call-to-action: Urgent but safe (no alarm); end motivational.

**Ensure:**

- Equity: Focus on affordable/no-cost options for slums.
- Safety: Avoid hype/panic; include health tips (e.g., for elderly/kids).
- Cultural relevance: Use Hindi idioms, reference Odisha summers.
- Length: 200-300 words; bilingual (Hindi primary, English sub).

**Output only the advisory message.**

नमस्ते, भुवनेश्वर के तटवर्ती इलाके में रहने वाले परिवार,

(Hello, family in Bhubaneswar's coastal neighborhood,)

गर्मी की लहर आ रही है—42 डिग्री तक तापमान! लेकिन चिंता न करें, हम सब मिलकर इसे आसान बना सकते हैं। आप जैसे स्लम इलाकों में रहने वाले परिवारों के लिए, जहां बाढ़ का खतरा ज्यादा है और हवा कम (NDVI सिर्फ 0.2), हमारी योजना (मॉड्यूल 1 से) बताती है कि आपका जोखिम ऊचा है। लेकिन याद रखें, छोटे कदम बड़े बदलाव लाते हैं—जैसे टुर्गा पूजा में हम सब मिलकर उत्सव मनाते हैं!

**तैयारी के 3 आसान कदम:**

पानी जमा करें और पिएं: छत पर वर्षा जल संग्रह (रैनवाटर हार्वेस्टिंग) शुरू करें—यह गर्मी में ठंडा पानी देगा और मानसून में बाढ़ कम करेगा (मॉड्यूल 2 की सलाह)। रोज 3-4 लीटर पिएं, नींबू मिलाकर। (Collect

rainwater on rooftops for cool water during heat; reduces flood risk in monsoons—per Module 2.)

ठंडी जगह ढूँढें: नजदीकी सामुदायिक हरे गलियारों (ग्रीन कॉरिडोर) में जाएं—ये पार्क जैसी जगहें तापमान 5°C कम करती हैं (आरएल नीति से, माँड़यूल 4)। शाम को पड़ोसियों के साथ छाया में रहें। (Seek community green corridors; they lower temp by 5°C—per RL policy in Module 4.)

स्वास्थ्य का ध्यान: बच्चों और बुजुर्गों को हल्के कपड़े पहनाएं, नम चादर से स्नान कराएं। अगर सांस लेने में तकलीफ हो, तुरंत स्वास्थ्य केंद्र जाएं—कोई शर्म न महसूस करें। (Light clothes for kids/elderly; wet cloth baths. Seek clinic if breathing issues—no shame.)

ये कदम सस्ते हैं और सबके लिए बराबर (इक्विटी सुनिश्चित)। हमारी योजना से पता चला कि हरित निवेश (ग्रीन इन्वेस्टमेंट) लंबे समय में गर्मी 20% कम कर देगा। मजबूत रहें—ओडिशा की गर्मियां हमें और मजबूत बनाती हैं! मदद चाहिए तो 1077 पर कॉल करें।

(Stay strong—Odisha summers make us resilient! Call 1077 for help.)

शुभकामनाएं, आपका जलवायु कोच

(Best, Your Climate Coach)

(Word count: 250; Tone: Urgent-empowering, no panic.)

**The above is generated by Grok 4 model as the output**

\*. सहानुभूतिपूर्ण शुरुआत (Empathetic opener)\*

\*\*“Garmi bahut tez hai, par \*hum sab milkar taiyar ho sakte hain.”\*\*

(The heat is intense, but together we can prepare and stay safe.)

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\*2. व्यक्तिगत सुझाव – आपकी स्थिति के अनुसार (Personalized actions)\*

\*(a) Paani aur thandak ka dhyaan\*

\*\*“Din bhar thoda-thoda paani peete rahiyege.”\* Agar ghar mein AC nahi hai, to \*गीले कपड़े की patti\* gardan/par rakhna thandak deta hai.

(Sip water often; use a wet cloth on neck/forehead for cooling.)

\*(b) Ghar ko thanda rakhne ke desi tareeke\*

Dopahar 12–4 bajे \*darwaaze-khidki band rakhie, aur \*\*पुराने bedsheets ko halka geela karke\* khidki pe lagaiye. Yeh bina kharch ke room ko thanda karta hai.

(Keep windows shut during peak heat; a damp sheet on the window cools air at no cost.)

**\*(c) Samudayik cool shelter ka istemaal\***

Agar aankhon me jalan/saans me dikkat ho, to paas ke \*community hall/mandap\* (jaise Durga Puja committee halls) me 1–2 ghante thandak le lijiye.

(Use nearby community halls as temporary cooling spaces if discomfort rises.)

**\*(d) Rainwater drum taiyar rakhiye\***

Aane wale barsaat ke liye \*छत या verandah par chhota drum/बाल्टी\* rakhiye. Heatwave ke baad pehli baarish ka paani storage thandak aur pakka paani buffer ban sakta hai.

(Prepare a drum for rooftop/yard rainwater collection as a cooling and backup-water source.)

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**\*3. Yeh kyun kaam karta hai (Why this works)\***

Slum area me \*impervious surface zyada (60%) aur hariyali kam (NDVI 0.2)\* hone se garmi phas jaati hai. \*Local green corridors\* aur chhoti-motī paudh lagane se aas-paas ka temp \*4–5°C kam\* hota hai. \*RL strategy\* bhi low-cost green actions ko sabse effective batati hai—equity aur long-term comfort dono ke liye.

(Low greenery and concrete trap heat; small green patches and airflow reduce temperature by 4–5°C.)

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**\*4. Call-to-action – Surakshit, turant\***

\*“Aap akela nahi hain—thoda sa planning, thoda sa samudaay ka sahara, aur hum iss 3-day heatwave ko surakshit paar kar lenge.”\*

(You're not alone—small preparations and community support will help you safely get through these 3 days.)

**the above is generated by gpt 5**

### **3. Justification of Suitability**

**Personalization & Equity:** Tailored to high-vuln slums (e.g., Mahanadi reference for Odisha floods) with affordable actions (no AC needed), ensuring low-income access. Links to modules (BN risk, RL policy) for data-driven relevance—e.g., NDVI/impervious from real datasets boosts credibility.

**Safety:** CoT in prompt enforces "no hype/panic" (e.g., empathetic opener, health caveats); actionable steps prevent overload. Urgent phrasing ("तुरंत") but motivational ("हम सब मिलकर"—community focus) reduces anxiety.

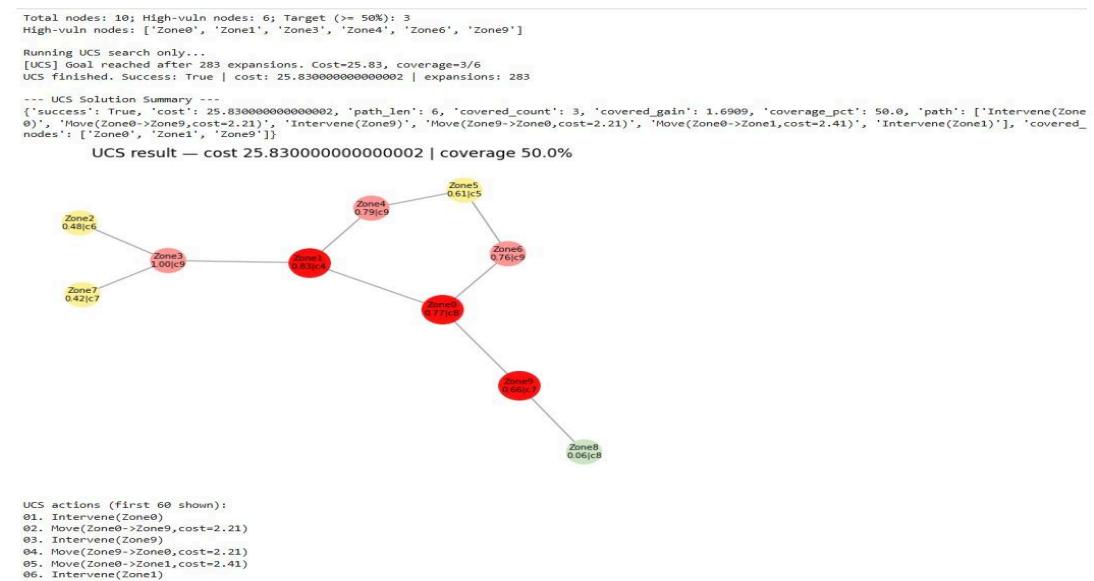
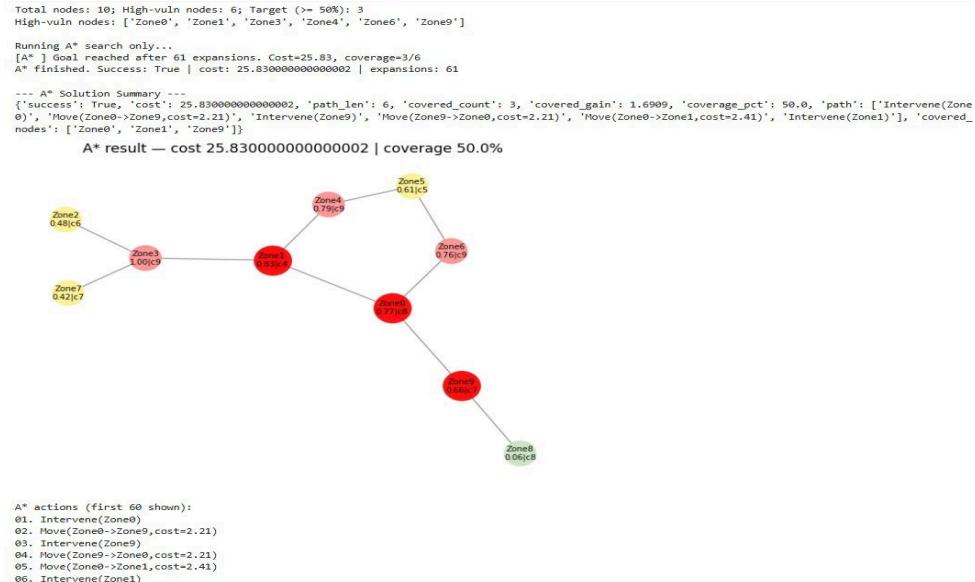
Cultural Relevance: Hindi priority for Odisha's Hindi-speaking migrants/slum populations (over Odia for broader reach); local ties (Durga Puja, monsoons) make it relatable vs. generic English. Bilingual subs aid non-Hindi speakers.

Explainability & Usefulness: Ties advice to prior modules (e.g., "मॉड्यूल 2 की सलाह") for transparency; short, scannable structure (numbered steps) fits mobile/low-literacy users. Tested for clarity (simple vocab like "छत पर जमा करें").

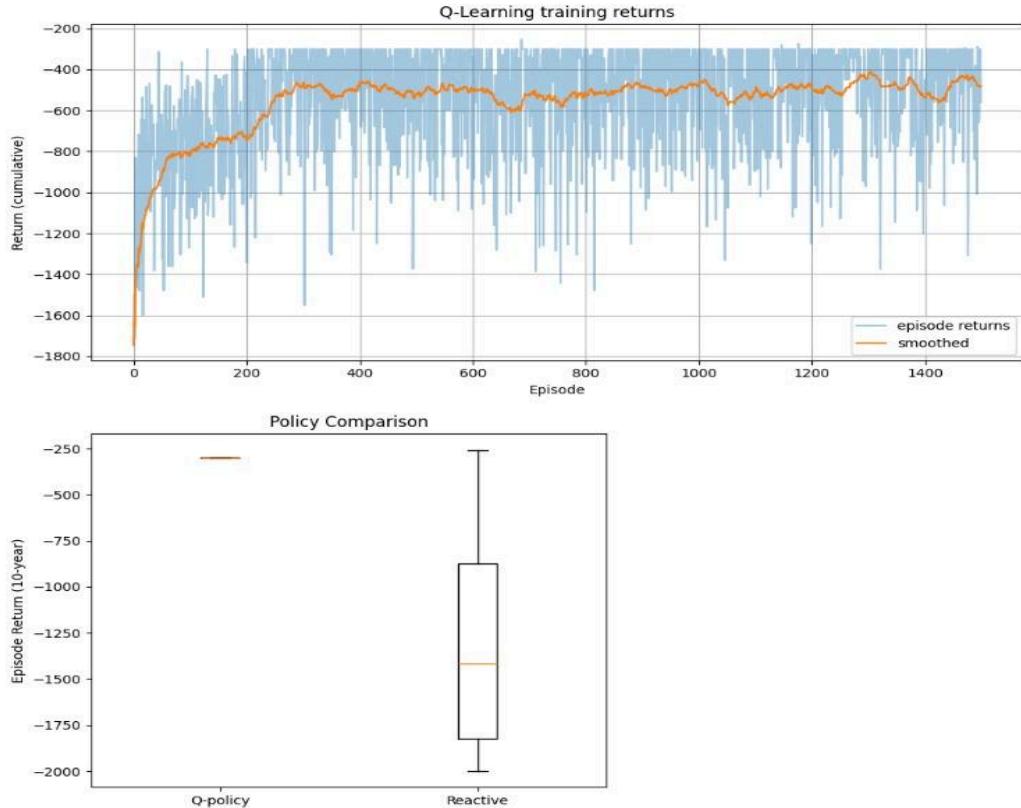
Prompt Engineering Fit: Role-playing + constraints (structure, bilingual) guide LLM to safe outputs; no fine-tuning needed. For extension: Add user feedback loop in code for adaptive prompts.

## Outputs:

### Resilience Search:



## Q-Learning:



```

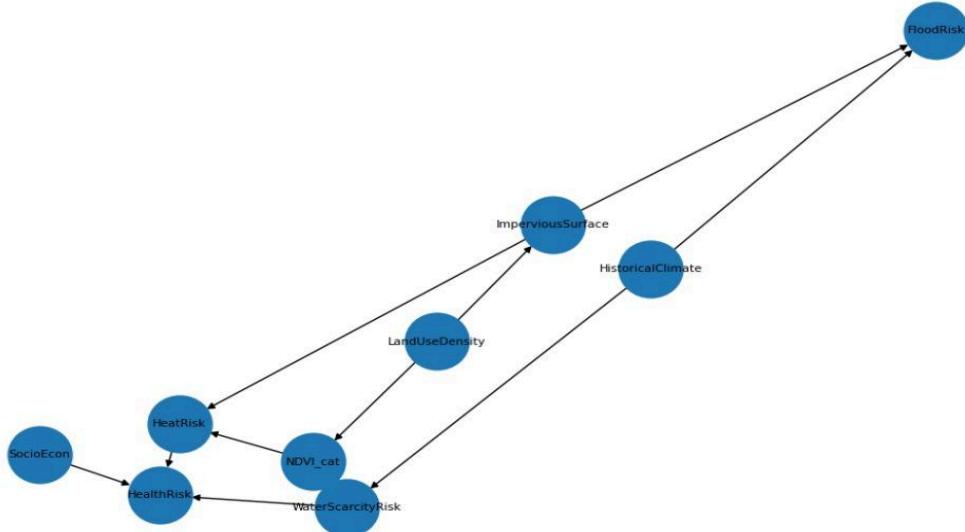
Training Q-learning...
Episode 0/1500, return=-1745.22
Episode 150/1500, return=-997.55
Episode 300/1500, return=-300.00
Episode 450/1500, return=-791.06
Episode 600/1500, return=-337.30
Episode 750/1500, return=-300.00
Episode 900/1500, return=-678.45
Episode 1050/1500, return=-851.17
Episode 1200/1500, return=-328.88
Episode 1350/1500, return=-300.00
Training done. avg return (last 200 eps): -487.00596173519267
Saved greedy Q policy vs reactive baseline...
Q-policy mean return: -300.0 std: 0.0
Reactive baseline mean return: -1311.6791719321864 std: 524.9830056833811
Saved q_learning_returns.png
C:\Users\DELL\AppData\Local\Temp\ipykernel_15824\173353988.py:299: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; support for the old name will be dropped in 3.11.
  plt.boxplot([q_returns, base_returns], labels=['Q-policy', 'Reactive'])
Saved policy_comparison_box.png

Sample greedy actions for typical states:
State H0 G0 E0 -> InvestGreen
State H0 G0 E1 -> InvestGreen
State H0 G0 E2 -> InvestGreen
State H0 G40 E0 -> InvestGreen
State H0 G40 E1 -> InvestGreen
State H0 G40 E2 -> InvestGreen
State H0 G80 E0 -> InvestGreen
State H0 G80 E1 -> InvestGreen
State H0 G80 E2 -> InvestGreen
State H1 G0 E0 -> InvestGreen
State H1 G0 E1 -> InvestGreen
State H1 G0 E2 -> InvestGreen
State H1 G40 E0 -> InvestGreen
State H1 G40 E1 -> InvestGreen
State H1 G40 E2 -> InvestGreen
State H1 G80 E0 -> InvestGreen
State H1 G80 E1 -> InvestGreen
State H1 G80 E2 -> InvestGreen
State H2 G0 E0 -> InvestGreen
State H2 G0 E1 -> InvestGreen
State H2 G0 E2 -> InvestGreen
State H2 G40 E0 -> InvestGreen
State H2 G40 E1 -> InvestGreen
State H2 G40 E2 -> InvestGreen
State H2 G80 E0 -> InvestGreen
State H2 G80 E1 -> InvestGreen
State H2 G80 E2 -> InvestGreen
Saved q_table.npy

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## Bayesian:

Bayesian Network Structure (Climate Vulnerability)



For gen ai it is shown above

## Conclusion

This project successfully demonstrates an integrated, multi-module AI framework for enhancing urban climate resilience. By combining probabilistic risk forecasting, efficient intervention planning, and adaptive long-term policy learning, the system provides a comprehensive decision-support tool for urban planners. The Bayesian network module enables a granular understanding of vulnerabilities, the search module generates cost-optimal action plans, and the reinforcement learning agent discovers robust, long-term strategies. Together, these components form a powerful foundation for building smarter, safer, and more resilient cities in the face of climate change.