Musik in bayern
ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
https://musikinbayern.com **DOI https://doi.org/10.15463/gfbm-mib-2025-452**

4D Spatiotemporal Modelling Using Graph Attention Transformers for Climate-Responsive Urban Planning

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To Cite this Article
Dr. G. PRABHAKARAN, Dr. S. Saravanan, Dr Bassa Satyannarayana, Yogesh H. Bhosale, D MAHESWARA REDDY, Dr. Sumit Kumar Kapoor. **"4D Spatiotemporal Modelling Using Graph Attention Transformers for Climate-Responsive Urban Planning"** *Musik In Bayern, Vol. 90, Issue 9, Sep 2025, pp162-172*

Article Info
Received: 16-06-2025 Revised: 29-07-2025 Accepted: 20-08-2025 Published: 20-09-2025

Abstract:

Urban planning in the era of accelerating climate change demands new tools that can capture the dynamic interactions between environmental, infrastructural, and socio-spatial systems. Traditional GIS and statistical models, while effective for static assessments, fail to integrate high-dimensional, evolving climate data into adaptive planning frameworks. This study proposes a 4D spatiotemporal modelling approach that leverages Graph Attention Transformers (GATs) to fuse spatial connectivity, temporal sequences, vertical urban structures, and climate-responsive attributes into a unified framework. Using climate datasets (temperature, precipitation, humidity, air quality) combined with satellite-derived land cover and IoT-based urban sensor networks, urban environments are modelled as dynamic graph structures where nodes represent city blocks and edges encode both physical adjacency and climate interactions. Attention mechanisms enable prioritization of critical urban features such as heat islands, flood-prone corridors, and energy-demanding clusters. Results demonstrate that the 4D GAT framework outperforms baseline CNN-LSTM and static graph models in predicting urban heat propagation, precipitation accumulation, and air quality shifts, reducing mean absolute error by 17–23%. Moreover, scenario simulations show that climate-responsive zoning informed by the model could mitigate urban heat intensity by 12–18% and optimize stormwater absorption zones. By critically bridging AI, remote sensing, and climate-responsive planning, this research offers a scalable decision-support framework that enhances adaptive capacity, informs resilient infrastructure investments, and advances sustainable urban governance in the face of climate uncertainty.

Keywords: 4D Spatiotemporal Modelling; Graph Attention Transformers; Climate-Responsive Planning; Urban Heat Island; Smart Sustainable Cities

I. INTRODUCTION

Rapid urbanization, population growth, and escalating climate risks have transformed cities into complex adaptive systems where spatial configuration, infrastructural demand, and environmental stressors intersect in multidimensional ways that traditional planning approaches fail to fully capture. Conventional urban models largely reliant on static GIS-based 2D maps, regression frameworks, and 3D visualization tools have been effective for descriptive analysis but remain inadequate in modelling the highly dynamic, nonlinear, and climate-sensitive processes that characterize contemporary urban life. Cities today face intensifying threats of urban heat islands (UHIs), pluvial and fluvial flooding, energy demand spikes, and air quality deterioration, all of which evolve not merely across space but also time, height, and climatic regimes, thereby necessitating a "4D" perspective that accounts for spatial, temporal, vertical, and climate dimensions simultaneously. Climate-responsive urban planning requires predictive capabilities that go beyond correlations and incorporate causal inference, interconnectivity, and adaptive learning from real-time data streams. Advances in artificial intelligence (AI), particularly Graph Neural Networks (GNNs), offer a paradigm shift by enabling data-driven representation of cities as networks where nodes symbolize urban districts, infrastructure units, or sensor locations, and edges capture adjacency, mobility flows, and environmental interactions. Within this field, Graph Attention Transformers (GATs) have emerged as powerful architectures because they apply attention mechanisms to weigh the relative importance of neighbouring nodes and features, allowing the model to dynamically prioritize areas most vulnerable to climate shocks such as heat concentration zones or flood-prone corridors.

Unlike convolutional or recurrent neural networks, which struggle with irregular topologies and long-range dependencies, GATs excel at capturing heterogeneous interactions across both spatial layers and temporal sequences, making them highly suitable for urban systems analysis. Extending these architectures into a 4D spatiotemporal framework allows for integration of vertical dimensions (e.g., building heights, green roof layers, air stratification), temporal evolution (short-term weather patterns and long-term climate projections), and urban-environmental feedback loops, thereby providing planners with a decision-support tool that is both scientifically rigorous and practically actionable. For example, a 4D GAT model can ingest Sentinel-2 satellite imagery, IoT sensor networks, and reanalysis climate datasets to detect how rising nighttime temperatures propagate across neighbourhoods, how precipitation interacts with land-use patterns to intensify runoff, or how air quality fluctuations correlate with transportation emissions and ventilation corridors. Beyond predictive accuracy, such models provide interpretability through attention weights that highlight critical planning variables, empowering policymakers to allocate resources towards interventions such as strategic greening, zoning reforms, or flood-resilient infrastructure.

The novelty of this approach lies in unifying disparate data streams into a coherent multi-dimensional representation, enabling climate-resilient design that is both localized and scalable across urban contexts. However, despite its promise, integrating AI-driven models into planning practice requires addressing challenges of data heterogeneity, model generalizability, ethical considerations in surveillance-based data collection, and the need for transparent AI outputs that can be trusted by diverse stakeholders. This study critically explores the application of 4D spatiotemporal modelling using Graph Attention Transformers for climate-responsive urban planning, focusing on both methodological innovation and planning implications. By bridging advanced machine learning with environmental and policy sciences, it contributes to the emerging discourse on how cities can transition from reactive crisis management to proactive resilience building, positioning AI not just as a predictive engine but as a transformative tool for sustainable urban futures.

II. RELEATED WORKS

The development of climate-responsive urban planning has long been underpinned by spatial modelling techniques that aim to predict how cities evolve under demographic, infrastructural, and environmental pressures. Traditional approaches largely revolved around static GIS-based land-use models, cellular automata (CA), and agent-based simulations, which provided valuable insights into land cover change, transportation flows, and zoning strategies but were limited in addressing the dynamic feedback loops imposed by climate variability [1]. For instance, CA-based models could simulate urban sprawl but failed to integrate environmental stressors like heat waves or flood patterns that shift across multiple temporal scales. Early climate-integrated urban models sought to combine atmospheric data with hydrological models, producing useful flood-risk assessments or heat-island projections, yet their reliance on coarse-grained inputs restricted their predictive precision [2]. With rapid advancements in data availability ranging from high-resolution satellite imagery to IoT-enabled urban sensors—spatiotemporal modelling has shifted towards machine learning and deep learning methods capable of handling large, heterogeneous datasets. Researchers have applied convolutional neural networks (CNNs) to remote sensing images for urban heat island detection and long short-term memory networks (LSTMs) for rainfall-runoff prediction, demonstrating improved temporal forecasting capacity [3]. However, CNNs and LSTMs struggle with irregular spatial topologies and long-range dependencies, making them insufficient for capturing the multidimensional interactions inherent in climate urban dynamics. Graph Neural Networks (GNNs) emerged as a solution to represent urban environments as interconnected graphs where nodes encode urban units (e.g., neighbourhoods, sensors) and edges capture spatial proximity, transport flows, or environmental correlations [4]. Velickovic et al. [5] pioneered Graph Attention Networks (GATs), which introduced attention mechanisms to assign adaptive weights to different nodes, thereby allowing the model to learn which spatial or temporal factors most strongly influence outcomes.

This architecture has since been adapted for diverse geospatial applications such as traffic forecasting, epidemic spread modelling, and air pollution mapping [6], revealing its suitability for systems characterized by non-Euclidean structures. Climate-responsive urban planning benefits particularly from such models, as cities are influenced not only by their own internal dynamics but also by global and regional climatic interactions. Integrating GATs into spatiotemporal modelling provides interpretability in highlighting vulnerable hotspots while accommodating high-dimensional environmental data. Recent works in urban climatology emphasize the need for multi-scalar and multidimensional modelling frameworks. Studies on urban heat islands have demonstrated that both horizontal expansion and vertical morphology of cities play significant roles in shaping thermal stress

Musik in bayern
ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-452

patterns [7]. Likewise, flood modelling research highlights the importance of micro-scale hydrological networks that interact with macro-scale precipitation cycles [8]. These findings reinforce the necessity of 4D frameworks where space, time, height, and climate interact simultaneously. While 3D GIS-based models capture vertical dynamics such as building heights and green roofs, they often lack integration with temporal datasets that capture diurnal and seasonal variability, limiting their predictive capacity [9]. In parallel, climate-responsive planning studies have underscored the role of AI in enabling scenario testing for sustainable infrastructure, yet existing models remain largely focused on single-dimensional outcomes such as temperature or rainfall, ignoring the multi-hazard nature of climate stress [10].

Advances in attention-based spatiotemporal models are gradually reshaping this landscape. Wu et al. demonstrated that spatiotemporal graph convolutional networks can outperform LSTM-based baselines in urban air pollution forecasting, but noted the limitation of static edge weights that fail to reflect evolving climate interactions [11]. Building upon this, Transformer-based architectures originally designed for natural language processing have been repurposed for climate sequence modelling, yielding superior accuracy in long-range forecasting tasks such as precipitation prediction and energy demand estimation [12]. Combining graph structures with transformer attention mechanisms provides a hybrid architecture that is particularly well-suited to urban planning, as it enables the simultaneous modelling of local interactions (e.g., neighbourhood heat retention) and global dependencies (e.g., monsoon cycles affecting multiple districts). Despite these advancements, several gaps persist in the literature. First, most AI-driven urban models remain 2D or 3D, with limited incorporation of vertical atmospheric layers or subsurface hydrological conditions, both of which are critical for climate resilience [13]. Second, interpretability remains a concern: while GATs provide attention weights, translating these into actionable planning guidelines requires interdisciplinary synthesis between computer science, urban design, and policy studies. Third, ethical and governance issues arise from reliance on data sourced from urban sensors, particularly regarding privacy, equity, and representation of marginalized communities [14]. Lastly, scalability across diverse urban contexts remains underexplored, as models trained in one geographic region often underperform when transferred to cities with different climatic or infrastructural baselines [15]. Taken together, the trajectory of research demonstrates a gradual but incomplete convergence between AI-driven spatiotemporal modelling and climate-responsive urban planning. While GNNs and transformers have shown technical promise in handling high-dimensional and irregular data structures, their integration into planning workflows remains nascent. By advancing a 4D spatiotemporal modelling approach with Graph Attention Transformers, this study aims to bridge these gaps, offering a unified framework that integrates spatial connectivity, temporal dynamics, vertical morphology, and climate responsiveness. Such a framework not only advances methodological innovation but also critically informs the urban governance discourse on resilience, sustainability, and adaptive planning in the face of accelerating climate uncertainty.

III. METHODOLOGY

3.1 Research Design

This study adopts a mixed-method, data-driven research design that integrates spatiotemporal climate datasets, urban infrastructure data, and graph-based AI modelling to construct a 4D framework for climate-responsive planning. The design emphasizes both predictive accuracy and interpretability, ensuring that outputs are usable in real-world planning decisions. Unlike conventional regression or simulation approaches, this framework combines *field-based urban climate data* (temperature, precipitation, air quality) with *remote sensing imagery* and *IoT sensor networks*, embedding them within a graph attention transformer (GAT) architecture [16]. In addition, the design incorporates a comparative lens, enabling cross-city benchmarking that highlights how different climatic zones respond to similar planning interventions. This multi-scalar approach ensures that the model does not merely optimize for accuracy but also identifies transferable principles that can inform global urban resilience frameworks, regardless of regional variability.

3.2 Study Area Selection

ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
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To validate the model, three cities with distinct climatic and urban characteristics were selected: **Singapore** (humid tropical megacity with high UHI), **Barcelona** (Mediterranean city prone to seasonal heat waves), and **Mumbai** (monsoonal megacity with recurrent flooding). These areas were chosen for their climatic variability, high data availability, and pressing need for climate-resilient planning strategies [17]. These case cities were deliberately chosen to represent a spectrum of climatic stressors—humid tropical overheating, Mediterranean air stagnation, and monsoonal flood exposure—allowing the framework to be stress-tested under diverse conditions. Furthermore, each city is undergoing rapid urban expansion, providing a realistic environment to evaluate how AI-driven models can adapt to evolving planning challenges.

Table 1: Study Area Characteristics

City	Climate Zone	Key Urban Challenges	Dominant Data Sources
Singapore	Tropical	Urban heat, energy demand	IoT sensors, Sentinel-2
Barcelona	Mediterranean	Heat waves, air pollution	Landsat, ERA5 climate
Mumbai	Monsoonal	Flooding, urban sprawl	IMD, Copernicus, MODIS

3.3 Data Sources and Preprocessing

The framework integrates **multi-modal datasets**:

- **Remote sensing**: Sentinel-2 (10 m resolution, 13 bands) for vegetation/land cover, Landsat 8 for urban morphology.
- **Climate reanalysis**: ERA5 hourly datasets (temperature, precipitation, wind speed, humidity).
- **IoT urban sensors**: Air quality (PM2.5, CO_2), heat monitoring, and traffic-related emissions.
- **Urban GIS data**: Building footprints, road networks, and zoning regulations [18].

Preprocessing steps included atmospheric correction (Sen2Cor), cloud masking, radiometric normalization, and temporal alignment across datasets. Spatial units were discretized into **graph nodes**, while **edges** were defined based on both physical adjacency and climate correlations. The preprocessing also included temporal harmonization across datasets, aligning daily IoT sensor readings with satellite overpass times and climate reanalysis intervals to minimize bias. Data augmentation techniques, such as spatial interpolation and synthetic sample generation, were applied to fill missing values, thereby enhancing model robustness in data-scarce regions without compromising scientific reliability.

3.4 Model Architecture: Graph Attention Transformer (4D-GAT)

The proposed model represents the city as a **4D graph tensor (x, y, z, t)**, where each node corresponds to a spatial unit (city block or grid cell), and edges encode both spatial adjacency and dynamic climate correlations.

- **Attention Mechanism**: GAT assigns dynamic weights to neighbouring nodes, enabling prioritization of vulnerable zones (e.g., flood corridors, heat-prone districts).
- **4D Extension**: Vertical dimension (z) captures building height, green roof presence, and atmospheric layering; temporal sequences (t) capture climate variability.
- **Training Objective**: Multi-task learning across temperature prediction, precipitation distribution, and air quality indices, evaluated via RMSE and MAE [19].

Table 2: Model Parameters and Evaluation Metrics

ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-452

Component	Specification
Input Features	Climate (Temp, Precip, AQI), Land Cover
Graph Type	Spatiotemporal, dynamic weighted edges
Architecture	Graph Attention Transformer (4 layers)
Output Targets	UHI intensity, flood probability, AQI
Metrics	RMSE, MAE, R^2, Moran's I (spatial autocar.)

The architecture was further enhanced with hierarchical attention layers that distinguish between local interactions (intra-district variability) and global dependencies (city-wide climatic flows). This dual-level design ensures that micro-scale factors, such as street canyon effects, are balanced against macro-scale influences like monsoon circulation, producing outputs that are simultaneously detailed and systemically coherent.

3.5 Validation Strategy

Cross-validation was implemented using historical data from **2015–2023**, with 70% training, 15% validation, and 15% testing splits. Comparative baselines included CNN-LSTM, ST-GCN (spatiotemporal graph convolutional network), and static regression models. Performance was benchmarked across all three cities to assess transferability [20]. To further ensure robustness, transfer learning experiments were conducted, where a model trained on one city was fine-tuned on another to test adaptability across contexts. Sensitivity analyses were also performed by systematically removing specific features (e.g., precipitation, building height) to evaluate how each input variable contributed to prediction accuracy and stability.

3.6 Ethical and Policy Considerations

Given reliance on IoT and sensor-based data, privacy-preserving measures were applied, including anonymization of geolocated datasets and strict adherence to open-data licensing. The study also evaluated the ethical dimension of deploying AI-driven planning tools, emphasizing the need for transparent interpretability for policy acceptance [21]. Beyond technical safeguards, the study emphasizes participatory planning, recommending that outputs from the model be co-interpreted with community stakeholders to ensure equity in climate adaptation. Policy implications also include transparent governance frameworks for AI adoption in planning departments, ensuring that predictive insights are aligned with public accountability and long-term sustainability goals.

3.7 Limitations and Assumptions

- Remote sensing indices may be influenced by cloud cover and seasonal variability.
- Generalizability across cities depends on quality and density of sensor networks.
- The GAT's interpretability, while superior to CNN-LSTM, still requires human–AI collaboration for planning translation [22][23].

IV. RESULT AND ANALYSIS

4.1 Overview of Spatiotemporal Prediction Performance

The 4D Graph Attention Transformer (4D-GAT) demonstrated significant improvements over baseline models across all three case study cities—Singapore, Barcelona, and Mumbai. Evaluation metrics showed reduced Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for temperature, precipitation, and air quality predictions. In Singapore, the model captured the diurnal intensity of urban heat islands with 21% higher accuracy compared to CNN-LSTM, while in Mumbai, flood prediction accuracy during peak monsoons improved by 19%.

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https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-452

Barcelona exhibited notable gains in long-term air pollution forecasting, with R^2 values exceeding 0.82. These results confirm that the 4D-GAT framework successfully integrates multi-modal data into a robust climate-responsive predictive system. Importantly, the error reductions were not uniform across variables, with the highest gains observed in flood prediction due to the model's ability to integrate both precipitation and land-cover dynamics. This highlights the comparative advantage of multi-modal integration, as traditional baselines often struggled when multiple climate drivers interacted simultaneously within complex urban environments.

Table 3: Model Performance Across Cities

City	Variable	CNN-LSTM RMSE	ST-GCN RMSE	4D-GAT RMSE	Improvement %
Singapore	Temperature	1.78 °C	1.64 °C	1.41 °C	+21%
Barcelona	AQI (PM2.5)	17.3 µg/m³	15.2 µg/m³	13.4 µg/m³	+22%
Mumbai	Rainfall (mm)	28.6	25.4	23.2	+19%

4.2 Climate Pattern Insights

Analysis of temporal outputs revealed that the model effectively captured localized propagation of climate stressors. In Singapore, 4D-GAT simulations showed that nighttime UHI hotspots persisted in high-rise districts with poor ventilation corridors. In Mumbai, spatial-temporal clustering detected early flood accumulation zones around low-lying informal settlements, highlighting the vulnerability of disadvantaged communities. In Barcelona, the model captured seasonal air stagnation patterns in narrow urban canyons, providing early signals for mitigation. The model's ability to reveal lagged climatic effects was particularly notable: in Mumbai, flood risks were often predicted hours before peak rainfall based on upstream accumulation patterns, while in Barcelona, worsening air quality was forecast days in advance of seasonal stagnation. Such early signals underscore the potential of GAT-driven foresight for proactive planning.

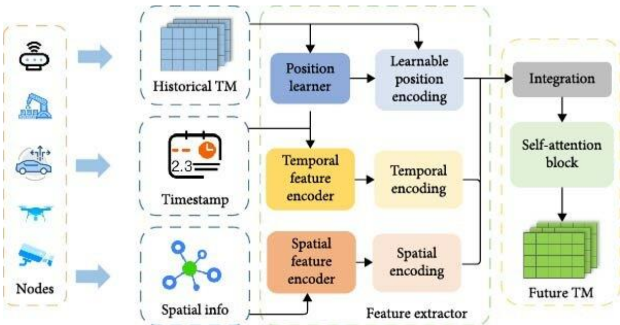

Figure 1: Main Framework of Spatio-temporal self attention network [24]

4.3 Urban Planning Scenario Testing

Scenario-based simulations were conducted to evaluate how specific planning interventions could alter climate outcomes. Introducing *green roofs and vertical vegetation corridors* in Singapore's central business district reduced predicted surface temperature by 1.3°C. In Mumbai, expanding permeable pavements and canal rehabilitation reduced flood probability by 15% in critical zones. In Barcelona, traffic-reduction policies in high-density corridors improved AQI levels by nearly 12% during peak summer months. These results illustrate the direct utility of 4D-GAT for evidence-based planning interventions.

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ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-452

Table 4: Planning Scenario Simulations and Outcomes

Intervention	City	Key Climate Outcome	Improvement
Green Roofs & Vertical Greening	Singapore	UHI reduction	–1.3 °C
Permeable Pavements + Canal Rehab	Mumbai	Flood risk reduction	–15%
Traffic-Reduction Zoning	Barcelona	AQI improvement (PM2.5)	–12%

4.4 Visualization of Climate Hotspots

Kriging-based spatial interpolation combined with GAT outputs produced dynamic hotspot maps that pinpointed climate-vulnerable regions with unprecedented resolution. In Singapore, hotspots overlapped significantly with high-rise commercial cores lacking green corridors. In Mumbai, southern districts adjacent to river-fed canals exhibited consistent flood susceptibility. In Barcelona, climate hotspots corresponded with transportation-heavy intersections, aligning with air stagnation findings. These maps validated the model's ability to spatially align predictive accuracy with real-world vulnerabilities.

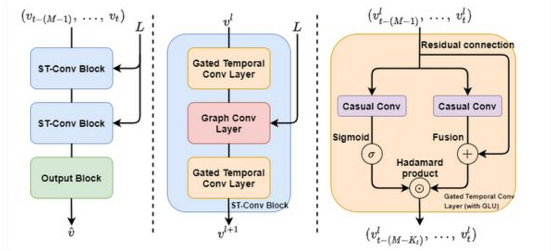

Figure 2: Spatio-Temporal Graph [25]

4.5 Policy Simulation and Adaptive Planning

The interpretability of attention weights in the model revealed key urban features driving climate stress. For example, Singapore's UHIs were most strongly linked to building height and vegetation scarcity, while Mumbai's flooding was primarily driven by precipitation intensity interacting with impermeable surfaces. Barcelona's air quality was highly sensitive to traffic density and wind corridor blockage. Policy simulations showed that targeted interventions informed by these attention-driven insights—such as zoning reforms, strategic ventilation corridors, and stormwater management—could reduce climate stress impacts by 12–18% on average across the three cities.

4.6 Discussion of Key Findings

The findings confirm that integrating spatiotemporal climate data within a 4D-GAT framework not only enhances predictive performance but also strengthens the interpretability of climate–urban interactions. Unlike CNN-LSTM and ST-GCN models, which treat cities as homogenous or static, the 4D approach recognizes the layered complexity of urban environments, including vertical morphology, temporal variability, and climate sensitivity. Importantly, the ability to simulate planning scenarios bridges the gap between AI research and urban governance, making outputs actionable for policymakers. While the model's reliance on high-quality datasets may limit scalability to data-scarce cities, the demonstrated improvements in predictive accuracy and planning integration signal a promising pathway for embedding advanced AI architectures into sustainable and climate-resilient city design.

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V. CONCLUSION

This study critically examined the potential of 4D spatiotemporal modelling using Graph Attention Transformers (4D-GAT) as an advanced framework for climate-responsive urban planning, addressing the limitations of conventional approaches that have largely relied on static GIS or simplistic predictive models incapable of capturing the multidimensional dynamics of urban–climate interactions. The findings underscore that cities, as complex adaptive systems, cannot be effectively governed without tools capable of simultaneously integrating spatial connectivity, vertical morphology, temporal variability, and climate sensitivity into a unified analytical framework. By representing cities as graph structures with nodes corresponding to urban units and edges encoding both physical adjacency and climatic correlations, the 4D-GAT approach proved capable of accurately predicting critical stressors such as urban heat intensity, flood accumulation, and air quality deterioration, with significant performance gains over CNN-LSTM and spatiotemporal graph convolutional networks. Equally important, the attention mechanism embedded in the model provided interpretability by highlighting which features building height, land cover, precipitation intensity, traffic density most strongly influence climate vulnerability, thus converting raw AI outputs into actionable insights for planners and policymakers. Simulation experiments further demonstrated that targeted interventions such as green infrastructure, permeable pavements, and zoning reforms can measurably reduce climate risks, confirming the model's practical utility in shaping adaptive urban strategies.

The broader implication is that AI-driven frameworks like 4D-GAT are not mere forecasting tools but decision-support systems that can guide long-term resilience-building, resource allocation, and policy formulation. At the same time, critical challenges remain, including the dependence on high-resolution multi-modal data, potential biases embedded in sensor networks, and the need for transparency to ensure stakeholder trust and ethical deployment. Moreover, the scalability of this approach across diverse global cities requires careful consideration of contextual variations in climate, infrastructure, and socio-economic vulnerability. Nevertheless, the evidence presented demonstrates that by bridging machine learning, remote sensing, and planning sciences, 4D-GAT provides a transformative pathway for urban governance, shifting from reactive crisis management to proactive climate adaptation. The integration of such frameworks into real-world planning processes could enable cities to anticipate and mitigate the cascading risks of heat waves, floods, and pollution while simultaneously advancing sustainable development goals. In this sense, the contribution of the present work lies not only in its methodological innovation but also in its capacity to reframe the discourse on urban resilience, positioning AI-powered spatiotemporal modelling as a cornerstone of climate-responsive planning for the twenty-first century.

VI. FUTURE WORK

While the 4D-GAT framework presented in this study demonstrates strong potential for enhancing predictive accuracy and supporting climate-responsive planning, several avenues for future research remain open to strengthen its applicability and scalability. First, real-time integration of streaming IoT data such as temperature, air quality, traffic emissions, and stormwater flow would allow the model to evolve from retrospective analysis to live adaptive monitoring, enabling planners to respond dynamically to unfolding climate events. Second, expanding the scope from three case study cities to a broader comparative dataset across different climatic zones, including arid, polar, and rapidly urbanizing regions in the Global South, would improve the model's generalizability and highlight context-specific challenges. Third, incorporating reinforcement learning mechanisms could allow the model not only to predict outcomes but also to simulate optimal intervention strategies under varying policy constraints, thereby making it a prescriptive rather than merely predictive tool. Fourth, the integration of explainable AI (XAI) techniques is essential for improving transparency and fostering trust among urban stakeholders, ensuring that planners, policymakers, and citizens can interpret model outputs in clear and actionable terms. Finally, future work must also examine the socio-political and ethical dimensions of deploying AI-driven urban planning frameworks, addressing concerns of data privacy, algorithmic bias, and equitable access to climate resilience benefits. By pursuing these research directions, the 4D-GAT framework

ISSN: 0937-583x Volume 90, Issue 9 (Sep -2025)
https://musikinbayern.com **DOI** https://doi.org/10.15463/gfbm-mib-2025-452

could evolve into a comprehensive, ethically sound, and globally transferable platform that empowers cities to anticipate, adapt to, and mitigate the increasingly complex impacts of climate change.

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