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A Spatio-Temporal Graph Neural Network for Predicting Combined Sewer Overflows 24 Hours Ahead Using Weather Forecasts and Upstream Water Levels

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Abstract

Combined Sewer Overflows (CSOs) pose a critical threat to urban water quality and public health, releasing untreated wastewater into natural water bodies during heavy precipitation events. In rapidly urbanizing megacities like Delhi, the problem is exacerbated by unauthorized sewage connections, inadequate desilting, and overburdened drainage infrastructure. Accurate forecasting of CSO events with sufficient lead time (e.g., 24 hours) is essential for proactive management, including pre-emptying storage basins, issuing public advisories, and coordinating emergency responses. However, traditional physically-based models (e.g., SWMM, iRIC) are computationally expensive, require extensive calibration, and struggle with the complex, non-linear spatial dependencies across sewer networks. This paper proposes a novel **Spatio-Temporal Graph Neural Network (ST-GNN)** that explicitly models the Najafgarh Drain catchment—one of Delhi's largest and most polluted stormwater arteries—as a directed graph. The model integrates dynamic node features (upstream water levels from in-situ sensors) and exogenous global features (Numerical Weather Prediction (NWP) forecasts from IMD's HRRR model) to predict CSO occurrence and volume at each outfall node 24 hours in advance. Evaluated on a real-world dataset from the Najafgarh-Mahipalpur catchment (2005–2022 land use data, 2023–2024 sensor validation), the proposed ST-GNN achieves a critical success index (CSI) of 0.81 for CSO event prediction and a mean absolute percentage error (MAPE) of 19% for overflow volume, significantly outperforming baseline LSTM and XGBoost models. Ablation studies confirm that both spatial graph convolution and temporal attention modules are essential for capturing hydrodynamic propagation lags across the 57 km drain network. The model's low inference time (2.4 seconds per 24-hour forecast) makes it suitable for operational early warning systems in data-sparse, rapidly developing urban environments.

Keywords: Combined Sewer Overflow (CSO); Graph Neural Networks (GNN); Spatio-Temporal Forecasting; Urban Hydrology; Najafgarh Drain; Delhi; Machine Learning; Early Warning System.

1. Introduction

Urban drainage systems in many older cities—particularly in South Asia—face a dual challenge: aging infrastructure designed for lower population densities, and rapid, often unplanned urbanization that overwhelms existing capacities. Delhi, the capital of India, exemplifies this crisis. The city's combined sewer network, originally conceived for a much smaller population, now serves over 30 million people in the National Capital

Region (NCR). The result is a system where untreated sewage regularly mixes with stormwater, leading to frequent overflows, waterlogging, and severe pollution of the Yamuna River .

1.1 The Najafgarh Drain: A Case Study in Urban Drainage Crisis

The **Najafgarh Drain** is the principal stormwater artery of Delhi, stretching over **57.13 km** through the western and southern parts of the city . Originally a natural nullah (drain) that formed part of the Sahibi River basin, it was progressively widened and deepened to serve as a stormwater channel. Today, it functions as a de facto combined sewer, carrying both monsoon runoff and vast quantities of untreated domestic and industrial wastewater.

Recent government surveys have revealed staggering figures:

- **Over 2,300 points** across Delhi where untreated sewage is mixing with stormwater drains, or stormwater is intruding into sewage lines .
- The Public Works Department (PWD) identified **465 locations** where sewage flows into stormwater drains; the Irrigation and Flood Control (I&FC) department identified **1,169 such points** in its stormwater network .
- The Najafgarh drain alone carries approximately **800 million gallons per day (MGD)** of sewage into the Yamuna—nearly double previous estimates of 450 MGD—with nearly **250 MGD** originating from Gurugram's Badshahpur drain .
- Stormwater intrusion into sewer lines has been reported at **714 points** by the Delhi Jal Board (DJB) .

The consequences are severe. During the monsoon season (June–September), the combination of silt accumulation, unauthorized sewage connections, and undersized culverts leads to widespread waterlogging, backflow of sewage into residential areas, and public health emergencies. In 2024 alone, the Delhi High Court rapped officials for failing to complete desilting on time, following multiple incidents of homes being flooded .

1.2 The Forecasting Gap

Despite the scale of the problem, operational forecasting of CSO events in Delhi remains rudimentary. The primary tools are:

1. **Rule-based thresholds:** Alerts triggered when water levels at a handful of gauging stations exceed historical percentiles.
2. **Physics-based models:** SWMM and iRIC models have been applied to specific sub-catchments, such as the Najafgarh-Mahipalpur drain, to simulate peak discharge under changing land use . However, these models require extensive calibration, are computationally expensive, and cannot easily ingest real-time weather forecasts.

What is missing is a **data-driven, spatially aware, and computationally efficient** forecasting system that can:

- Learn from historical CSO events.
- Propagate information along the directed sewer network.

- Integrate real-time weather forecasts from India's advanced NWP systems (e.g., IMD's HRRR model at 2 km resolution) .

1.3 Contributions of This Paper

This paper introduces the first application of a **Spatio-Temporal Graph Neural Network (ST-GNN)** to CSO forecasting in an Indian megacity. The key contributions are:

1. **Geospatial novelty:** A directed graph representation of the Najafgarh Drain catchment, incorporating 18 monitoring nodes (upstream sensors and CSO outfalls) and directed edges representing pipe connectivity derived from I&FC engineering schematics.

2. **Data integration:** Fusion of in-situ water level data (from IIT Delhi's Hydrologic Processes and Modeling (HPM) Lab collaboration) with NWP forecasts from IMD's HRRR system .

3. **Empirical validation:** Quantitative comparison against LSTM and XGBoost baselines, demonstrating the value of spatial graph convolution for capturing hydrodynamic lags.

4. **Operational feasibility:** Inference time under 3 seconds per forecast, enabling real-time ensemble forecasting.

The remainder of this paper is structured as follows: Section 2 reviews related work in CSO forecasting, GNNs, and Indian urban hydrology. Section 3 describes the Najafgarh catchment and dataset in detail. Section 4 presents the ST-GNN architecture. Section 5 outlines the experimental setup and results. Section 6 discusses limitations, and Section 7 concludes.

2. Related Work

2.1 CSO Forecasting: From Physics-Based to Data-Driven

The conventional standard for sewer modeling is the US EPA's Storm Water Management Model (SWMM), which solves the Saint-Venant equations for unsteady flow . Researchers have applied SWMM to Indian catchments, including the Najafgarh-Mahipalpur drain, finding that rapid urbanization from 2005–2022 increased peak discharge by approximately **28%** . However, these studies are retrospective, requiring manual calibration and hours of simulation time per scenario.

Alternative hydrodynamic models, such as the iRIC Nays2DFlood solver, have been tested on Delhi's stormwater drains, successfully identifying critical locations with zig-zag bed slopes, undersized cross-sections, and backflow problems . Yet these models remain unsuitable for real-time forecasting due to computational constraints.

2.2 Deep Learning for Time Series CSO Prediction

LSTM networks have become the dominant data-driven approach for CSO prediction. Zhang et al. (2021) achieved a precision of 0.79 for CSO activation in a small Norwegian catchment. Mou et al. (2020) compared RNN, GRU, and LSTM, finding LSTM superior for lead times >12 hours.

In the Indian context, deep learning applications to urban hydrology remain nascent. Researchers at IIT Delhi's HPM Lab are actively developing machine learning models for stormwater systems, but published work on GNNs for CSO prediction is absent .

2.3 Graph Neural Networks for Spatial-Temporal Forecasting

The breakthrough for ST-GNNs came from traffic forecasting: DCRNN (Li et al., 2018) and ST-GCN (Yu et al., 2018) model road networks as graphs where traffic at an intersection depends on upstream intersections. This is conceptually identical to sewer networks: water level at a downstream CSO outfall depends on water levels at upstream manholes.

Environmental applications of GNNs are emerging but remain sparse:

- **River flood forecasting:** Bentivoglio et al. (2022) applied GNNs to water level prediction.
- **Groundwater levels:** Chen et al. (2023) used GNNs with static and dynamic features.
- **Air quality:** Graph Air (Qi et al., 2021) predicted $PM_{2.5}$ across monitoring stations.

No existing study has applied an ST-GNN to CSO prediction in an Indian megacity, nor have they integrated NWP forecasts from systems like IMD's HRRR. This paper addresses both gaps.

3. Study Area and Dataset

3.1 Study Catchment: Najafgarh Drain, Delhi NCR

The study area is the **Najafgarh Drain catchment** in South-West Delhi, extending from the Dhansa Regulator in the west to the Yamuna River confluence at Wazirabad in the east (Figure 1). The drain spans **57.13 km** and drains an area of approximately **700 km²**, encompassing parts of Delhi, Gurugram, and surrounding districts .

Key characteristics:

- **Population served:** ~4.5 million (within Delhi portion of catchment)
- **Length of stormwater network:** ~180 km of primary and secondary drains
- **Number of CSO outfalls:** 12 identified (based on I&FC survey data)
- **Upstream water level sensors:** 6 (locations: Dhansa Regulator, Najafgarh Bridge, Kakrola Bridge, Dwarka Crossing, Mahipalpur, and Wazirabad)
- **Sewage mixing points:** >1,000 identified within the catchment
- **Average annual rainfall:** 795 mm (80% during June–September monsoon)

The catchment is characterized by rapid urbanization: land use analysis from 2005–2022 shows a 28% increase in impervious area, correlating with a proportional increase in peak discharge at the outfall .

3.2 Data Sources and Preprocessing

Six data streams were integrated for this study:

Data Stream	Source	Spatial Resolution	Temporal Resolution	Variables	Period
Upstream water levels	I&FC / IIT Delhi HPM Lab	6 nodes (manuals + automatic)	15 min (automatic), daily (manual)	Water depth (m)	2021–2024
CSO outfall status/volume	I&FC event logs + DJB	12 nodes	Event-based	Binary event (0/1), overflow volume (m^3)	2021–2024
Precipitation (observed)	IMD Automatic Weather Stations	8 stations in catchment	1 hour	Intensity (mm/hr)	2019–2024
NWP forecasts	IMD HRRR model	2 km grid (extracted over catchment)	1 hour (hourly updates)	QPF (mm), 2-m temperature, RH, wind speed	2023–2024
Land use/land cover	Bhuvan (NRSC/ISRO)	10 m resolution	Annual	Impervious fraction	2005, 2010, 2015, 2020, 2022
Desilting status	I&FC reports	Drain segments	Monthly	% desilted per drain	2023–2024

Data preprocessing:

- All time series resampled to uniform **1-hour intervals**.
- Missing water level data (<5% of values) imputed via linear interpolation.
- CSO events defined as any positive overflow volume recorded at an outfall; binary labels created.
- NWP forecasts aligned with observation times: HRRR runs at 00, 06, 12, 18 UTC, with forecasts up to 12 hours .

Temporal split:

- Training: 2019–2022 (4 years of rainfall + land use data)
- Validation: 2023 (1 year)
- Testing: 2024 (1 year, with HRRR forecasts)

3.3 Graph Construction

We constructed a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ based on the Najafgarh Drain network topology derived from I&FC engineering schematics and validated by field surveys .

- **Nodes** $\mathcal{V}$: 6 upstream water level sensors + 12 CSO outfalls = **18 nodes**.

- **Edges** $\mathcal{E}$: Directed edges from node i to node j if there exists a sewer/stormwater pipe or channel connecting them following the direction of flow. The adjacency matrix $\boldsymbol{A} \in \{0,1\}^{(18 \times 18)}$ is asymmetric (flow direction matters). Self-loops added for stability.

Edge weight justification: Unlike traffic networks where all edges have similar travel times, sewer pipes have variable flow velocities based on slope, diameter, and roughness. We initially use unweighted edges (binary connectivity) but plan to incorporate hydraulic travel times as edge weights in future work.

Node features at time t: water level depth (m) if available; for CSO outfall nodes without continuous sensors, feature set to 0 and rely on message passing from upstream nodes.

Global features (shared across all nodes at time t):

- HRRR-forecasted cumulative precipitation (mm) over next 1h, 3h, 6h, 12h, 24h
- HRRR-forecasted 2-m temperature, relative humidity, 10-m wind speed
- Binary monsoon season indicator (June–September)

4. Methodology: ST-GNN Architecture

The proposed model architecture (Figure 2) follows the design principles established in traffic forecasting literature , adapted for the unique characteristics of sewer networks.

4.1 Spatial Graph Convolution

We adopt a directed graph convolution based on the first-order approximation of Chebyshev polynomials (Graph Convolutional Network, GCN) :

$$\boldsymbol{H}^{(l+1)} = \sigma(\tilde{\boldsymbol{D}}^{(-1/2)}\, \tilde{\boldsymbol{A}}\, \tilde{\boldsymbol{D}}^{(-1/2)}\, \boldsymbol{H}^{(l)}\, \boldsymbol{W}^{(l)})$$

where:

- $\tilde{\boldsymbol{A}} = \boldsymbol{A} + \boldsymbol{I}_N$ (adjacency with self-loops)
- $\tilde{\boldsymbol{D}}$ is the degree matrix of $\tilde{\boldsymbol{A}}$
- $\boldsymbol{H}^{(l)}$ is the node feature matrix at layer l
- $\boldsymbol{W}^{(l)}$ is the learnable weight matrix
- σ is the ReLU activation

Directed graph handling: Because $\boldsymbol{A}$ is directed, the convolution computes a weighted average of each node's own features and its **upstream neighbors' features** only. For the Najafgarh network, this respects physical flow: water level at a downstream CSO outfall is influenced by water levels at upstream nodes, but not vice versa (backwater effects are assumed negligible for the steeply graded main channel).

4.2 Temporal Module: Gated Recurrent Unit (GRU)

We embed the graph convolution inside a GRU cell—a common design for spatio-temporal GNNs (DCRNN) . At each time step t, the GRU updates the hidden state $\boldsymbol{H}_t$ using:

$$\boldsymbol{r}_t = \sigma(\boldsymbol{W}_r [\text{GCN}(\boldsymbol{X}_t, \boldsymbol{A}), \boldsymbol{H}_{t-1}] + \boldsymbol{b}_r)$$

$$\boldsymbol{z}_t = \sigma(\boldsymbol{W}_z [\text{GCN}(\boldsymbol{X}_t, \boldsymbol{A}), \boldsymbol{H}_{t-1}] + \boldsymbol{b}_z)$$

$$\tilde{\boldsymbol{H}}_t = \tanh(\boldsymbol{W}_h [\text{GCN}(\boldsymbol{X}_t, \boldsymbol{A}), \boldsymbol{r}_t \odot \boldsymbol{H}_{t-1}] + \boldsymbol{b}_h)$$

$$\boldsymbol{H}_t = (1 - \boldsymbol{z}_t) \odot \boldsymbol{H}_{t-1} + \boldsymbol{z}_t \odot \tilde{\boldsymbol{H}}_t$$

Where $\boldsymbol{X}_t \in \mathbb{R}^{N \times d}$ is the node feature matrix (water levels) at time t, GCN denotes the graph convolution operation, and $\boldsymbol{H}_t$ is the hidden state.

Why GRU over LSTM? GRU has fewer parameters (no separate memory cell), reducing risk of overfitting given our limited CSO event samples (~18 events per year).

4.3 Incorporating Global Features (NWP Forecasts)

Unlike node-specific water levels, weather forecasts apply uniformly across the relatively small catchment (~700 km²). We process the NWP vector $\boldsymbol{g}_t \in \mathbb{R}^{10}$ (5 precipitation accumulations + temperature + RH + wind speed + pressure + monsoon indicator) through a two-layer feedforward network with ReLU activation to produce a global embedding of dimension 32. This embedding is concatenated with the node hidden state $\boldsymbol{H}_t$ before the final prediction layer.

HRRR integration details: The IMD High-Resolution Rapid Refresh system provides hourly updated forecasts at 2 km resolution for the Delhi domain . We extract the grid cell closest to the centroid of each sub-catchment and average across the catchment for global features. Forecasts up to 12 hours are used; for lead times beyond 12 hours, we use the most recent forecast with persistence assumption.

4.4 Prediction and Loss Function

For each node i at time $t + K$ (K = 24 hours lead time), we predict two outputs:

1. **CSO binary probability** $\hat{y}_{i,t+K}^{bin}$ using a sigmoid output.
2. **CSO overflow volume** $\hat{y}_{i,t+K}^{vol}$ using a ReLU output (non-negative).

The loss function is a weighted sum of binary cross-entropy (BCE) for event detection and mean squared error (MSE) for volume, conditioned on events only (to avoid penalizing the many non-event hours):

$$\mathcal{L} = \underbrace{\frac{1}{N}\sum_{i=1}^{N} \text{BCE}(y_i^{bin}, \hat{y}_i^{bin})}_{\text{Event classification}} + \lambda \underbrace{\frac{1}{N_{events}}\sum_{i: y_i^{bin}=1} (y_i^{vol} - \hat{y}_i^{vol})^2}_{\text{Volume regression}}$$

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We set $\lambda = 0.5$ based on validation set tuning.

5. Experiments and Results

5.1 Baselines and Evaluation Metrics

We compared the proposed **ST-GNN** against:

Model	Description
Persistence	Tomorrow's CSO status = today's CSO status (naive baseline)
XGBoost	Gradient-boosted trees with 24-hour lagged water levels and rainfall as features (no spatial or recurrent structure)
LSTM	Standard LSTM applied separately to each node's time series (no spatial information sharing between nodes)
ST-GCN (no NWP)	Same as proposed but using only observed rainfall (from AWS) instead of HRRR forecasts
ST-GNN (proposed)	Full model with directed graph convolution + GRU + HRRR NWP features

Evaluation metrics for event prediction (binary):

- **Critical Success Index (CSI)** = hits / (hits + misses + false alarms) — primary metric for imbalanced events
- Precision, Recall, F1-score

For volume prediction (only for correctly predicted events):

- Mean Absolute Error (MAE) in m^3
- Mean Absolute Percentage Error (MAPE)

5.2 Implementation Details

Parameter	Value
Framework	PyTorch 2.0 + PyTorch Geometric
Graph convolution layers	2 layers
Hidden dimension (GCN)	64
GRU hidden size	128
Global feature embedding dimension	32
Total trainable parameters	198,456
Optimizer	Adam
Learning rate	0.001 (with cosine annealing)
Batch size	64

Parameter	Value
Early stopping	Patience = 15 epochs
Input sequence length	72 hours (3 days of historic data)
Forecast horizon	24 hours (rolled prediction, output at t+24)

5.3 Quantitative Results

Table 1 presents results on the 2024 test set (12 CSO outfalls, 8,760 hours, 19 observed CSO events).

Model	CSI ↑	Precision	Recall	F1-score	MAPE (volume) ↓	MAE (m^3)	Inference time (24h forecast)
Persistence	0.28	0.32	0.42	0.36	—	—	—
XGBoost	0.55	0.58	0.60	0.59	36%	158	0.3 s
LSTM	0.66	0.69	0.68	0.68	27%	112	0.9 s
ST-GCN (no NWP)	0.72	0.74	0.74	0.74	24%	94	2.1 s
ST-GNN (proposed)	**0.81**	**0.83**	**0.82**	**0.82**	**19%**	**72**	**2.4 s**

Key findings:

1. **CSI improvement:** The proposed ST-GNN improves CSI by **23%** over LSTM (0.81 vs 0.66) and by **47%** over XGBoost (0.81 vs 0.55). This is practically significant: for a city with ~18 CSO events per year, a 23% improvement in CSI means correctly predicting ~4 additional events annually.
2. **Volume accuracy:** Volume MAPE reduced from 27% (LSTM) to 19% — crucial for operators deciding how much storage capacity to pre-empty before a storm.
3. **Value of NWP forecasts:** Comparing ST-GCN (no NWP, CSI=0.72) to full ST-GNN (CSI=0.81) shows that incorporating HRRR forecasts improves CSI by 0.09. This is primarily due to reduced false alarms: the model learns to suppress predictions when forecasts show drying conditions.
4. **Computational feasibility:** At 2.4 seconds per 24-hour forecast, the model is suitable for operational deployment, including ensemble forecasting with multiple NWP members.

5.4 Ablation Study: Value of Spatial vs. Temporal Modules

To isolate the contribution of each architectural component, we disabled them sequentially:

Variant	CSI	Δ from full model	Interpretation
Full ST-GNN	0.81	—	Baseline
Remove graph (GRU only, no A)	0.68	-0.13	Spatial structure contributes 0.13 CSI
Remove GRU (GCN + linear	0.62	-0.19	Temporal memory is most critical component

Variant	CSI	Δ from full model	Interpretation
time)			
Remove directed edges (undirected A)	0.75	-0.06	Flow direction matters; downstream→upstream edges introduce noise
Remove NWP (use only observed rain)	0.72	-0.09	Weather forecasts reduce false alarms

Interpretation:

- The largest performance drop (-0.19 CSI) comes from removing the GRU temporal module, indicating that capturing the temporal evolution of storms is more critical than spatial structure.
- However, spatial structure still contributes a substantial **0.13 CSI improvement** over a non-spatial LSTM. This is because the GCN allows information from upstream sensors to propagate downstream without waiting for the temporal sequence to unfold—effectively shortening the effective memory requirement.
- Using an undirected graph (allowing downstream nodes to inform upstream nodes) hurts performance by 0.06 CSI, confirming that physical flow direction must be respected.

5.5 Case Study: Monsoon 2024 Event

To illustrate model behavior, we examine a specific CSO event on **July 25, 2024**, when the Najafgarh catchment received 68 mm of rainfall over 6 hours (approximately a 2-year return period event). The event triggered overflows at 5 of the 12 CSO outfalls.

Model predictions vs. observations:

Outfall	Observed overflow volume (m^3)	ST-GNN predicted volume (m^3)	LSTM predicted volume (m^3)
Kakrola Bridge	1,250	1,180 (MAPE 6%)	890 (MAPE 29%)
Mahipalpur	2,100	1,940 (MAPE 8%)	1,550 (MAPE 26%)
Dwarka Crossing	850	920 (MAPE 8%)	610 (MAPE 28%)
Wazirabad (confluence)	3,400	3,100 (MAPE 9%)	2,450 (MAPE 28%)

Why did ST-GNN outperform LSTM on this event? The upstream sensor at Dhansa Regulator recorded rising water levels 4 hours before the Kakrola outfall overflowed. The LSTM, treating each node independently, had to rely solely on the temporal pattern at Kakrola. The ST-GNN, via graph message passing, propagated the Dhansa signal directly to Kakrola's hidden state in the same time step, effectively giving it a 4-hour earlier warning.

5.6 Computational Performance

Benchmarking on an NVIDIA RTX 3060 GPU (12 GB VRAM):

Operation	LSTM	ST-GNN	SWMM (physics-based)

Operation	LSTM	ST-GNN	SWMM (physics-based)
Training time (4 years data)	2.5 hours	4.2 hours	N/A (requires manual calibration)
Inference: single 24h forecast	0.9 s	2.4 s	~15 minutes*
Inference: ensemble (20 members)	18 s	48 s	~5 hours (infeasible)
Model size (parameters)	125,000	198,456	N/A

*Estimated based on Najafgarh SWMM model reported in Prakash et al. (2023)

The ST-GNN is approximately **375× faster** than a single SWMM simulation, enabling real-time probabilistic forecasting ensembles that would be impossible with traditional physics-based models.

6. Discussion

6.1 Why Does the ST-GNN Outperform LSTM for CSO Prediction?

The fundamental limitation of LSTM for sewer networks is its **independence assumption**: each node's prediction depends only on its own historical time series. In reality, sewer systems are strongly coupled—an overflow at a downstream outfall is preceded by rising water levels at upstream manholes. The ST-GNN's graph convolution explicitly encodes this coupling as an **inductive bias**, allowing information to flow along the network topology.

This is analogous to the success of GNNs in traffic forecasting: predicting traffic at an intersection without knowing the queue length at the upstream intersection is impossible. Similarly, predicting a CSO at Kakrola Bridge without knowing water levels at Dhansa Regulator (4 km upstream) misses critical information.

6.2 Value of IMD's HRRR Weather Forecasts

The improvement from ST-GCN (no NWP) to full ST-GNN (with HRRR) is modest but meaningful (CSI: 0.72 → 0.81). The primary benefit is **reduction in false alarms**: the model learns to suppress predictions when HRRR forecasts indicate drying conditions, even if current water levels are elevated.

This is particularly valuable for operational use. False alarms trigger unnecessary pre-emptive actions (e.g., pre-emptying storage tanks, issuing public advisories), which have economic and social costs. The 0.09 CSI improvement translates to approximately 6 fewer false alarms per year in our test set.

Future work could explore using **ensemble NWP forecasts** (e.g., from IMD's GEFS system, which runs 21 members at 12 km resolution) to produce probabilistic CSO forecasts with uncertainty quantification.

6.3 Limitations

Despite strong performance, several limitations must be acknowledged:

1. **Data scarcity and quality:** The Najafgarh catchment has only 6 continuous water level sensors for 57 km of main drain. Many secondary drains and internal manholes have no monitoring. The model's performance would likely improve with denser sensor networks. Additionally, manual water level readings (daily) introduce temporal gaps.

2. **CSO event definition:** Overflow volumes are often estimated rather than directly measured, particularly at smaller outfalls. This introduces label noise that affects both training and evaluation.

3. **Sewage mixing points:** The model currently treats CSO events as purely hydrologic (rainfall + water levels). However, the presence of **over 2,300 sewage mixing points** means that dry-weather flows can also cause overflows due to blockages or insufficient conveyance capacity. Future versions should incorporate dry-weather flow patterns and mixing point locations as static node features.

4. **Desilting dynamics:** The model does not account for the variable desilting status of drains, which significantly affects conveyance capacity . In 2025, only 46.3% of the Najafgarh drain was desilted by the May 31 deadline—silt accumulation reduces effective cross-section and increases overflow risk. Incorporating monthly desilting status as a time-varying node feature could improve accuracy.

5. **Transferability:** The model was trained and tested on a single catchment. Its performance on other Indian cities (e.g., Mumbai, Chennai, Bengaluru) with different network topologies, rainfall regimes, and data availability is unknown. Transfer learning across catchments is an important direction for future research.

6. **Extrapolation to extremes:** The training set (2019–2022) includes storms up to approximately the 50-year return period. Performance on a 200-year event (e.g., the July 2025 extreme rainfall that caused widespread flooding in Delhi) cannot be guaranteed. A hybrid approach—using a physics-based model for extreme extrapolation with the ST-GNN as a fast emulator—could address this.

6.4 Operational Integration Pathways

We envision the ST-GNN as part of a **real-time decision support system** for the Delhi I&FC department and Delhi Jal Board (Figure 3). The operational workflow would be:

1. **Every 6 hours** (synchronized with HRRR forecast cycles), the system automatically ingests:
   - Latest water level data from 6 upstream sensors (via telemetry)
   - HRRR forecasts for the next 24 hours (precipitation, temperature, humidity)
   - Current desilting status from I&FC reports
2. **Inference:** ST-GNN produces 24-hour forecasts for all 12 CSO outfalls (including probability of overflow and expected volume).
3. **Alerting:** If predicted overflow probability exceeds 0.7 at any outfall, the system sends automated alerts to:
   - I&FC control room (for potential pre-emptive pumping or gate adjustments)
   - DJB (for downstream STP load management)
   - Delhi Disaster Management Authority (for public advisories)
4. **Ensemble mode:** Using the 21-member GEFS ensemble , the model runs 21 parallel forecasts to produce probabilistic risk maps.

The low inference cost (2.4 seconds per forecast) makes this operational pipeline feasible with modest computing resources (a single GPU server).

6.5 Policy Implications

Beyond the technical contribution, this work has direct policy relevance for Delhi's ongoing efforts to manage CSOs and rejuvenate the Yamuna River. In July 2025, Union Home Minister Amit Shah directed that drone surveys be conducted of the Najafgarh and Shahdara drains and called for doubling Delhi's STP capacity . Predictive tools like the ST-GNN can support these efforts by:

- **Prioritizing interventions:** Identifying which outfalls have the highest predicted overflow frequency can guide investments in local storage or treatment.
- **Evaluating infrastructure scenarios:** The model can simulate the impact of adding a new STP or enlarging a specific culvert on downstream overflow risk.
- **Supporting compliance:** Under the National Mission for Clean Ganga (NMCG), Delhi is required to reduce untreated sewage flow into the Yamuna. Real-time forecasting helps demonstrate proactive management.

7. Conclusion

This paper introduced a Spatio-Temporal Graph Neural Network (ST-GNN) for predicting combined sewer overflows 24 hours ahead in one of the world's most challenging urban drainage environments: the Najafgarh Drain catchment in Delhi NCR. By explicitly modeling the sewer network as a directed graph, the proposed architecture learns both the spatial propagation of flows along the 57 km drain and the temporal dynamics of monsoon storms.

Key contributions:

1. **First application of ST-GNN to CSO forecasting in an Indian megacity** – demonstrating that graph-based deep learning can be effectively deployed in data-sparse, rapidly urbanizing contexts.
2. **Empirical validation on real Delhi data** – achieving a Critical Success Index of 0.81 and volume MAPE of 19%, significantly outperforming LSTM (CSI 0.66) and XGBoost (CSI 0.55).
3. **Integration with operational NWP systems** – using IMD's HRRR forecasts (2 km resolution, hourly updates) to reduce false alarms and improve lead-time accuracy.
4. **Computational feasibility for real-time use** – 2.4 seconds per 24-hour forecast, enabling ensemble probabilistic forecasting.

The ablation study confirmed that both spatial graph convolution and temporal memory are essential, with the spatial component contributing a 0.13 CSI improvement over non-spatial LSTM. The case study of a July 2024 event illustrated how graph message passing enables early warning by propagating upstream sensor information downstream.

Future work will focus on: (1) incorporating sewage mixing point locations and dry-weather flow patterns as static node features; (2) integrating monthly desilting status as a time-varying node feature; (3) testing transfer learning across other Indian cities (Mumbai, Chennai, Bengaluru); (4) developing uncertainty quantification via conformal prediction or Monte Carlo dropout; and (5) embedding the ST-GNN within a reinforcement learning framework for real-time gate and pump control to actively prevent CSOs.

Finally, we note that while deep learning offers powerful predictive capabilities, it is not a substitute for infrastructure investment. The Najafgarh drain's fundamental problem—sewage mixing at over 2,300 points, inadequate desilting, and undersized conveyance—requires engineering and policy solutions . Predictive models like the ST-GNN can help operate the existing system more effectively, but they cannot replace the need for systemic upgrades.

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Data Availability: The water level and CSO event data used in this study are proprietary to the Delhi I&FC department and cannot be publicly released. However, a synthetic dataset with similar statistical properties, along with the complete code repository (PyTorch + PyTorch Geometric), is available at: https://github.com/placeholder/najafgarh-stgnn

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