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Digital Twin Framework for Real-Time Structural Health Monitoring and Flood Resilience in Urban Smart Infrastructure

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Urban infrastructure systems face compounding threats from structural deterioration and climate-driven flood events. This paper proposes an integrated Digital Twin (DT) framework that couples real-time Structural Health Monitoring (SHM) with urban flood resilience management for smart city environments. The framework leverages a heterogeneous Internet of Things (IoT) sensor network — comprising accelerometers, strain gauges, piezometers, and water-level sensors — feeding continuously into a cloud-hosted digital replica of urban built assets. A hybrid machine learning pipeline combining Long Short-Term Memory (LSTM) autoencoders for anomaly detection with ensemble Kalman filtering for real-time model state updating is presented. The flood resilience module integrates hydrodynamic simulation with sensor-driven early-warning logic, enabling proactive emergency response. Architecture components, data flows, computational requirements, and implementation challenges are systematically described. The proposed framework provides a replicable, scalable foundation for data-driven urban resilience, directly applicable to bridges, drainage networks, and critical urban assets. Key contributions include a unified ontology linking structural and hydrological digital twin layers, a latency-optimised edge-cloud processing pipeline, and a multi-criteria decision support module for infrastructure managers.

Keywords: *digital twin; flood resilience; smart city; urban infrastructure*

1. Introduction

The convergence of accelerating urbanisation, ageing civil infrastructure, and the intensification of extreme weather events driven by climate change has created a critical imperative for intelligent, adaptive infrastructure management systems. Urban areas concentrate population, economic activity, and interdependent critical systems in ways that amplify both the probability and consequences of structural failures and flood events (Alibrandi, 2022). Traditional inspection-based approaches — relying on periodic visual assessment and post-hoc damage surveys — are increasingly inadequate for managing the dynamic risks facing modern cities.

Structural Health Monitoring (SHM) has evolved substantially over the past two decades from point-sensor campaigns to continuously operating, data-rich sensor networks capable of delivering real-time structural performance data (Malekloo et al., 2022). In parallel, digital twin (DT) technology has emerged as a powerful paradigm for creating live, continuously updated virtual replicas of physical systems, integrating sensor data, computational models, and decision-support logic into a unified cyber-physical architecture (Liu et al., 2023). The application of DTs to civil infrastructure remains, however, fragmented: structural monitoring and flood risk management have largely developed as separate domains with separate data architectures and stakeholder communities.

Flood events represent one of the most damaging and frequently occurring natural hazards globally. According to the 2020 global natural disaster assessment, floods were the most frequent disaster type, affecting more than 200 countries (Tanoue et al., 2023). Urban drainage infrastructure, frequently under-dimensioned against projected future precipitation intensities, constitutes a critical vulnerability node. The integration of flood early-warning systems with real-time structural assessment within a shared digital twin architecture offers significant untapped potential for urban resilience.

This paper addresses this gap by proposing a unified DT framework that integrates real-time SHM and urban flood resilience management. The framework is designed for scalability across heterogeneous urban asset types and for interoperability with existing smart city data platforms. The contributions of this work are threefold: (i) a formal architectural specification for a hybrid structural-hydrological digital twin; (ii) a machine learning pipeline for real-time anomaly detection and model state updating; and (iii) a multi-criteria decision support module linking structural condition assessment with flood risk scenarios.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the proposed framework architecture. Section 4 describes the machine learning and data assimilation components. Section 5 discusses the flood resilience integration. Section 6 addresses implementation challenges and scalability considerations. Section 7 concludes with directions for future research.

2. Literature Review

The concept of the digital twin, originally formulated in the context of aerospace manufacturing by Grieves (2014), has been progressively adapted to the built environment over the past decade. In civil infrastructure applications, a DT is defined as a dynamic, bi-directional digital representation of a physical asset that is continuously synchronised with its physical counterpart through sensor data streams, enabling real-time condition assessment, predictive analytics, and decision support (Liu et al., 2023).

Building Information Modelling (BIM) has provided the geometric and semantic foundation for many DT implementations in the construction domain. Baghalzadeh Shishehgarkhaneh et al. (2022) conducted a bibliometric review of IoT, BIM, and DT integration in the construction industry, identifying accelerating research output and highlighting the growing importance of interoperability standards. Li et al. (2022) reviewed advanced information technologies in civil infrastructure construction and maintenance, emphasising the role of sensor fusion and data analytics platforms. The integration of BIM with IoT sensing and structural analysis into a coherent DT framework for SHM was demonstrated by Hu et al. (2024), who developed a wireless sensing system coupled to a finite-element updating pipeline.

A key enabler of operational DTs is the availability of standards for data exchange and model interoperability. Liu et al. (2023) reviewed DT technologies for civil infrastructure through the lens of the Journal of Infrastructure Intelligence and Resilience, documenting the fragmented standards landscape and calling for unified ontologies. Kong and Hucks (2023) presented a photogrammetry-based DT framework specifically tailored to historic structures, demonstrating the extension of DT principles beyond conventional engineered systems.

Contemporary SHM systems deploy diverse sensor modalities — accelerometers, strain gauges, displacement sensors, fibre Bragg gratings, and increasingly vision-based systems — in permanently installed configurations that generate continuous data streams (Malekloo et al., 2022). The assimilation of these data into computational models for damage detection, localisation, and severity estimation has been the central research challenge in the field for two decades.

Machine learning approaches have transformed SHM practice, enabling the extraction of damage-sensitive features from high-dimensional sensor data without explicit physical model assumptions. Malekloo et al. (2022) provided a comprehensive overview of machine learning in SHM, documenting the shift from supervised classification approaches requiring labelled damage data towards unsupervised anomaly detection methods suitable for operational infrastructure where damage examples are rarely available. LSTM neural networks have demonstrated particular efficacy for temporal anomaly detection in continuously monitored structures due to their capacity to learn complex temporal dependencies in vibration and strain response data (Rizvi et al., 2023).

Autoencoders — neural networks trained to reconstruct their input from a compressed latent representation — have become a dominant paradigm for unsupervised SHM anomaly detection. Reconstruction errors elevated above a learned baseline threshold provide a principled, data-driven damage indicator (Pan et al., 2023). The integration of railway bridge SHM into a digital twin architecture using low-cost wireless IoT sensors and clustering-based machine learning was demonstrated in a real operational deployment, confirming the practical viability of this approach (Bado et al., 2024). Sakr and Sadhu (2023) further demonstrated the visualisation of SHM information within BIM-integrated IoT platforms.

The application of digital twin principles to urban flood management has accelerated substantially in response to growing recognition of urban flood risk as a climate adaptation priority (Tanoue et al., 2023). Urban Digital Twins for flood applications typically integrate hydrodynamic simulation models with real-time sensor networks, satellite remote sensing, and meteorological forecast data to enable dynamic flood inundation mapping and early-warning functionality (Ferré-Bigorra et al., 2022).

The DestinEarth initiative launched by the European Commission in 2022 represents the most ambitious publicly funded effort to develop a high-resolution digital twin of the Earth system for climate resilience applications, including urban flood simulation. Tanoue et al. (2023) explored the potential of DT, 3D city models, and sensor networks for climate resilience in smart cities, conducting a systematic review of 68 articles across three databases and documenting the maturation of early-warning system development. Backhaus and Stamm (2023) presented a city-scale urban DT for flood risk management in Dresden, Germany, integrating a 3D web application with a comprehensive urban data platform supporting automated generation of 2D hydro-numerical models.

The integration of machine learning with physics-based hydrodynamic simulation has emerged as a key approach for balancing computational efficiency with predictive accuracy (Ferré-Bigorra et al., 2022). Ensemble Kalman filtering provides a mathematically rigorous framework for assimilating real-time sensor observations into running simulation models, enabling continuous state estimation under uncertainty (Lei et al., 2023). Yuan et al. (2022) reviewed community-scale big data sources — including infrastructure sensor data, mobility data, and crowdsourced feeds — as inputs to smart flood resilience systems, identifying machine learning and deep learning as key analytical technologies.

Despite parallel advances in structural DTs and flood risk DTs, the integration of these two domains within a unified cyber-physical architecture remains largely unexplored. Structural monitoring systems typically focus on load effects and material degradation without considering hydrological boundary conditions, while flood management platforms rarely incorporate structural condition data. This decoupling misses critical interactions: flood events exert dynamic hydrostatic and hydrodynamic loads on bridges, retaining walls, and drainage infrastructure; conversely, structural deterioration may reduce flood-critical assets below design performance thresholds. A unified DT framework that simultaneously tracks structural condition and flood risk, sharing sensor infrastructure and computational platforms, would significantly enhance the analytical and decision-support capability available to urban infrastructure managers.

3. Methodology

The proposed framework, designated Urban Infrastructure Digital Twin (UIDT), consists of four principal layers: (i) a Physical Asset Layer comprising the monitored infrastructure and its embedded sensor network; (ii) a Data Acquisition and Communication Layer handling real-time data ingestion and edge processing; (iii) a Digital Twin Core comprising the structural simulation, hydrological model, and machine learning pipeline; and (iv) a Decision Support and Visualisation Layer providing actionable outputs to stakeholders. Figure 1 (conceptual) illustrates the inter-layer data flows and principal computational components.

The UIDT architecture follows a cyber-physical systems design principle (Ferré-Bigorra et al., 2022), wherein bidirectional coupling between the physical and virtual domains is maintained continuously. Physical sensor observations update the digital twin state; DT-generated predictions and alerts are fed back to operational decisions governing physical asset management. This closed-loop architecture distinguishes operational digital twins from conventional asset models.

The physical asset layer encompasses the instrumented infrastructure — bridges, retaining walls, drainage tunnels, and surface water control structures — along with the embedded and deployed sensor network. The sensor suite is designed as a heterogeneous array combining complementary measurement modalities to capture the full spectrum of structural and hydrological state variables relevant to both SHM and flood resilience assessment.

Structural sensors include triaxial micro-electro-mechanical systems (MEMS) accelerometers deployed at key structural nodes for continuous vibration monitoring; resistive and fibre Bragg grating (FBG) strain gauges for direct stress measurement at fatigue-critical cross-sections; linear displacement sensors monitoring joint openings and deflections; and corrosion potential probes for reinforced concrete durability assessment. Environmental sensors include temperature and humidity transducers, precipitation gauges, and barometric pressure sensors whose measurements are essential for separating environmental and structural contributions to monitored responses (Malekloo et al., 2022).

The flood resilience sensor array comprises ultrasonic and pressure-transducer water-level sensors in drainage channels, culverts, and at-risk urban watercourses; soil moisture sensors in embankments and ground adjacent to retaining structures; flow velocity meters in combined sewer overflow structures; and optical and radar-based remote sensing feeds from low-Earth orbit satellites providing areal precipitation and inundation extent data. All sensor nodes are equipped with IoT communication modules transmitting data over LoRaWAN for low-power, long-range telemetry or over cellular 4G/5G links for higher-bandwidth accelerometer and FBG channels (Sakr and Sadhu, 2023).

Raw sensor streams are received by gateway nodes deployed at each monitored asset. Edge processing, implemented on low-power system-on-chip platforms, performs local signal conditioning — anti-aliasing filtering, spike rejection, and timestamp synchronisation — before transmitting compressed data packages to the cloud platform. Edge processing capacity is further used to compute first-order feature statistics (root mean square acceleration, peak strain, water level rate-of-change) that enable low-latency local alerting independent of cloud connectivity, ensuring fail-safe operation under network outage conditions.

The communication architecture follows a three-tier topology: sensor node to local edge gateway (short-range IEEE 802.15.4 or Bluetooth Low Energy); edge gateway to cloud ingestion service (LoRaWAN or cellular); cloud ingestion service to DT processing pipeline (MQTT publish-subscribe protocol with QoS Level 1 delivery guarantee). Data latency from sensor measurement to DT state update is maintained below 5 seconds for water-level and accelerometer channels designated as safety-critical, consistent with operational requirements for urban flood early-warning systems.

The DT Core comprises three tightly coupled computational modules: the Structural Finite Element (FE) Model, the Hydrodynamic Flood Model, and the Machine Learning Inference Engine. The FE model is an as-built, validated representation of each monitored structural asset, implemented in an open-source FE framework and parameterised using material properties derived from construction records, non-destructive testing, and BIM data (Liu et al., 2023; Kong and Hucks, 2023). The FE model is updated continuously using sensor-derived modal parameters through an ensemble Kalman filter assimilation algorithm.

The Hydrodynamic Flood Model implements a two-dimensional shallow-water equation solver for the urban drainage and surface water network, discretised on a high-resolution computational mesh derived from airborne LiDAR survey data and BIM-linked infrastructure geometry. Real-time boundary conditions are provided by the water-level and flow sensor array, with meteorological forecast forcing ingested from national hydrological services. The model produces probabilistic inundation maps at 15-minute forecast horizons, updated at each sensor data assimilation cycle (Backhaus and Stamm, 2023).

The Machine Learning Inference Engine hosts the LSTM autoencoder ensemble responsible for structural anomaly detection, the gradient-boosted regression models for flood impact prediction, and the multi-criteria decision analysis module. All ML models are retrained periodically on accumulated operational data to maintain representativeness of current structural condition and seasonal hydrological regimes.

4. Results and Discussion

The structural anomaly detection pipeline is based on an ensemble of LSTM autoencoders trained on extended baseline periods of sensor data recorded under normal structural conditions. Each autoencoder in the ensemble consists of a bidirectional LSTM encoder that compresses the multivariate sensor time series into a fixed-length latent vector representation, followed by an LSTM decoder that reconstructs the original sequence. The reconstruction error, measured as the mean absolute error between input and reconstructed sequences over a sliding window, constitutes the primary anomaly indicator.

The ensemble approach, combining N = 20 independently initialised autoencoders trained on bootstrap resamples of the baseline dataset, provides uncertainty estimates on the anomaly score in addition to point estimates. Anomaly thresholds are set at the 99th percentile of the reconstruction error distribution observed across the baseline period, separately for each sensor channel and environmental condition stratum. This stratification is essential to prevent false positives arising from temperature-driven reversible changes in structural stiffness — a well-documented confounding factor in SHM (Malekloo et al., 2022; Pan et al., 2023).

Encoder architecture comprises three stacked bidirectional LSTM layers of dimensions [64, 32, 16] with layer normalisation and dropout regularisation (rate 0.2) applied between layers. The bottleneck latent dimension is set to 8 for single-structure deployments. Decoder architecture mirrors the encoder. Training employs the Adam optimiser with an initial learning rate of 1e-3 and cosine annealing scheduling over 200 epochs. Sequence length is set to 1024 samples, corresponding to approximately 10 minutes at 100 Hz sampling for accelerometer channels.

Continuous synchronisation of the FE model with the physical structure is achieved through an ensemble Kalman filter (EnKF) implementation. The EnKF maintains a probabilistic ensemble of N = 100 FE model realisations, each perturbed by samples from the prior uncertainty distribution over structural parameters — primarily elastic moduli, boundary condition stiffnesses, and mass distributions. At each assimilation step, the ensemble is propagated forward in time using the FE model, and the ensemble spread is updated using the Kalman gain matrix computed from the cross-covariance between model-predicted and observed sensor responses.

The EnKF implementation follows the square-root ensemble formulation for numerical stability under small ensemble sizes. Localisation is applied to manage spurious long-range correlations between sensors and model parameters that may arise in large-dimensional model spaces. The computational cost of the EnKF, dominated by N parallel FE model evaluations per assimilation step, is managed through model reduction — the FE model is reduced to a modal subspace representation preserving the lowest 50 vibration modes — enabling near-real-time updating at 1-minute assimilation intervals on commodity cloud computing hardware.

Flood impact on monitored structural assets is predicted through a hybrid physics-machine learning approach. The hydrodynamic model provides probabilistic water-level and flow velocity fields at each asset location at 15-minute forecast horizons. These fields are converted to structural load demands — hydrostatic lateral pressures, scour potential at bridge foundations, and overtopping risk for retaining walls — through empirically calibrated transfer functions derived from physical model tests and historical flood event data.

A gradient-boosted regression model (XGBoost) is trained on historical paired records of flood conditions and observed structural responses to predict the structural response increment expected under forecast flood loading. The predicted structural response is superimposed on the current DT state estimate to produce a conditional anomaly probability — the probability that the structural response will exceed the anomaly detection threshold given the forecast flood loading. This conditional probability drives the flood-structural risk score reported to decision-makers (Yuan et al., 2022; Lei et al., 2023). The flood resilience module integrates the real-time hydrodynamic model outputs with a rule-based early warning logic to generate tiered alert levels for urban infrastructure managers and emergency responders. The alert hierarchy comprises four levels: Level 1 (Watch) triggered by precipitation forecast exceedance of a site-specific threshold; Level 2 (Advisory) triggered by water-level sensor readings exceeding the 2-year return period discharge threshold; Level 3 (Warning) triggered by forecast inundation extent intersecting critical infrastructure; and Level 4 (Emergency) triggered by observed structural anomaly detection coinciding with Level 2 or Level 3 hydrological conditions.

The tiered alert architecture is designed to support progressive mobilisation of emergency resources, reducing both the cost of false alarms and the response latency under genuine threat conditions. Alert dissemination is achieved through integration with national emergency communication systems and direct notification to infrastructure asset managers via the UIDT dashboard application. Alert metadata — including the spatial extent of forecast inundation, the identity and condition score of at-risk structural assets, and the recommended inspection or operational response actions — are included in all alerts above Level 2.

The multi-criteria decision support module synthesises structural condition scores, flood risk indicators, and asset criticality data to generate prioritised intervention recommendations for infrastructure managers. The decision logic implements a weighted scoring approach in which each monitored asset receives a composite risk score as a linear combination of: (i) the current structural anomaly probability (weight 0.40); (ii) the 24-hour flood impact probability (weight 0.35); (iii) the asset criticality index reflecting traffic volume, redundancy, and consequence of failure (weight 0.25).

Assets with composite risk scores exceeding pre-defined intervention thresholds are flagged for immediate inspection, operational restriction, or pre-emptive protective measures. The decision support outputs are presented through an interactive geospatial dashboard displaying the real-time condition state of all monitored assets overlaid on the forecast inundation maps, enabling spatial reasoning about the co-location of structural vulnerability and flood hazard. Dashboard functionality includes time-series visualisation of individual sensor channels, FE model animation, and scenario comparison tools (Ferré-Bigorra et al., 2022; Backhaus and Stamm, 2023).

5. Discussion

A primary challenge in operationalising the UIDT framework is the integration of heterogeneous data sources generated by different asset owners, management systems, and sensor vendors operating under different data standards and communication protocols. Urban infrastructure is typically owned and managed by multiple entities — national highway authorities, local government drainage departments, utility companies — each maintaining separate asset management systems with limited interoperability. The UIDT framework addresses this through a standardised data ingestion layer that implements conversion to a unified data model based on the OGC SensorThings API standard, enabling semantic interoperability across data sources without requiring upstream system changes (Liu et al., 2023).

The computational demands of a city-scale UIDT deployment — maintaining real-time FE model updates and EnKF assimilation for tens to hundreds of structures simultaneously alongside high-resolution hydrodynamic simulation — pose significant cloud infrastructure requirements. A hierarchical compute architecture is proposed in which computationally intensive model updates are distributed across a cloud computing cluster with horizontal auto-scaling capacity, while lightweight anomaly scoring and alert generation run on dedicated low-latency compute nodes with guaranteed response times. The modal reduction of FE models, described in Section 4.2, is critical for achieving the required update frequency within practical compute budget constraints.

Permanently deployed sensor networks in urban environments are subject to vandalism, physical damage from flood events and vehicular impact, communication infrastructure outages, and progressive sensor drift. A robust data quality management pipeline is essential for maintaining the integrity of DT state estimates. The UIDT framework implements multi-scale data quality assessment: at the edge node level, range checks and rate-of-change limits detect obvious sensor failures; at the ingestion level, cross-sensor consistency checks exploit the spatial correlation structure of structural response to detect anomalous channels; at the model assimilation level, innovation monitoring within the EnKF provides a model-consistent check on incoming observations (Sakr and Sadhu, 2023).

The technical capabilities of the UIDT framework are necessary but insufficient conditions for operational impact. Successful deployment requires clear governance frameworks defining data ownership, alert authority, liability for DT-informed decisions, and protocols for integration with existing emergency management procedures. The co-design of the decision support interfaces with infrastructure managers and emergency responders is essential for ensuring that DT outputs are interpretable, actionable, and trusted. Barriers to adoption including resistance to changing established inspection practices, concerns over cybersecurity of connected infrastructure, and limited availability of skilled personnel for DT operation require structured change management approaches alongside technical implementation.

6. Conclusions

This paper has presented the UIDT framework — an integrated digital twin architecture for real-time structural health monitoring and flood resilience management in urban smart infrastructure. The principal contributions are: (i) a formal specification of a four-layer cyber-physical architecture coupling heterogeneous IoT sensor networks, physics-based structural and hydrological simulation models, and machine learning inference pipelines within a unified digital twin platform; (ii) an LSTM autoencoder ensemble methodology for unsupervised structural anomaly detection that explicitly accounts for environmental confounding through condition-stratified threshold setting; (iii) an EnKF-based continuous model state updating approach enabling real-time finite element model synchronisation at operationally relevant update rates; and (iv) a hybrid flood impact prediction approach combining hydrodynamic simulation with data-driven structural response modelling to generate conditional structural risk probabilities under forecast flood loading.

The framework addresses a critical gap in the current urban resilience literature by providing a unified architecture that simultaneously manages structural deterioration risk and flood hazard risk, capturing the physical interactions between these hazards that are missed by domain-siloed approaches. The multi-criteria decision support module translates complex technical outputs into prioritised, actionable recommendations aligned with the operational needs of infrastructure managers and emergency responders.

Future work will focus on the quantitative validation of the framework components through deployment on operational urban infrastructure, the development of reduced-order modelling approaches to further reduce computational costs, the investigation of physics-informed neural network architectures as alternatives to purely data-driven anomaly detection, and the extension of the framework to additional hazard types including seismic events and extreme temperature excursions. International pilot deployments across different urban morphologies and infrastructure asset classes will be necessary to establish the generalisability and robustness of the proposed approach.

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