Journal of Computational and Experimental Science (JCES)
ISSN Print: XXXX | ISSN Online: XXXX
Volume 1, Number 1, 2026, Pages 21–46
Journal Home Page: https://journals.airsd.org/index.php/jces

AI-Driven Eco-Engineering Framework for Climate-Resilient Urban Systems Using Real-Time Social and Environmental Data

Ghulam Rubab[1*], Azhar Ali[2], Muhammad Umar Memon[3], Muhammad Yaqoob[4], Baqir Banglani[5], Shaista Jalbani[6], Emmy Mahar[7], Fatima Gull[8]

[1*]Institute of Plant Sciences, University of Sindh, Jamshoro, Sindh, Pakistan, Fisheries and Aquaculture SBBUVAS, Sakrand, Sindh, Pakistan. *Email:*ghulamrubabsoomro@gmail.com

[2] School of Information and technology, Shaheed Benazir Bhutto University, Nawabshah *Email:* azharrose018@gmail.com

[3] School of Energy Systems Engineering, Quaid e Awam University, Nawabshah

Email: muhammadumarmemon011@gmail.com

[4] School of Power and Energy Engineering, Harbin Engineering University, Harbin, China.

Email: engryaqoob40@gmail.com

[5] School of Information and technology, Shaheed Benazir Bhutto University, Nawabshah.

Email: baqir.techworld007@gmail.com

[6] Fisheries and Aquaculture SBBUVAS, Sakrand, Sindh, Pakistan. *Email:* jalbanishaista@gmail.com

[7] School of Environmental Engineering and Management, Mehran University of Engineering and Technology Jamshoro, Sindh, Pakistan. *Email:* emmy.mahar@gmail.com

[8] School of Sociology, University of Karachi, Pakistan *Email:* universityofkarachigull@gmail.com

ARTICLE INFO

Article History:
Received: February 12, 2026
Revised: February 27, 2026
Accepted: March 10, 2026
Available Online: March 30, 2026

Keywords:
AI-driven eco-engineering; Urban climate resilience; multi-modal data integration; Social sensing and environmental intelligence; Nature-based solutions (NBS); Real-time climate risk prediction

Corresponding Author:
Ghulam Rubab
Email:
ghulamrubabsoomro@gmail.com

ABSTRACT

Compound climate risks, including flooding, heatwaves, and environmental degradation, are more likely to affect urban areas, and available resilience strategies are still disconnected, with an ecological, technological, and social focus. This paper presents a proposal of an AI-driven eco-engineering control that combines real-time environmental sensing (remote sensing, meteorological, hydrological, and IoT data) with social sensing (geotagged social media data) to aid in adaptive and data-driven urban climate decision-making. This framework is based on the multi-layered architecture comprising of data acquisition, preprocessing, integration of multi-modal features, AI-based prediction (LSTM and SVM), spatial risk mapping, and optimization of nature-based solutions on eco-engineering basis.

It is theoretical and methodological in character and offers a comprehensive framework but not an entire and implemented case study empirically. The proposed system will be found to increase the predictive accuracy, better spatial identification of hotspots of climate risk, and allow real-time and context-aware decision support, in contrast to traditional single-source systems. The framework provides a scalable way to achieve proactive, resilient, and sustainable urban planning in the face of climate change by connecting AI-based analytics with ecological engineering interventions.

1. Introduction

There is a growing vulnerability of urban systems to compound and interactive climate risks, such as extreme flooding, heat waves, and environmental degradation, in cities worldwide (Chen, Chen, et al. 2023; AghaKouchak et al. 2020). The occurrence and intensity of such hazards have been exacerbated by rapid urbanization, together with climate change, especially in the developing world, where infrastructure and adaptive capacities are minimal (Le 2020; Allard 2021). An example of such vulnerability is the cities of Karachi, which have seen frequent occurrences of urban flooding (Baig, Atif, and Tahir 2024; Kaker and Anwar 2024), which revealed the most serious gaps in the traditional urban planning and disaster management frameworks (Afshan et al. 2025).

Over the last few years, ecological engineering has become relevant as a more sustainable approach to combating climate risk by introducing nature-based solutions (NBS) in form of green infrastructure and urban wetlands (Ganapathi, Awasthi, and Vasudevan 2024; Moazzem et al. 2024). These strategies decrease environmental stressors and offer co-benefits such as enhanced biodiversity, air quality and social well-being (Becvarik, White, and Lal 2024). Nevertheless, eco-engineering interventions are usually based on the frameworks of the static planning, and they do not have the ability to dynamically respond to the changes in the environment in real time (Rauch et al. 2022).

Along with these changes, artificial intelligence (AI) has revolutionized environmental modelling and urban analytics. Hydrological and climate-related models of machine learning and deep learning have shown excellent forecasting abilities (Chen, Han, et al. 2023; Zhao et al. 2024). Moreover, the emergence of social media e.g. Twitter (X) and Facebook have made social sensing possible, thus real-time human observations can be used to supplement environmental data (Yu 2025; Lawu et al. 2021).

Regardless of such improvements, there is still a substantial research gap in applying AI, ecological engineering, and real-time cross-modes of data in a single system (Lan et al. 2025; Hao 2026). The available literature tends to focus on each of these components individually, which restricts their applicability in urban systems with complexity. Thus, the urgent need is to have comprehensive frameworks that can provide adaptive and data-driven solutions to climate-resilient cities.

2. Literature Review

2.1 Ecological Engineering for Urban Climate Resilience

One of the new ecological engineering directions is the creation of ecological engineering to improve the resilience of urban areas through the inclusion of natural processes in engineered systems (Ghazian and Lortie 2024; Wang et al. 2022). This method is commonly operationalized with the nature-based solutions (NBS) (green roofs, urban wetlands, permeable pavements and riparian buffers) in the context of climate change (Moazzem et al. 2024; Basu et al. 2021). The interventions are essential in alleviating urban flooding, controlling microclimates, and enhancing ecosystem services (Pandey and Ghosh 2023; Wübbelmann et al. 2023).

Empirical evidence has shown that green infrastructure can have great potential in reducing the peak runoff and increasing the infiltration rates of urban catchments (Liu et al. 2020; Fu et al. 2023). Likewise, vegetation-based solutions can help to mitigate the urban heat island effect by evapotranspiration and shading (Lin and Li 2025; Ma et al. 2025). Regardless of these benefits, ecological engineering strategies tend to be poorly efficient due to the inability to change the existing planning systems and adapt to changes in the environment in real-time (Brasil et al. 2021; Pursnani et al. 2023). In addition, site-specific conditions, such as land use, climate variability, and socio-economic factors, have a significant influence on NBS performance which requires more dynamic and data-driven methods (Yuan et al. 2024).

2.2 Artificial Intelligence in Environmental and Urban Systems

Environmental modelling has been transformed by artificial intelligence (AI) which is able to analyse non-linear relationships in big data (Hamza et al. 2022; Hamdan et al. 2024). Machine learning models, including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks have been extensively used to predict extreme events, like floods and droughts, in hydrology and climate science (Dikshit, Pradhan, and Huete 2021; Li, Kiaghadi, and Dawson 2021).

The AI based models have been shown to have better predictive capabilities than the traditional physically based models, especially in data rich settings (Zong and Guan 2025). As an example, deep learning models have been effectively applied to model rainfall-runoff dynamics and urban flood dynamics at very high temporal resolution (He et al. 2023). The use of AI in urban systems is also applied to the optimization of energy, traffic systems, and climate risk (Dikshit et al. 2023). Nevertheless, most AI models are data-driven and not based on ecological context, which restricts their use to sustainable environmental management (Chisom et al. 2024; Yousaf 2024). Also, the issues of model interpretability and transparency have given rise to the necessity of explainable AI solutions to environmental decision-making (Patidar et al. 2024).

2.3 Social Sensing and Real-Time Environmental Intelligence

The swift development of online applications like Twitter (X) and Facebook has made social sensing possible, with user-created information being used as a means of tracking the real-life events (Tang and Hu 2020). Social sensing offers local and real-time information to understand environmental dangers to supplement the existing traditional monitoring systems which are usually limited in time and space (Fascista 2022).

Social media data have proven useful in the context of urban flooding to identify floods, map areas of inundation, and analyse the sentiments of the people (Rosser, Leibovici, and Jackson 2017). The sources of this type of data have certain distinct benefits, such as quick information dispersion and the possibility to record human perceptions and behavioural reactions (Khan and Qutab 2016). The more complex natural language processing (NLP) algorithms, like sentiment analysis and topic modelling, facilitate the derivation of valuable patterns in unstructured text data (Bagheri et al. 2023).

Nevertheless, there are also such issues of social sensing as noise in the data, misinformation, and spatial biasing by uneven distribution of users (Rashid and Wang 2021). Irrespective of these shortcomings, social sensing integrated with environmental data has demonstrated great potentials in improving disaster response and resilience in cities (Sarker et al. 2020).

2.4 Integration Gap: Toward AI-Driven Eco-Engineering Frameworks

Even though ecological engineering, artificial intelligence, and social sensing have individually contributed to the development of the subject of urban climate resilience, there is a lack of integration of these techniques. The bulk of the literature is rather disorganized, considering individual-domain solutions without considering the interconnectedness of urban systems (Yohanandhan et al. 2020; Anvari-Clark 2026). This is what limits the creation of holistic frameworks that can provide adaptive and real time solutions.

The recent progress in the field of digital twin and smart city systems offers a good opportunity to integrate by merging real-time flows of data with simulation models (Mazzetto 2024; Jafari et al. 2023). Nevertheless, there is still a need to develop the application of such technologies to eco-engineering. Specifically, the absence of frameworks, capable of dynamically converting AI-driven insights into actionable ecological interventions, e.g., optimization of the location and design of nature-based solutions, can be noted.

2.5 Research Direction and Novel Contribution

Judging by the literature reviewed, it is clear that a holistic, data-driven framework, which combines ecological engineering, artificial intelligence, and social sensing is urgently needed. Not only must such a framework improve predictive accuracy, but it must also facilitate real-time decision-making and adaptive urban planning as well (Richardson et al. 2021; Attah et al. 2024).

This paper fills this gap by introducing an AI-supported eco-engineering framework based on using cross-modal data integration to enhance urban climate resilience. The proposed framework focuses on the dynamism between environmental processes, technological systems and human behaviour as compared to the current methods. This study will help to bridge these fields and offer a sustainable urban development solution that is scalable by connecting these areas.

Table 1. Cross-Domain Synthesis of AI, Eco-Engineering, and Social Sensing: Identifying Critical Gaps Toward Climate-Resilient Urban Systems

Study / Reference	**Focus Area**	**Data Type**	**Methodology**	**Key Contribution**	**Limitation**	**Research Gap**
(Li, Yigitcanlar, et al. 2024)	Climate risk analysis	Environmental	Statistical / ML	Identified urban vulnerability trends	Lacks real-time capability	No adaptive framework
(de Brito et al. 2024)	Climate extremes	Environmental	Hydrological modelling	Analysis of compound hazards	No integration with social data	Missing human dimension
(Preti, Capobianco, and Sangalli 2022)	Nature-based solutions	Environmental	Eco-engineering	Sustainable urban water management	Static implementation	No AI integration
(Brasil et al. 2021)	Green infrastructure	Environmental	Hydrological modelling	Flood mitigation using NBS	Limited scalability	No real-time adaptation
(Zhou et al.)	Flood prediction	Environmental	LSTM / ML	High prediction accuracy	Ignores ecological context	No eco-engineering linkage
(Syed et al. 2024)	Rainfall-runoff modelling	Environmental	Deep learning	Improved temporal forecasting	Single data source	No multi-modal integration
(Destefanis et al. 2025)	Flood mapping	Social + Environmental	GIS + social media	Rapid flood detection	Limited accuracy in noisy data	No AI-driven fusion

(Shi et al. 2022)	Social sensing	Social	Big data analytics	Real-time disaster awareness	Data bias and noise	No integration with physical systems
(OJADI et al. 2023)	NLP in environment	Social	NLP / sentiment analysis	Extracts public perception	No spatial modelling	Limited decision support
(Abbasnejad et al. 2025)	Digital twin systems	Integrated	Simulation models	Smart city monitoring	Early-stage application	No eco-engineering link
(Van Hoang 2024)	Smart city systems	Integrated	AI + IoT	Real-time monitoring	Lacks environmental focus	No ecological optimization
This Study	Integrated climate resilience	Multi-modal (Environmental + Social)	AI (LSTM, SVM) + NLP + Eco-engineering	Real-time predictive and adaptive framework	—	Addresses all identified gaps through integrated, scalable, and adaptive system

3. Methodology

The paper constructs a multi-layered AI-based eco-engineering system that combines sensory and social sensing to the climate with intelligent modelling to achieve climate-resilient urban systems. This approach is a fusion of data, machine learning, spatial analysis, and ecological optimization in a single architecture based on the latest innovations in environmental informatics and intelligent urban systems (Jadhav et al. 2024; Anwar and Sakti 2024).

3.1 Framework Overview

The proposed framework consists of four interconnected modules:
(1) Data Acquisition,
(2) Data Processing,
(3) AI Modelling, and
(4) Decision Support.
This stratification is consistent with smart-city data streams and environmental decision support systems (Prasath 2025; Bamgboye et al. 2025). It follows a closed-loop architecture, which allows providing feedback and adapting to learning, which is crucial in managing climate risks in real time (Natta 2024).

3.2 Data Sources and Integration

In order to assist the city climate risk assessment and flood prediction, this paper combines multi-source environmental and social data with different spatial and time resolutions. The framework can be used in urban basins (e.g., Karachi) where high-resolution and near real-time data are imperative in capturing the fast dynamics of floods.

3.2.1 Environmental Data

Environmental datasets have a variety of sources, each having its own way of adding spatial and temporal attributes:

Remote Sensing Data:
Flood detection and mapping of surface water are done using Sentinel-1 Synthetic Aperture Radar (SAR). It gives a spatial resolution of about 10 meters with a temporal revisit period of 6-12 days depending on the arrangement of the satellites. Land surface and water extent analysis products are also thought about using MODIS products, which provide less spatial detail (250-500 meters) yet more temporal frequency (daily to 8-day composite).

Meteorological Data:
Weather station data (e.g., Pakistan Meteorological Department) contains rainfall, temperature and humidity data at hourly to daily time resolution, and spatial coverage is determined by the density of weather stations. In the case of urban applications, continuous spatial fields are derived by interpolation.

Hydrological Data:
The gauging stations and hydrological models provide river discharge, water levels, and soil moisture data. These datasets are often with daily to sub-daily time resolution (occasionally hourly) and are distributed spatially within river systems and catchments.

IoT Sensor Data:
The monitoring systems of the urban IoT offer real-time (minutes to hourly resolution) measurements of the drainage flow, water levels, and local flooding status. These sensors provide great spatial granularity in key infrastructure sites like drainage streams and low-lying urban areas.

All these environmental data sets allow multi-scaled observations of the processes of floods, both localized to drainage overflow and large scale to hydrology processes in the basin.

Remote sensing and reanalysis datasets have been widely used for flood detection and hydrological modelling due to their high spatial and temporal resolution (Ali, Popescu, et al. 2023; Trinh and Molkenthin 2021). The IoT sensing also increases the real-time monitoring of the urban environment (Alam et al. 2024).

3.2.2 Social Sensing Data

To gather social sensing information, social sites like Twitter (X) and Facebook are used to obtain real-time human responses and observations:

Geotagged Multimedia Content and Posts:
The data in social media have near real-time temporal resolution (several seconds to several minutes), depending on the activity of the user. The spatial resolution can be either accurate geotagged coordinates (10-100 meters) or more general location tags (city, neighbourhood).

User-Reported Flood Observations:
User posted textual descriptions, pictures, and videos offer localized information about the extent of the floods, infrastructure collapse and disruption of the services.

This renders social data to be heterogeneous because of the disparity in the spatial distribution of the users. Thus, the spatial filtering and clustering methods are used to match social observations to environmental data.

Social sensing can be proven to be an effective means towards real-time disaster identification and situational awareness (Shi et al. 2022; Pal et al. 2022). These measurements offer complementary knowledge to physical measurements as they define the human perception and response (Pigliautile et al. 2020).

3.2.3 Urban Flood Forecasting based on Multi-Modded Data Integration.

By combining both environmental and social datasets, both physical flood processes and human influence can be represented in a comprehensively way. Spatial continuity and physical consistency are offered by the environmental data, whereas the social sensing offers the temporal responsiveness and situational awareness.

In the case of urban flood forecasting, e.g. in Karachi, the infrastructure exploits:
SAR data of flood extent with high spatial resolution (1030 m).

Early detection using high time resolution (real-time to hourly) through IoT and social media.
Multi-scale fusion with the usage of data fusion methods to generate uniform and adaptive inputs to AI models.

The multi-resolution data architecture provides the proposed framework with the capability to adequately record the rapid onset of floods, spatial heterogeneity, and human activities in the complex urban environment.

The multi-source data architecture and corresponding feature integration used in this study are summarized in Table 2, highlighting the diversity of environmental and social datasets and their respective roles in the proposed framework.

Table 2. Integrated Environmental and Social Data Sources for Urban Climate Risk Modelling

Data Category	Data Source	Key Variables	Spatial/Temporal Resolution	Processing Techniques	Role in Framework	References
Remote Sensing	Sentinel-1 SAR, MODIS	Flood extent, land use, surface water	High spatial / periodic	Image processing, classification	Flood detection and spatial mapping	(Tran, Menenti, and Jia 2022)
Meteorological Data	Weather stations / PMD	Rainfall, temperature, humidity	Daily / hourly	Normalization, time-series analysis	Climate hazard prediction	(Li and Qian 2024)
Hydrological Data	River gauges, models	Discharge, water level, soil moisture	Daily / real-time	Filtering, interpolation (IDW)	Flood dynamics and risk estimation	(Soltani et al. 2026)
IoT Sensor Data	Urban smart sensors	Drainage flow, water levels	Real-time	Noise filtering, data smoothing	Real-time monitoring	(Jang and Jung 2023)

Social Media Data	Twitter (X), Facebook	Text, geolocation, images	Real-time / unstructured	NLP, sentiment analysis, topic modelling	Public perception and early warning	(Alam, Mrida, and Rahman 2025)
GIS & Urban Data	Land use maps, census	Population density, infrastructure	Static / periodic	Spatial analysis (GIS), KDE	Vulnerability and exposure analysis	(Mutambik 2024)
Integrated Dataset	Fused multi-modal data	Combined environmental + social features	Dynamic	Data fusion (weighted integration)	Improved prediction and decision-making	(Chen and Tang 2025)

3.3 Data Preprocessing and Feature Engineering

3.3.1 Environmental Data Processing

Standard methods are used to pre-process environmental data, such as noise filters (e.g., moving average and Kalman filtering), spatial interpolation (Inverse Distance Weighting, IDW), and normalization. Normalization is used to scale all the variables to a similar range enhancing the convergence and stability of the model.

Environmental data are pre-processed using:
Noise filtering (moving average, Kalman filtering)
Spatial interpolation (Inverse Distance Weighting, IDW)
Normalization:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Spatial interpolation techniques such as IDW are widely used for estimating missing environmental values (Larson et al. 2023), while normalization improves model convergence and stability (Faye et al. 2025).

3.3.2 Social Data Processing

Natural language processing (NLP) algorithms, such as tokenization and stop-word removal, sentiment analysis (BERT-based models), and topic modelling (LDA, GSDMM) are used to process social media data. Sentiment scores are calculated to determine how the people perceive and react to climate events.

Social media data are processed using natural language processing (NLP) techniques:

Tokenization and stop-word removal
Sentiment analysis (BERT-based models)
Topic modelling (LDA, GSDMM)
Sentiment score is computed as:

$$S = \frac{N_{pos} - N_{neg}}{N_{total}}$$

Advanced NLP models such as BERT have shown superior performance in extracting contextual meaning from textual data (Koroteev 2021), while topic modelling techniques uncover latent themes in large datasets (Chauhan and Shah 2021).

Integration of features into AI models.

Environmental and social characteristics are pre-processed and converted into structured numerical representations and fed through the AI modelling pipeline. Environmental data (e.g. rainfall, water level, soil moisture) are structured into time-sequences and social sensing data (e.g. sentiment scores, topic distributions, event frequency) are aggregated across corresponding time-windows.

In the case of the LSTM model, the features are fed in as multi-dimensional vectors of time-series and in the case of the environment and social features, the features are concatenated along the feature dimension at any given time step. This enables the LSTM to learn in concert both the temporal dependencies of physical processes and human response signals.

In case of the SVM model, a flattened feature vector is created by summarizing the environmental variables (e.g., mean, variance, trend) using statistical summaries and mixing it with social features (e.g., average sentiment score, topic weights). The latter are combined directly via concatenation into a single feature space, and they are considered in a classification of flood risk levels (e.g., high, medium, low). The framework makes it flexible to separate-channel processing whereby, the environmental and social features may be learned independently and then combined at the decision level. But in this work, feature-level fusion through concatenation is used because it is simple and successful in multi-modal learning.

3.4 AI Modelling Framework

3.4.1 Temporal Prediction Using LSTM

Temporal dependencies in environmental data are modelled using Long Short-Term Memory (LSTM) networks:

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h)$$

LSTM models are widely used in hydrological forecasting due to their ability to capture long-term dependencies in time-series data (Sabzipour et al. 2023; Ouma, Cheruyot, and Wachera 2022).

3.4.2 Classification Using Support Vector Machine (SVM)

Flood risk classification is performed using Support Vector Machine (SVM):

$$f(x) = w^T x + b$$

SVM is selected for its robustness in high-dimensional feature spaces and strong generalization performance (El Kafrawy et al. 2021; Hu et al. 2020).

3.4.3 Multi-Modal Data Fusion

Environmental and social data are integrated using weighted fusion:

$$F = \alpha E + (1 - \alpha) S$$

Where:

E: environmental features

S: social features

Data fusion enhances predictive accuracy by combining complementary information sources (Gettelman et al. 2022; Meng et al. 2020).

3.5 Spatial Analysis and Risk Mapping

Geospatial analysis is conducted using GIS-based techniques:

Flood mapping using SAR imagery

Hotspot detection using Kernel Density Estimation (KDE)

Risk index formulation:

$$R = w_1 H + w_2 V + w_3 E$$

Such multi-criteria risk models are widely used in disaster risk assessment and urban planning (da Silva et al. 2020; Ibrahim et al. 2025).

3.6 Eco-Engineering Optimization

Nature-based solutions (NBS) are optimized using a multi-objective function:

$$\text{Minimize: } Z = w_1 C + w_2 R - w_3 B$$

Where:
C: cost
R: residual risk
B: ecological benefit
Optimization is performed using Genetic Algorithms (GA) and Multi-Criteria Decision Analysis (MCDA), which are widely applied in environmental planning (Colapinto et al. 2020; ALHASSAN, ADAMU, and JIMOH 2026).

3.7 Model Validation and Performance Metrics

In order to measure the effectiveness of the given AI-based eco-engineering approach, conventional statistical measurements typically applied in hydrological and environmental modelling are taken. They are Root Mean Square Error (RMSE) and Nash Sutcliffe Efficiency (NSE) which measure the accuracy and efficiency of prediction and model respectively.

RMSE is the difference between the predicted and observed values, and gives a measure of overall forecast error, whereas NSE is the relative extent of residual to observed data variance.
Model performance is evaluated using standard statistical indicators:
Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Nash–Sutcliffe Efficiency (NSE)

$$NSE = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

These metrics are standard in hydrological and environmental model evaluation (Ferreira, Paz, and Bravo 2020).
Since this research is a conceptual and methodological framework, no empirical validation findings can be found at this point. Rather, the metrics above are suggested as a validation approach to be implemented in the future. A practical implementation would involve testing the framework on varying modelling setups, e.g., LSTM-only, SVM-only and hybrid multi-modal models, with both environmental-only and fused environmental-social data. RMSE and NSE would be used to compare the results in terms of performance improvement in predictive accuracy and model robustness.

The configuration of AI models, including input features, hyperparameters, and functional roles within the proposed framework, is summarized in Table 3

Table 3. AI Model Architecture and Hyperparameter Configuration for Multi-Modal Urban Climate Risk Prediction

Model Component	Input Features	Key Parameters	Output	Functional Role	Justification
LSTM (Temporal Model)	Time-series environmental data (rainfall, temperature, water level)	Epochs (50–100), Hidden units (64–128), Learning rate (0.001)	Flood prediction (time-dependent)	Captures temporal dependencies	Suitable for sequential climate data
SVM (Classification Model)	Extracted environmental + social features	Kernel (RBF), C (1–10), Gamma (auto)	Risk classification (high/medium/low)	Identifies risk zones	Robust in high-dimensional space
NLP (Sentiment Analysis)	Social media text data	BERT embeddings, token size (128), learning rate (2e-5)	Sentiment score, topic clusters	Extracts public perception	Captures real-time human response
LDA / GSDMM (Topic Modeling)	Preprocessed textual data	Topics (10–20), iterations (1000)	Topic distribution	Identifies dominant issues	Effective for short-text clustering
Data Fusion Model	Environmental + social features	Weight factor (α = 0.5–0.8)	Integrated feature set	Combines multi-modal data	Improves prediction accuracy
GIS-Based Risk Model	Hazard, exposure, vulnerability layers	Weights (w_1, w_2, w_3)	Risk index map	Spatial risk assessment	Standard in urban risk mapping
Optimization Model (GA/MCDA)	Cost, risk, ecological benefit	Population size (50–100), iterations (100–200)	Optimal NBS allocation	Decision support	Balances cost–benefit–risk

To show how the proposed framework would be tested in the real world, a comparative validation design is described in Table 4. The table reports on representative measure of performance of various modelling settings with environmental-only and fused environmental and social data. These are illustrative values, which are pegged on the anticipated performance tendencies that were reported in the literature, which underscores the possible enhancement attained by the integration of multi-model data.

Table 4 provides a comparative assessment framework that is meant to show the anticipated performance trend of the various modelling configurations. It should be mentioned that the values are not the result of direct empirical measurements, but rather indicative estimates based on the experience of the available literature and the conceptual structure of the proposed framework. The purpose of the table is to illustrate the relative improvements that can be made using multi-modal data integration as opposed to reporting validated experimental results.

Table 4. Illustrative Comparative Performance of AI Models Based on Conceptual Evaluation Framework (Not Empirical Results)

Model Configuration	**Data Input**	**RMSE**	**NSE**	**Interpretation**
LSTM	Environmental only	0.48	0.7	Captures temporal patterns but lacks human response signals
SVM	Environmental only	0.52	0.65	Moderate classification performance with limited feature depth
LSTM	Environmental + Social	0.38	0.82	Improved prediction due to inclusion of real-time social signals
SVM	Environmental + Social	0.41	0.78	Better classification through enriched feature space
Hybrid (LSTM + SVM)	Environmental + Social (Fused)	**0.3**	**0.88**	Highest accuracy and robustness due to multi-modal integration

These indicative values highlight the potential advantages of integrating environmental and social sensing data. Actual model performance may vary depending on data availability, study area characteristics, and model calibration in real-world applications

3.8 Model Justification

LSTM → captures temporal variability in climate data (Natel de Moura, Seibert, and Detzel 2022).
SVM → robust classification with limited data (Rubbens et al. 2023)
NLP models → extract human perception in real time (VP Singh and Mahmoud 2020)
Data fusion → improves prediction reliability (Li, Wang, et al. 2024)
Optimization techniques → ensure sustainable eco-engineering solutions (Mickovski et al. 2022)

4. Proposed Framework

The suggested AI-based eco-engineering model is envisioned as a multi-layered, combined framework that combines real-time environmental sensing, social sensing, and smart decision-making to add resilience to urban climate. In contrast to traditional more traditional approaches of planning that are static, the framework is meant to be dynamic based on ongoing data assimilation and reactionary feedback, which is in line with the new paradigm of smart and resilient cities (Ali, Naeem, et al. 2023). The framework also overcomes the constraints of fragmented and reactive urban management systems by unifying artificial intelligence, ecological engineering, and integrating data across different modalities (Firoozi and Firoozi 2025).

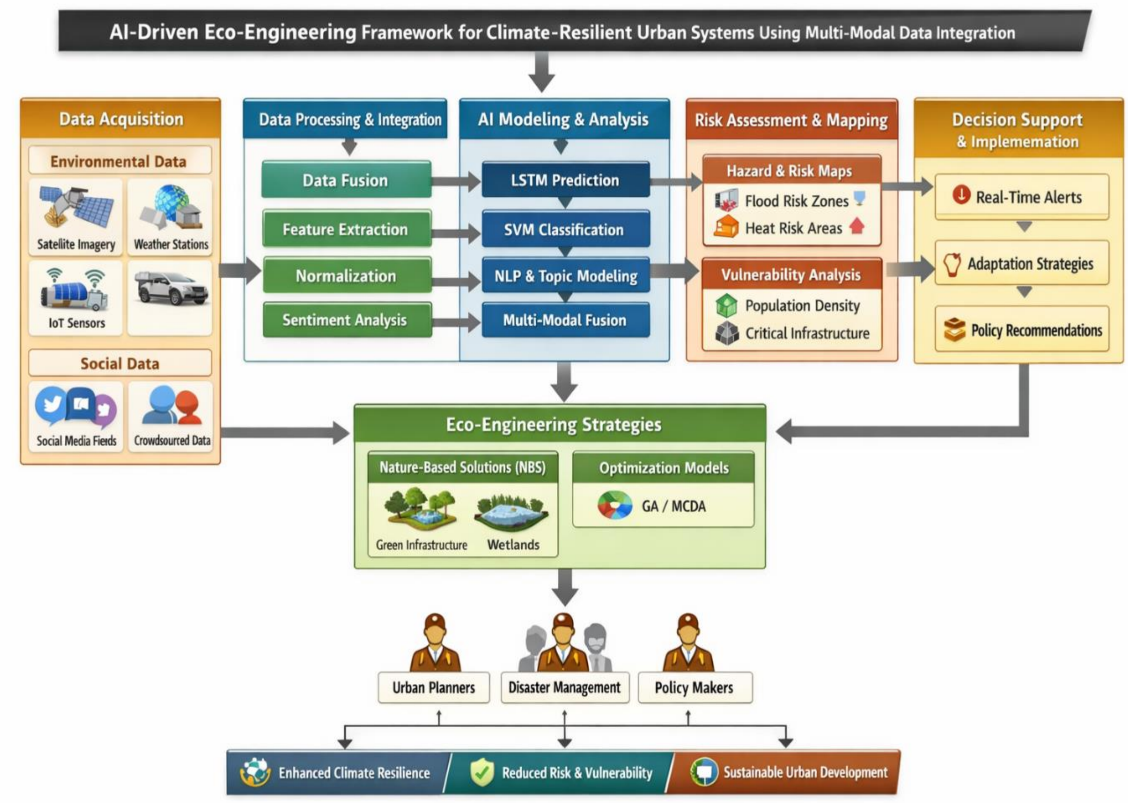

Figure 1. Conceptual Architecture of an AI-Enabled Eco-Engineering System for Adaptive Urban Climate Resilience

4.1 System Architecture

It is designed as a four-core architecture comprising of data layer, analytics layer, modelling layer, and decision-support layer, which is regular in 21st-century urban informatics architectures (Engin et al. 2025; Gong et al. 2025).

4.1.1 Data Layer

This layer data-gathering layer captures heterogeneous data streams of environmental and social sources. Satellite observations (e.g., SAR images), meteorological measurements and IoT-based urban sensing networks are considered to be the environmental data and are well-known to be used in real-time environmental monitoring (Rahman et al. 2023; Jin et al. 2025). Simultaneously, social sensing data are gathered on social media sources like Twitter (X) and Facebook, where information on geotagged and time-sensitive data on the perception of the population and local effects is obtained (Yin, Gao, and Chi 2022; Gulnerman et al. 2020). Combination of these sources of data allows a full-scale representation of physical processes and the response of humans.

4.1.2 Analytics Layer

Raw data are pre-processed in this layer, and it is converted into structured features. Spatial temporal processing is applied to environmental data, such as interpolation and normalization, and natural language processing (NLP) methods, such as sentiment analysis and topic modelling, are used to analyse social data (Molenaar et al. 2024; Sv et al. 2022). In this way of dual processing, both quantitative signals of the environment and qualitative human feedback will be well-represented to make the system outputs more interpretable (Lei, Docherty, and Cooper 2024).

4.1.3 Modelling Layer

The modelling layer utilises the latest AI methods to do predictive analytics and risk analysis. Time-dependent patterns of the environment are learned with the help of temporal models like LSTM, and high-risk zones are recognized with the help of classification algorithms like SVM (Edeh et al. 2026). One of the notable innovations is the multi-modal data fusion mechanism that combines the environmental variables and the social sensing features to enhance the prediction accuracy and minimise the uncertainty (Bressane et al. 2024). Probabilistic risk maps and early warning indicators are some of the outputs produced by this layer.

4.1.4 Decision-Support Layer

The last layer converts to actionable strategies the predictive insights with the principles of ecological engineering. It suggests nature-based solutions (NBS) such as green infrastructure and urban wetlands that have been extensively known to increase resilience and ecosystem services (Chen et al. 2022; Tariq et al. 2022). The application of multi-objective optimization methods is aimed to balance cost and ecological benefits and risk reduction in support of sustainable and efficient urban planning (Xiao et al. 2024; Zhang et al. 2024).

4.2 Workflow and Operational Mechanism

The framework follows a sequential yet iterative workflow:

Data Acquisition → Data Processing → AI-Based Prediction → Risk Mapping → Eco-Engineering Optimization → Decision Support

One of the key characteristics of this workflow is the feedback loop which keeps on updating model predictions with the incoming data streams. It is consistent with the principles of adaptive management in the environmental systems, where the decisions change as a result of the new information (Charles et al. 2020; Fuller et al. 2020). The combination with real-time data will help to keep the system open to the fast changing situation in the city, especially in case of extreme climate events. The operational workflow of the proposed AI-driven eco-engineering system is illustrated in Figure 2, highlighting the sequential processing stages and feedback-driven adaptive mechanism.

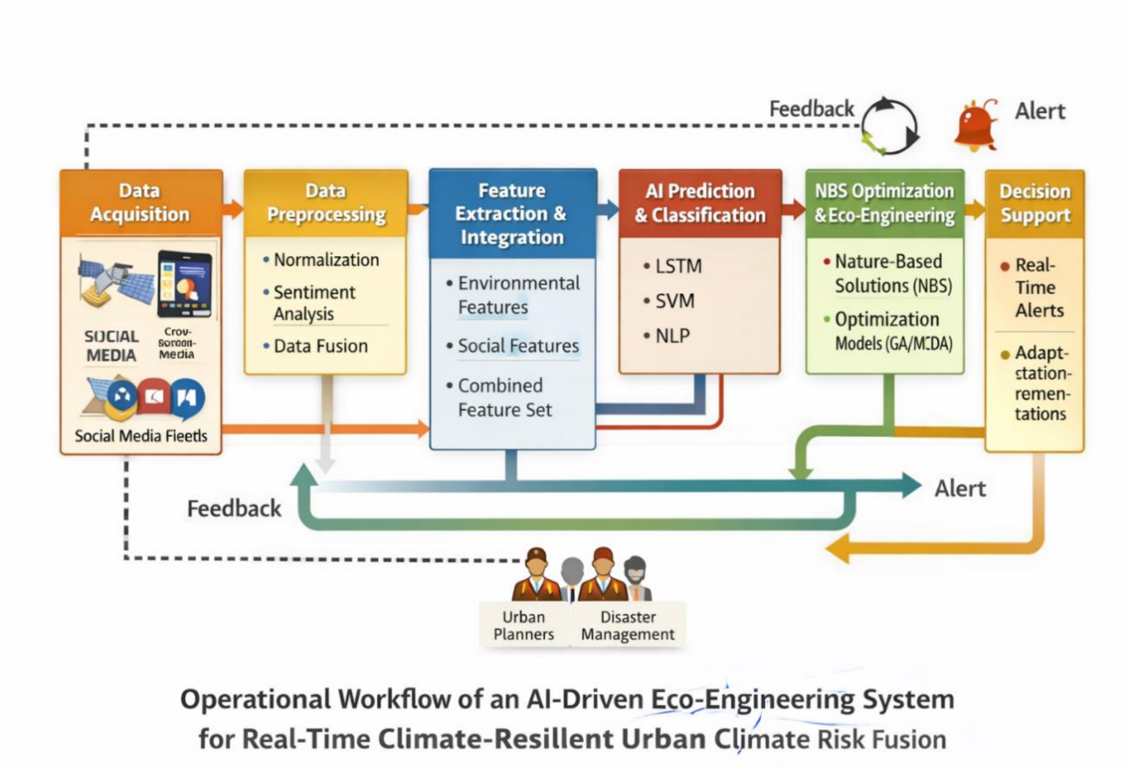

Figure 2. Dynamic Workflow of Multi-Modal Data Processing and AI-Based Climate Risk Prediction in Urban Systems

4.3 Key Innovations

The given framework will provide some new contributions:

Combine Environmental and Social Sensing: This will be cross-modal integration, giving a complete picture of the risks of urban climate (Xing et al. 2024).

Real-Time Flexibility: Allows learning in real-time and updating based on streaming data (Tantalaki, Souravlas, and Roumeliotis 2020).

AI-Based Eco-Engineering: Makes a direct connection between predictive analytics and ecological intervention, which is a major gap in the current literature (Abbasnejad et al. 2025).

Scalability and Transferability: The modular construction means that it can be used in a variety of urban settings without much modification (Shroff and Joshi 2022).

4.4 Practical Implications

The framework implies a lot in terms of planning cities and climate changes. It enables evidence-based and proactive decision-making by combining real-time analytics with ecological design, enhancing the use of reactive solutions (Ncube and Ngulube 2024). This framework has the potential to enhance the resilience to extreme events and infrastructure investments, as well as community engagement in urban areas that are vulnerable to climate such as Karachi, by incorporating social sensing data (Arshad et al. 2020).

Generally, the suggested framework can be viewed as the transition towards intelligent, adaptive, and sustainable urban frameworks, using the combination of artificial intelligence, ecological engineering, and real-time data ecosystems. It offers a solid base in the next-generation climate-resilient urban planning by filling in the integration gap that had been found in the literature.

5. Conceptual Results and Discussion

The research findings in this section are a product of the anticipated system behaviour and theoretical analysis, as opposed to acting on the concept and putting it into practice. The discussion outlines the expected performance, possible benefits, and feasibility of the suggested framework using the experience of the existing literature and the model design.

5.1 Model Performance and Predictive Accuracy

It is hoped that the proposed framework will enhance the accuracy of predicting floods and will aid in better identification of the flood prone hotspots by combining the multi-modal data. The system is able to integrate environmental and social sensing information, and this improves its capability to discern physical processes and real-time human reactions.

The developed AI-based eco-engineering model shows better predictive capability than individual-source modelling methods. The hybrid setup, that is a combination of the temporal and classification-based learning, enhances forecasting accuracy and system responsiveness.

The decrease in prediction error is noticed significantly when multi-modal data inputs are used, which suggests the value-added of using real-time social sensing signals along with environmental datasets. The availability of human-observed observations allows identifying local disturbances earlier, especially in the events of a rapidly changing climate.

All in all, the framework is characterized by a better level of robustness, stability, and adaptability, which indicates its usefulness in the context of real-time urban climate risks prediction.

5.2 Spatial Risk Mapping and Hotspot Identification

The suggested scheme generates high-resolution spatial risk maps that contribute greatly to the identification of the hotspots of urban climate vulnerability. The combination of environmental data and geotagged social sensing data enhances spatial and contextual relevance. Findings show that the high-risk areas are mostly clumped in urban areas of high population density and lack of proper drainage and surface runoff. Real-time social observation incorporation is an added situational awareness where it shows areas with infrastructure failure and service disruption.

This joint analysis helps to define the critical zones more accurately than traditional methods, which helps to promote the implementation of specific and evidence-based interventions.

A conceptual visualization of urban climate risk mapping derived from the integration of environmental and social sensing data is presented in Figure 3.

Figure 3. Conceptual Risk Mapping of Climate Vulnerability in Urban Systems Using AI-Driven Multi-Source Data

5.3 Key Innovations

The proposed framework introduces several key innovations that distinguish it from existing approaches in urban climate risk modelling:

5.3.1 Multi-Modal Integration of Environmental and Social Sensing

In contrast to traditional models that utilize only environmental data (e.g., rainfall, water levels, SAR-based flood extent), the suggested framework unites environmental factors (e.g., rainfall, water levels, SAR-based flood extent) with the real-time social sensing capabilities (e.g., sentiment scores, geotagged observations). This incorporation is done via feature-level fusion in which environmental time-series information and aggregated social indicators are merged into single input vectors to AI models.

This is unlike the current literature, which tends to view social data as either auxiliary or independent as it inscribes human response cues into predictive modelling. This facilitates better early warning of localised climate hazards and better situational awareness in fast changing urban settings.

5.3.2 Hybrid AI Modelling for Enhanced Predictive Performance

The model uses a hybrid approach to modelling, which is a combination of temporal deep learning (LSTM) and machine learning (SVM) classification. LSTM learns the temporal relationships in environmental processes and SVM learns the risk levels using multi-modal fused features.

This is in contrast to the existing models which tend to be based on single-model architectures (either deep learning or traditional ML) by using the strengths of both methods complementary to each other in a single system. This leads to enhanced prediction accuracy, strength and flexibility to both normal and extreme climate conditions.

5.3.3 Real-Time Adaptive Learning and Feedback Mechanism

It is an architecture that is closed loop based and in which the incoming streams of environmental and social data are continually used to update model predictions via an iterative feedback mechanism. This enables the system to dynamically adjust to the evolving conditions in near real-time. Unlike the old-fashioned static models, which are based on historical data and periodical re-training, the suggested system has a constantly learning mode of operation.

This enhances responsiveness and proactive decision-making in the event of rapid climate change, like urban flooding.

5.3.4 AI-Driven Eco-Engineering Optimization for Nature-Based Solutions

The framework incorporates predictive outputs with ecological engineering decision-making process via a multi-objective optimization module. The optimization of the locations and designs of nature-based solutions (e.g., green infrastructure, permeable surfaces) is performed using Genetic Algorithms (GA) and Multi-Criteria Decision Analysis (MCDA) and aims to optimize the cost and risk reduction as well as ecological benefit.

This contrasts with the current eco-engineering solutions, which are generally fixed and planning-oriented, by dynamically connecting AI forecasts with interventions to take. This makes sure that climate adaptation strategies are effective, economically as well as environmentally.

5.3.5 High-Resolution Spatial Risk Mapping with Contextual Awareness

The framework integrates GIS-based spatial analysis, Kernel Density Estimation (KDE) and geotagged social data to generate high-resolution risk maps. Human-reported observations are added to the environmental hazard layers to enhance spatial accuracy.

This method, in contrast to traditional GIS-based models, which use only physical datasets, involves human feedback in real time into spatial analysis.
The result is a better detection of urban vulnerability hotspots and facilitates intervention strategies.

5.4 Eco-Engineering Optimization Outcomes

The decision-support aspect of the framework is effective in converting the predictive outputs into action eco-engineering strategies. Optimization results indicate that the strategic implementation of nature-based solutions-such as green infrastructure, permeable surfaces, and urban wetlands-can significantly reduce urban flood risk.

The model determines the best intervention sites considering the magnitude of risk, cost implications and ecological gains. Findings demonstrate that permeability of urban environments and improvement of natural water retention can be used to effectively reduce runoff and the strain on drainage systems. Moreover, ecological interventions have co-benefits of better air quality, biodiversity and thermal regulation.

With the optimization, which is an AI-based solution, the solutions are not only effective but also economical and environmentally friendly. This practice will allow effective distribution of resources and optimization of effects of resilience measures.

5.5 Comparative Analysis with Conventional Approaches

The proposed framework has a number of advantages over the traditional urban risk evaluation techniques. Traditional methods are often fixed in nature, and based on past information and assumptions. Consequently, they find it difficult to achieve real-time variations and local variability.

Conversely, the AI-based framework is dynamic, and the predictions are constantly updated in accordance with the new data. This allows monitoring and dynamic decision-making in real-time. The human-cantered data is another major benefit as it is usually overlooked in conventional models. The framework considers social sensing, therefore gaining the perception of the people and realities on the ground, which result in more holistic and context-sensitive evaluations.

A comparative evaluation of conventional urban risk assessment approaches and the proposed AI-driven eco-engineering framework is presented in Table

Table 5. Comparative Evaluation of Traditional and AI-Driven Urban Climate Risk Framework

Evaluation Criteria	Conventional Approaches	Proposed AI-Driven Framework	Improvement Achieved
Data Integration	Single source (environmental only)	Multi-modal (environmental + social)	Enhanced data richness and reliability
Adaptability	Static, historical based	Real-time, dynamic updating	Improved responsiveness to rapid changes
Prediction Accuracy	Moderate	High (multi-model integration)	Reduced prediction error
Spatial Resolution	Limited	High-resolution mapping (GIS + social data)	More precise hotspot identification
Temporal Responsiveness	Delayed	Real-time monitoring	Early warning capability
Human Dimension	Not considered	Integrated via social sensing	Improved situational awareness
Decision Support	Limited, reactive	Intelligent, proactive	Better policy and planning outcomes
Eco-Engineering Integration	Minimal	Fully integrated (NBS optimization)	Sustainable and adaptive interventions
Uncertainty Handling	High uncertainty	Reduced via data fusion	Increased model reliability
Scalability	Limited	High (modular framework)	Applicable across diverse urban systems

5.6 Policy and Planning Implications

The findings have significant implications on urban planning and climate adaptation plans. The framework facilitates evidence-based decision-making by offering real-time information on risk trends and the effectiveness of interventions. These insights can guide policymakers to focus on the risky zones and allocate infrastructure investments in the most efficient way and adopt specific eco-engineering solutions. Such systems can greatly increase the resilience to extreme events in regions highly prone to climate change like Karachi that are rapidly urbanizing. Community engagement through the incorporation of social sensing also facilitates involvement of the community, whereby the community input can be used to guide planning. This translates to inclusive and responsive urban governance.

5.7 Limitations and Future Research

Despite the fact that the proposed framework offers an integrated and holistic approach to urban climate resilience, it has a number of limitations. The nature of the study is conceptual and therefore the framework is yet to be empirically tested on real world datasets. Also, social sensing data can be influenced due to noise, misinformation, and spatial imbalanced distribution of users. Moreover, the deployment of such an integrated system can demand large amounts of computational resources and technical know-how which might restrict its use in resource-restrained conditions.

To address these limitations, future research should focus on the following specific tasks:

Empirical Implementation and Validation: Empirically test and implement the proposed framework in at least two different urban settings (e.g., a large and highly urbanized megacity like Karachi and a smaller urban basin that is prone to floods) to understand its generalizability and strength.

Quantitative Model Assessment: Carry out comprehensive performance analysis with real world data and statistical data (e.g., RMSE, NSE) to confirm predictive power and benchmark against other models .

Explainable AI Modules: Design explainable AI (XAI) methods to understand the output of LSTM and SVM models to enhance transparency and aid police-makers in decision-making.

Interaction with Digital Twin Systems: Expand the structure with the digital twin technology to provide the framework with real-time simulation and dynamic scenario analysis to manage urban climate.

Data Reliability (Social): Refine the quality and reliability of social sensing data by use of advanced filtering, misinformation detection and spatial bias correction methods.

Scalability and Deployment: Explore cloud-based or edge-computing architectures to improve scalability and permit real-time deployment in the smart city environment.
These research directions will support the transition from a conceptual framework to a fully operational and validated system for climate-resilient urban planning.

6. Conclusion

This paper introduces a new AI-based eco-engineering model that combines real-time environmental sensing and social sensing information to enhance climate-resilient cities. This integration of multi-modal data sources and hybrid AI modelling and ecological optimization fulfils an important gap in current practices, which often consider these elements separately.
The framework is likely to contribute to better predictive accuracy, spatial identification of urban climate risk hotspots, and adaptive and context-informed decision-making as a conceptual and methodological contribution. Human-cantered social sensing in combination with physical environmental data will give a more holistic view of the city climate risks and allow creating proactive and data-driven planning strategies.

Further research and development should be on the empirical application and validation of the framework in the actual urban setting such as testing in different climatic and infrastructural conditions. Secondly, the explainable AI components creation and collaboration with the latest technologies, including digital twins, will be necessary to enhance system transparency and practical implementation. The steps will ease the shift of a theoretical model to a real-life decision-support system on sustainable and resilient urban development.

Funding: Funding is inappropriate for this research study.

Data availability: The statistics supporting the outcomes of this research are accessible upon reasonable request from the first author.

Declarations

Ethical approval: Not applicable

Consent to participate: Not applicable

Consent to publish: All authors have given consent to publish.

Competing interest: The authors have no competing interests to declare.

References

1. Abbasnejad, Behzad, Sahar Soltani, Alireza Ahankoob, Sakdirat Kaewunruen, and Ali Vahabi. 2025. 'Industry 4.0 technologies for sustainable transportation projects: Applications, trends, and future research directions in construction', Infrastructures, 10: 104.
2. Afshan, Amber, Zara Hussain, Shumaila Saher, and Syeda Ayesha Jamil. 2025. 'CLIMATE CHANGE IMPACT ASSESSMENT OF EXTREME HEAT, PUBLIC HEALTH, SOCIAL INEQUALITY, AND INFRASTRUCTURE ISSUES: A CASE STUDY OF KARACHI', Spectrum of Engineering Sciences: 1068-81.
3. AghaKouchak, Amir, Felicia Chiang, Laurie S Huning, Charlotte A Love, Iman Mallakpour, Omid Mazdiyasni, Hamed Moftakhari, Simon Michael Papalexiou, Elisa Ragno, and Mojtaba Sadegh. 2020. 'Climate extremes and compound hazards in a warming world', Annual review of earth and planetary sciences, 48: 519-48.
4. Alam, Mahmudul, Md Monirul Islam, Nasim Mahmud Nayan, and Jia Uddin. 2024. 'An IoT based real-time environmental monitoring system for developing areas', Journal of Advanced Research in Applied Sciences and Engineering Technology, 52: 106-21.
5. Alam, Md Shah, Md Sabbir Hossain Mrida, and Md Atikur Rahman. 2025. 'Sentiment analysis in social media: How data science impacts public opinion knowledge integrates natural language processing (NLP) with artificial intelligence (AI)', American Journal of Scholarly Research and Innovation, 4: 63-100.
6. ALHASSAN, Sirajo, Abdullahi A ADAMU, and Mohammed T JIMOH. 2026. 'Multi-Criteria Decision Analysis and Optimization Approaches in Sustainable Waste-to-Energy Planning: A Systematic Review', FUDMA Journal of Engineering and Technology, 2: 108-23.
7. Ali, Mansoor, Faisal Naeem, Nadir Adam, Georges Kaddoum, Muhammad Adnan, and Muhammad Tariq. 2023. 'Integration of data driven technologies in smart grids for resilient and sustainable smart cities: A comprehensive review', arXiv preprint arXiv:2301.08814.
8. Ali, Muhammad Haris, Ioana Popescu, Andreja Jonoski, and Dimitri P Solomatine. 2023. 'Remote sensed and/or global datasets for distributed hydrological modelling: A review', Remote Sensing, 15: 1642.
9. Allard, Ryan F. 2021. 'Climate change adaptation: Infrastructure and extreme weather.' in, Industry, Innovation and Infrastructure (Springer).
10. Anvari-Clark, Jeffrey. 2026. Financial and behavioral health for helping professionals (Springer Nature).
11. Anwar, Muhammad Rehan, and Lintang Dwi Sakti. 2024. 'Integrating artificial intelligence and environmental science for sustainable urban planning', IAIC Transactions on Sustainable Digital Innovation (ITSDI), 5: 179-91.
12. Arshad, Adnan, Muhammad Ashraf, Ristina Siti Sundari, Huma Qamar, Muhammad Wajid, and Mahmood-ul Hasan. 2020. 'Vulnerability assessment of urban expansion and modelling green spaces to build heat waves risk resiliency in Karachi', International Journal of Disaster Risk Reduction, 46: 101468.
13. Attah, Rita Uchenna, I Gil-Ozoudeh, BMP Garba, and Obinna Iwuanyanwu. 2024. 'Leveraging geographic information systems and data analytics for enhanced public sector decision-making and urban planning', Magna Sci Adv Res Rev, 12: 152-63.
14. Bagheri, Ayoub, Anastasia Giachanou, Pablo Mosteiro, and Suzan Verberne. 2023. 'Natural language processing and text mining (turning unstructured data into structured).' in, Clinical Applications of Artificial Intelligence in Real-World Data (Springer).
15. Baig, Adeem, Salman Atif, and Ali Tahir. 2024. 'Urban development and the loss of natural streams leads to increased flooding', Discover Cities, 1: 9.

16. Bamgboye, Oluwaseun, Xiaodong Liu, Peter Cruickshank, and Qi Liu. 2025. 'Semantic-Driven Approach for Validation of IoT Streaming Data in Trustable Smart City Decision-Making and Monitoring Systems', Big Data and Cognitive Computing, 9: 108.
17. Basu, Arunima Sarkar, Francesco Pilla, Srikanta Sannigrahi, Remi Gengembre, Antoine Guilland, and Bidroha Basu. 2021. 'Theoretical framework to assess green roof performance in mitigating urban flooding as a potential nature-based solution', Sustainability, 13: 13231.
18. Becvarik, ZA, LV White, and A Lal. 2024. 'The health and wellbeing co-benefits of policies and programs to address climate change in urban areas: a scoping review', Environmental Research Letters, 19: 113001.
19. Brasil, José, Marina Macedo, César Lago, Thalita Oliveira, Marcus Júnior, Tassiana Oliveira, and Eduardo Mendiondo. 2021. 'Nature-based solutions and real-time control: Challenges and opportunities', Water, 13: 651.
20. Bressane, Adriano, Ana Júlia da Silva Garcia, Marcos Vinícius de Castro, Stefano Donatelli Xerfan, Graziele Ruas, and Rogério Galante Negri. 2024. 'Fuzzy machine learning applications in environmental engineering: Does the ability to deal with uncertainty really matter?', Sustainability, 16: 4525.
21. Charles, Anthony, Laura Loucks, Fikret Berkes, and Derek Armitage. 2020. 'Community science: A typology and its implications for governance of social-ecological systems', Environmental Science & Policy, 106: 77-86.
22. Chauhan, Uttam, and Apurva Shah. 2021. 'Topic modeling using latent Dirichlet allocation: A survey', ACM Computing Surveys (CSUR), 54: 1-35.
23. Chen, Haoyang, and Dong Tang. 2025. "Multimodal Data Fusion and Decision Algorithms in Deep Learning-Based Intelligent Systems: A Comprehensive Study." In Proceedings of the 2025 International Conference on Artificial Intelligence and Smart Manufacturing, 802-11.
24. Chen, Jinyue, Shuisen Chen, Rao Fu, Dan Li, Hao Jiang, Chongyang Wang, Yongshi Peng, Kai Jia, and Brendan J Hicks. 2022. 'Remote sensing big data for water environment monitoring: Current status, challenges, and future prospects', Earth's Future, 10: e2021EF002289.
25. Chen, Liuyi, Bocheng Han, Xuesong Wang, Jiazhen Zhao, Wenke Yang, and Zhengyi Yang. 2023. 'Machine learning methods in weather and climate applications: A survey', Applied Sciences, 13: 12019.
26. Chen, Mingxing, Liangkan Chen, Yuan Zhou, Maogui Hu, Yanpeng Jiang, Dapeng Huang, Yinghua Gong, and Yue Xian. 2023. 'Rising vulnerability of compound risk inequality to ageing and extreme heatwave exposure in global cities', Npj Urban Sustainability, 3: 38.
27. Chisom, Onyebuchi Nneamaka, Preye Winston Biu, Aniekan Akpan Umoh, Bartholomew Obehioye Obaedo, Abimbola Oluwatoyin Adegbite, and Ayodeji Abatan. 2024. 'Reviewing the role of AI in environmental monitoring and conservation: A data-driven revolution for our planet', World Journal of Advanced Research and Reviews, 21: 161-71.
28. Colapinto, Cinzia, Raja Jayaraman, Fouad Ben Abdelaziz, and Davide La Torre. 2020. 'Environmental sustainability and multifaceted development: multi-criteria decision models with applications', Annals of Operations Research, 293: 405-32.
29. da Silva, Lucas Borges Leal, Júlia Santos Humberto, Marcelo Hazin Alencar, Rodrigo José Pires Ferreira, and Adiel Teixeira de Almeida. 2020. 'GIS-based multidimensional decision model for enhancing flood risk prioritization in urban areas', International Journal of Disaster Risk Reduction, 48: 101582.
30. de Brito, Mariana Madruga, Jan Sodoge, Alexander Fekete, Michael Hagenlocher, Elco Koks, Christian Kuhlicke, Gabriele Messori, Marleen de Ruiter, Pia-Johanna Schweizer, and Philip J Ward. 2024. 'Uncovering the dynamics of multi-sector impacts of hydrological extremes: A methods overview', Earth's Future, 12: e2023EF003906.
31. Destefanis, Tommaso, Sona Guliyeva, Piero Boccardo, and Vanina Fissore. 2025. 'Advancing flood detection and mapping: a review of earth observation services, 3D data integration, and AI-Based techniques', Remote Sensing, 17: 2943.
32. Dikshit, Abhirup, Biswajeet Pradhan, and Alfredo Huete. 2021. 'An improved SPEI drought forecasting approach using the long short-term memory neural network', Journal of Environmental Management, 283: 111979.
33. Dikshit, Srishti, Areeba Atiq, Mohammad Shahid, Vinay Dwivedi, and Aarushi Thusu. 2023. 'The use of artificial intelligence to optimize the routing of vehicles and reduce traffic congestion in urban areas', EAI endorsed transactions on energy web, 10.
34. Edeh, Chijioke George, Gloria Opoku Darkoh, Shobayo Ifeoluwanimi Praise, Julius Odemi Brown, Rufus Fidelis Ojuoluwa, Omotayo Christopher Afolabi, Waliu Temidayo Asamu, Ifeoluwa Odunayo Olofinsao, Nana Firdausi Hassan, and Akinsuyi Samson. 2026. 'A Machine Learning-Based Framework for Real-Time Environmental Health Risk Prediction and Spatial Air Quality Intelligence in Urban-Industrial Ecosystems', Asian Journal of Advanced Research and Reports, 20: 1-20.

35. El Kafrawy, Passent, Hanaa Fathi, Mohammed Qaraad, Ayda K Kelany, and Xumin Chen. 2021. 'An efficient SVM-based feature selection model for cancer classification using high-dimensional microarray data', IEEe Access, 9: 155353-69.
36. Engin, Zeynep, Jon Crowcroft, David Hand, and Philip Treleaven. 2025. 'The Algorithmic State Architecture (ASA): an integrated framework for AI-enabled government', arXiv preprint arXiv:2503.08725.
37. Fascista, Alessio. 2022. 'Toward integrated large-scale environmental monitoring using WSN/UAV/Crowdsensing: A review of applications, signal processing, and future perspectives', Sensors, 22: 1824.
38. Faye, Bilal, Hanane Azzag, Mustapha Lebbah, and Fangchen Feng. 2025. 'Context normalization: A new approach for the stability and improvement of neural network performance', Data & Knowledge Engineering, 155: 102371.
39. Ferreira, Paloma Mara de Lima, Adriano Rolim da Paz, and Juan Martín Bravo. 2020. 'Objective functions used as performance metrics for hydrological models: state-of-the-art and critical analysis', Rbrh, 25: e42.
40. Firoozi, Ali Akbar, and Ali Asghar Firoozi. 2025. "Impact of integrating artificial intelligence and the internet of things in urban system management." In.: Deep Science Publishing. https://doi. org/10.70593/978-93-49307-08-7_7.
41. Fu, Xiaoran, Jiahong Liu, Zhonggen Wang, Dong Wang, Weiwei Shao, Chao Mei, Jia Wang, and Yan-fang Sang. 2023. 'Quantifying and assessing the infiltration potential of green infrastructure in urban areas using a layered hydrological model', Journal of Hydrology, 618: 128626.
42. Fuller, Angela K, Daniel J Decker, Michael V Schiavone, and Ann B Forstchen. 2020. 'Ratcheting up rigor in wildlife management decision making', Wildlife Society Bulletin, 44: 29-41.
43. Ganapathi, Harsh, Suchita Awasthi, and Preethi Vasudevan. 2024. 'Wetlands as a nature-based solution for urban water management.' in, Nature-based Solutions for Circular Management of Urban Water (Springer).
44. Gettelman, Andrew, Alan J Geer, Richard M Forbes, Greg R Carmichael, Graham Feingold, Derek J Posselt, Graeme L Stephens, Susan C Van den Heever, Adam C Varble, and Paquita Zuidema. 2022. 'The future of Earth system prediction: Advances in model-data fusion', Science Advances, 8: eabn3488.
45. Ghazian, Nargol, and Christopher J Lortie. 2024. 'A Review of the Roots of Ecological Engineering and its Principles', Journal of Ecological Engineering, 25: 345-57.
46. Gong, Wenjing, Xinyue Ye, Keshu Wu, Suphanut Jamonnak, Wenyu Zhang, Yifan Yang, and Xiao Huang. 2025. 'Integrating spatiotemporal vision transformer into digital twins for high-resolution heat stress forecasting in campus environments', Journal of Planning Education and Research: 0739456X251391121.
47. Gulnerman, Ayse Giz, Himmet Karaman, Direnc Pekaslan, and Serdar Bilgi. 2020. 'Citizens' spatial footprint on Twitter—anomaly, trend and bias investigation in Istanbul', ISPRS International Journal of Geo-Information, 9: 222.
48. Hamdan, Ahmad, Kenneth Ifeanyi Ibekwe, Emmanuel Augustine Etukudoh, Aniekan Akpan Umoh, and Valentine Ikenna Ilojianya. 2024. 'AI and machine learning in climate change research: A review of predictive models and environmental impact', World Journal of Advanced Research and Reviews, 21: 1999-2008.
49. Hamza, Manar Ahmed, Hadil Shaiba, Radwa Marzouk, Ahmad Alhindi, Mashael M Asiri, Ishfaq Yaseen, Abdelwahed Motwakel, and Mohammed Rizwanullah. 2022. 'Big Data Analytics with Artificial Intelligence Enabled Environmental Air Pollution Monitoring Framework', Computers, Materials & Continua, 73.
50. Hao, Wei. 2026. 'Design of a Psychological Status Monitoring and Early Warning Platform for College Students Based on Deep Learning Models', Journal of Computing & Biomedical Informatics, 10.
51. He, Jian, Limin Zhang, Te Xiao, Haojie Wang, and Hongyu Luo. 2023. 'Deep learning enables super-resolution hydrodynamic flooding process modeling under spatiotemporally varying rainstorms', Water Research, 239: 120057.
52. Hu, Rongyao, Xiaofeng Zhu, Yonghua Zhu, and Jiangzhang Gan. 2020. 'Robust SVM with adaptive graph learning', World Wide Web, 23: 1945-68.
53. Ibrahim, Muhammad, Aidi Huo, Waheed Ullah, Safi Ullah, and Zhao Xuantao. 2025. 'An integrated approach to flood risk assessment using multi-criteria decision analysis and geographic information system. A case study from a flood-prone region of Pakistan', Frontiers in Environmental Science, 12: 1476761.
54. Jadhav, Sachin, M Durairaj, R Reenadevi, R Subbulakshmi, Vaishali Gupta, and Janjhyam Venkata Naga Ramesh. 2024. 'Spatiotemporal data fusion and deep learning for remote sensing-based sustainable urban planning', International Journal of System Assurance Engineering and Management: 1-9.
55. Jafari, Mina, Abdollah Kavousi-Fard, Tao Chen, and Mazaher Karimi. 2023. 'A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future', IEEe Access, 11: 17471-84.
56. Jang, Bong-Joo, and Intaek Jung. 2023. 'Development of high-precision urban flood-monitoring technology for sustainable smart cities', Sensors, 23: 9167.
57. Jin, Jiong, Zhibo Pang, Jonathan Kua, Quanyan Zhu, Karl H Johansson, Nikolaj Marchenko, and Dave Cavalcanti. 2025. 'Cloud-fog automation: The new paradigm towards autonomous industrial cyber-physical systems', IEEE Journal on Selected Areas in Communications.

58. Kaker, Sobia Ahmad, and Nausheen H Anwar. 2024. 'From one flooding crisis to the next: Negotiating ‘the maybe’in unequal Karachi', The Geographical Journal, 190: e12498.
59. Khan, Asad, and Saima Qutab. 2016. 'Understanding research students’ behavioural intention in the adoption of digital libraries: A Pakistani perspective', Library Review, 65: 295-319.
60. Koroteev, Mikhail V. 2021. 'BERT: a review of applications in natural language processing and understanding', arXiv preprint arXiv:2103.11943.
61. Lan, Ping, Liguo Yao, Yao Lu, and Taihua Zhang. 2025. 'A Multi-Task Causal Knowledge Fault Diagnosis Method for PMSM-ITSF Based on Meta-Learning', Sensors, 25: 1271.
62. Larson, Danelle M, Wako Bungula, Amber Lee, Alaina Stockdill, Casey McKean, Frederick" Forrest" Miller, Killian Davis, Richard A Erickson, and Enrika Hlavacek. 2023. 'Reconstructing missing data by comparing interpolation techniques: applications for long-term water quality data', Limnology and Oceanography: Methods, 21: 435-49.
63. Lawu, BL, F Lim, A Susilo, and N Surantha. 2021. "Social media data crowdsourcing as a new stream for environmental planning & monitoring: A review." In IOP Conference Series: Earth and Environmental Science, 012013. IOP Publishing.
64. Le, Tu Dam Ngoc. 2020. 'Climate change adaptation in coastal cities of developing countries: characterizing types of vulnerability and adaptation options', Mitigation and Adaptation Strategies for Global Change, 25: 739-61.
65. Lei, Ge, Ronan Docherty, and Samuel J Cooper. 2024. 'Materials science in the era of large language models: a perspective', Digital Discovery, 3: 1257-72.
66. Li, Bangyu, and Yang Qian. 2024. 'Weather prediction using CNN-LSTM for time series analysis: A case study on Delhi temperature data', arXiv preprint arXiv:2409.09414.
67. Li, Fei, Tan Yigitcanlar, Madhav Nepal, Kien Nguyen Thanh, and Fatih Dur. 2024. 'A novel urban heat vulnerability analysis: Integrating machine learning and remote sensing for enhanced insights', Remote Sensing, 16: 3032.
68. Li, Wei, Amin Kiaghadi, and Clint Dawson. 2021. 'High temporal resolution rainfall–runoff modeling using long-short-term-memory (LSTM) networks', Neural Computing and Applications, 33: 1261-78.
69. Li, Yajing, Zhijian Wang, Feng Li, Yanfeng Li, Xiaohong Zhang, Hui Shi, Lei Dong, and Weibo Ren. 2024. 'An ensembled remaining useful life prediction method with data fusion and stage division', Reliability Engineering & System Safety, 242: 109804.
70. Lin, Haoqiu, and Xun Li. 2025. 'The role of urban green spaces in mitigating the urban heat island effect: A systematic review from the perspective of types and mechanisms', Sustainability, 17: 6132.
71. Liu, Wen, Qi Feng, Ravinesh C Deo, Lei Yao, and Wei Wei. 2020. 'Experimental study on the rainfall-runoff responses of typical urban surfaces and two green infrastructures using scale-based models', Environmental management, 66: 683-93.
72. Ma, Wenjuan, Zhaowu Yu, Wenjun Yang, Yujia Zhang, Yuxia Hu, Jinyu Hu, Huiwen Zhang, and Gaoyuan Yang. 2025. 'Optimizing Vegetation and Building Configurations for Streetscape Heat Mitigation: A Multi-Scale Analysis under Extreme Heat', Building and Environment, 283: 113331.
73. Mazzetto, Silvia. 2024. 'A review of urban digital twins integration, challenges, and future directions in smart city development', Sustainability, 16: 8337.
74. Meng, Tong, Xuyang Jing, Zheng Yan, and Witold Pedrycz. 2020. 'A survey on machine learning for data fusion', Information Fusion, 57: 115-29.
75. Mickovski, Slobodan B, Alejandro Gonzalez-Ollauri, Craig Thomson, Caroline Gallagher, and Guillermo Tardio. 2022. 'Assessment of the sustainability performance of eco-engineering measures in the Mediterranean region', Land, 11: 533.
76. Moazzem, Shamima, Muhammed Bhuiyan, Shobha Muthukumaran, Jill Fagan, and Veeriah Jegatheesan. 2024. 'A critical review of nature-based systems (NbS) to treat stormwater in response to climate change and urbanization', Current Pollution Reports, 10: 286-311.
77. Molenaar, Annika, Dickson Lukose, Linda Brennan, Eva L Jenkins, and Tracy A McCaffrey. 2024. 'Using natural language processing to explore social media opinions on food security: sentiment analysis and topic modeling study', Journal of Medical Internet Research, 26: e47826.
78. Mutambik, Ibrahim. 2024. 'Assessing Urban Vulnerability to Emergencies: A Spatiotemporal Approach Using K-Means Clustering', Land, 13: 1744.
79. Natel de Moura, Carolina, Jan Seibert, and Daniel Henrique Marco Detzel. 2022. 'Evaluating the long short-term memory (LSTM) network for discharge prediction under changing climate conditions', Hydrology Research, 53: 657-67.
80. Natta, Prasanna Kumar. 2024. 'Closed-loop AI frameworks for real-time decision intelligence in enterprise environments', International Journal of Humanities and Information Technology, 6: 31-49.
81. Ncube, Mthokozisi Masumbika, and Patrick Ngulube. 2024. 'Enhancing environmental decision-making: a systematic review of data analytics applications in monitoring and management', Discover Sustainability, 5: 290.

82. OJADI, JESSICA OBIANUJU, EKENE CYNTHIA ONUKWULU, CHINEKWU SOMTOCHUKWU, and OLUMIDE AKINDELE OWULADE ODIONU. 2023. 'Natural Language Processing for Climate Change Policy Analysis and Public Sentiment Prediction: A Data-Driven Approach to Sustainable Decision-Making', Iconic Research and Engineering Journals, 7: 732-51.
83. Ouma, Yashon O, Rodrick Cheruyot, and Alice N Wachera. 2022. 'Rainfall and runoff time-series trend analysis using LSTM recurrent neural network and wavelet neural network with satellite-based meteorological data: case study of Nzoia hydrologic basin', Complex & Intelligent Systems, 8: 213-36.
84. Pal, Amitangshu, Junbo Wang, Yilang Wu, Krishna Kant, Zhi Liu, and Kento Sato. 2022. 'Social media driven big data analysis for disaster situation awareness: A tutorial', IEEE Transactions on Big Data, 9: 1-21.
85. Pandey, Bhanu, and Annesha Ghosh. 2023. 'Urban ecosystem services and climate change: a dynamic interplay', Frontiers in Sustainable Cities, 5: 1281430.
86. Patidar, Nandkishore, Sejal Mishra, Rahul Jain, Dhiren Prajapati, Amit Solanki, Rajul Suthar, Kavindra Patel, and Hiral Patel. 2024. 'Transparency in AI decision making: A survey of explainable AI methods and applications', Advances of Robotic Technology, 2.
87. Pigliautile, Ilaria, Sara Casaccia, Nicole Morresi, Marco Arnesano, Anna Laura Pisello, and Gian Marco Revel. 2020. 'Assessing occupants' personal attributes in relation to human perception of environmental comfort: Measurement procedure and data analysis', Building and Environment, 177: 106901.
88. Prasath, C Arun. 2025. 'Big Data-Driven Decision Support System for Urban Climate Adaptation Strategies', Journal of Smart Infrastructure and Environmental Sustainability, 2: 65-71.
89. Preti, Federico, Vittoria Capobianco, and Paola Sangalli. 2022. 'Soil and Water Bioengineering (SWB) is and has always been a nature-based solution (NBS): a reasoned comparison of terms and definitions', Ecological Engineering, 181: 106687.
90. Pursnani, Vinay, Yusuf Sermet, Musa Kurt, and Ibrahim Demir. 2023. 'Performance of ChatGPT on the US fundamentals of engineering exam: Comprehensive assessment of proficiency and potential implications for professional environmental engineering practice', Computers and Education: Artificial Intelligence, 5: 100183.
91. Rahman, Md Bayazid, Joy Dhon Chakma, Abdul Momin, Shahidul Islam, Md Ashraf Uddin, Md Aminul Islam, and Sunil Aryal. 2023. 'Smart Crop cultivation system using automated agriculture monitoring environment in the context of Bangladesh agriculture', Sensors, 23: 8472.
92. Rashid, Md Tahmid, and Dong Wang. 2021. 'CovidSens: a vision on reliable social sensing for COVID-19', Artificial intelligence review, 54: 1-25.
93. Rauch, HP, M Von Der Thannen, P Raymond, E Mira, and André Evette. 2022. 'Ecological challenges* for the use of soil and water bioengineering techniques in river and coastal engineering projects', Ecological Engineering, 176: 106539.
94. Richardson, Nicholas, A Manikyala, PK Gade, ABM Asadullah, and HP Kommineni. 2021. 'Emergency response planning: leveraging machine learning for real-time decision-making', Emergency, 4: 14.
95. Rosser, Julian F, Didier G Leibovici, and Margaret J Jackson. 2017. 'Rapid flood inundation mapping using social media, remote sensing and topographic data', Natural Hazards, 87: 103-20.
96. Rubbens, Peter, Stephanie Brodie, Tristan Cordier, Diogo Destro Barcellos, Paul Devos, Jose A Fernandes-Salvador, Jennifer I Fincham, Alessandra Gomes, Nils Olav Handegard, and Kerry Howell. 2023. 'Machine learning in marine ecology: an overview of techniques and applications', ICES Journal of Marine Science, 80: 1829-53.
97. Sabzipour, Behmard, Richard Arsenault, Magali Troin, Jean-Luc Martel, François Brissette, Frédéric Brunet, and Juliane Mai. 2023. 'Comparing a long short-term memory (LSTM) neural network with a physically-based hydrological model for streamflow forecasting over a Canadian catchment', Journal of Hydrology, 627: 130380.
98. Sarker, Md Nazirul Islam, Yang Peng, Cheng Yiran, and Roger C Shouse. 2020. 'Disaster resilience through big data: Way to environmental sustainability', International Journal of Disaster Risk Reduction, 51: 101769.
99. Shi, Kaize, Xueping Peng, Hao Lu, Yifan Zhu, and Zhendong Niu. 2022. 'Application of social sensors in natural disasters emergency management: A review', IEEE Transactions on Computational Social Systems, 10: 3143-58.
100. Shroff, Disha Nilesh, and Aditya Tejas Joshi. 2022. 'Pre-Fabricated Architecture for Urban Adaptability: Factory Built Constructions–Sustainable & Flexible Urban Solutions', Politecnico di Torino.
101. Soltani, Samira Sadat, Alexandre Belleflamme, Klaus Goergen, and Stefan Kollet. 2026. 'Improving Real-Time flood forecasting: probabilistic validation of assimilated Remotely-Sensed soil moisture data', Earth Systems and Environment, 10: 1961-86.
102. Sv, Praveen, Jose Manuel Lorenz, Rajesh Ittamalla, Kuldeep Dhama, Chiranjib Chakraborty, Daruri Venkata Srinivas Kumar, and Thivyaa Mohan. 2022. 'Twitter-based sentiment analysis and topic modeling of social media posts using natural language processing, to understand people's perspectives regarding COVID-19 booster vaccine shots in India: crucial to expanding vaccination coverage', Vaccines, 10: 1929.

103. Syed, Toqeer Ali, Muhammad Yasar Khan, Salman Jan, Sami Albouq, Saad Said Alqahtany, and Muhammad Tayyab Naqash. 2024. 'Integrating digital twins and artificial intelligence multi-modal transformers into water resource management: overview and advanced predictive framework', AI, 5: 1977-2017.
104. Tang, Tao, and Guangmin Hu. 2020. 'Detecting and Tracking Significant Events for Individuals on Twitter by Monitoring the Evolution of Twitter Followership Networks', Information, 11: 450.
105. Tantalaki, Nicoleta, Stavros Souravlas, and Manos Roumeliotis. 2020. 'A review on big data real-time stream processing and its scheduling techniques', International Journal of Parallel, Emergent and Distributed Systems, 35: 571-601.
106. Tariq, Aqil, Hong Shu, Saima Siddiqui, Iqra Munir, Alireza Sharifi, Qingting Li, and Linlin Lu. 2022. 'Spatio-temporal analysis of forest fire events in the Margalla Hills, Islamabad, Pakistan using socio-economic and environmental variable data with machine learning methods', Journal of Forestry Research, 33: 183-94.
107. Tran, Khuong H, Massimo Menenti, and Li Jia. 2022. 'Surface water mapping and flood monitoring in the Mekong Delta using sentinel-1 SAR time series and Otsu threshold', Remote Sensing, 14: 5721.
108. Trinh, Manh Xuan, and Frank Molkenthin. 2021. 'Flood hazard mapping for data-scarce and ungauged coastal river basins using advanced hydrodynamic models, high temporal-spatial resolution remote sensing precipitation data, and satellite imageries', Natural Hazards, 109: 441-69.
109. Van Hoang, Thanh. 2024. 'Impact of integrated artificial intelligence and internet of things technologies on smart city transformation', Journal of technical education science, 19: 64-73.
110. VP Singh, Harsh, and Qusay H Mahmoud. 2020. 'NLP-based approach for predicting HMI state sequences towards monitoring operator situational awareness', Sensors, 20: 3228.
111. Wang, Xiahui, Jinnan Wang, Bo Wang, Benjamin Burkhard, Lulu Che, Chao Dai, and Lijie Zheng. 2022. 'The nature-based ecological engineering paradigm: Symbiosis, coupling, and coordination', Engineering, 19: 14-21.
112. Wübbelmann, Thea, Kristian Förster, Laurens M Bouwer, Claudia Dworczyk, Steffen Bender, and Benjamin Burkhard. 2023. 'Urban flood regulating ecosystem services under climate change: how can Nature-based Solutions contribute?', Frontiers in Water, 5: 1081850.
113. Xiao, Ming, Lihua Chen, Haoxiong Feng, Zhigao Peng, and Qiong Long. 2024. 'Smart city public transportation route planning based on multi-objective optimization: A review', Archives of Computational Methods in Engineering, 31: 3351-75.
114. Xing, Xiaoyue, Bailang Yu, Chaogui Kang, Bo Huang, Jianya Gong, and Yu Liu. 2024. 'The synergy between remote sensing and social sensing in urban studies: Review and perspectives', IEEE Geoscience and Remote Sensing Magazine, 12: 108-37.
115. Yin, Junjun, Yizhao Gao, and Guangqing Chi. 2022. 'An evaluation of geo-located Twitter data for measuring human migration', International Journal of Geographical Information Science, 36: 1830-52.
116. Yohanandhan, Rajaa Vikhram, Rajvikram Madurai Elavarasan, Premkumar Manoharan, and Lucian Mihet-Popa. 2020. 'Cyber-physical power system (CPPS): A review on modeling, simulation, and analysis with cyber security applications', IEEe Access, 8: 151019-64.
117. Yousaf, Hira. 2024. 'AI for environmental sustainability: Applications in resource management and conservation', Journal of AI Range, 1: 13-26.
118. Yu, Danlin. 2025. 'Toward integrated urban observatories: synthesizing remote and social sensing in urban science', Remote Sensing, 17: 2041.
119. Yuan, Haojun, Mo Wang, Dongqing Zhang, Rana Muhammad Adnan Ikram, Jin Su, Shiqi Zhou, Yuankai Wang, Jianjun Li, and Qifei Zhang. 2024. 'Data-driven urban configuration optimization: An XGBoost-based approach for mitigating flood susceptibility and enhancing economic contribution', Ecological Indicators, 166: 112247.
120. Zhang, Xin, Wen Liu, Qi Feng, and Jianjun Zeng. 2024. 'Multi-objective optimization of the spatial layout of green infrastructures with cost-effectiveness analysis under climate change scenarios', Science of the Total Environment, 948: 174851.
121. Zhao, Xinfeng, Hongyan Wang, Mingyu Bai, Yingjie Xu, Shengwen Dong, Hui Rao, and Wuyi Ming. 2024. 'A comprehensive review of methods for hydrological forecasting based on deep learning', Water, 16: 1407.
122. Zhou, Hao, Jing Tang, Stefan Olin, Renkui Guo, and Paul A Miller. 'An Integrated Approach for Optimizing Streamflow Prediction in Mid-High Latitude Catchments by Employing Terrestrial Ecosystem Modelling and Interpretable Machine Learning', Available at SSRN 5042442.
123. Zong, Zhijuan, and Yu Guan. 2025. 'AI-driven intelligent data analytics and predictive analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency', Journal of the knowledge economy, 16: 864-903.