



Explainable Ensemble Learning for Stormwater-Drainage Failure Prediction under Nonstationary Extreme Precipitation: Integrating LiDAR, Land-Cover, Soil, and Infrastructure Data

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Doi: [10.63125/6s60f508](https://doi.org/10.63125/6s60f508)

Policy Page DOI: [10.63125/ajates-crossmark-policy](https://doi.org/10.63125/ajates-crossmark-policy)

Received: 11 September 2024; Revised: 16 October 2024; Accepted: 10 November 2024; Published: 30 December 2024;

Abstract

This study addresses the growing problem of stormwater-drainage failure under nonstationary extreme precipitation, where conventional rainfall-based or single-factor assessments may not adequately represent the combined effects of terrain, land cover, soil hydrology, infrastructure condition, and changing rainfall extremes. The purpose of the research is to develop and empirically evaluate an explainable ensemble-learning framework for predicting Stormwater-Drainage Failure Susceptibility (SDFS) by integrating LiDAR-derived terrain and surface characteristics (LDTSC), Land-Cover and Imperviousness Conditions (LCIC), Soil Infiltration and Hydrologic Characteristics (SIHC), Stormwater-Drainage Infrastructure Condition (SDIC), and extreme-precipitation variables. A quantitative, cross-sectional, explanatory-predictive case-study design was employed within a selected urban drainage catchment using purposive sampling, structured expert questionnaires, and multimodal geospatial and infrastructure data. Of 320 questionnaires distributed, 306 were returned and 294 were valid, while 48 drainage subcatchments formed the analytical spatial cases. Data analysis combined descriptive statistics, reliability and validity testing, Pearson correlation, multiple regression, Random Forest, XGBoost, LightGBM, ensemble learning, cross-validation, and SHAP-based explainability. SDFS recorded $M = 4.21$, $SD = 0.52$, while SDIC showed the strongest correlation with SDFS, $r = .76$, $p < .001$, followed by LCIC, $r = .72$, LDTSC, $r = .68$, and SIHC, $r = .65$, all $p < .001$. The regression model explained 70.3% of SDFS variance, $R^2 = .703$, adjusted $R^2 = .699$, $F(4,289) = 171.42$, $p < .001$, with SDIC the strongest predictor, $\beta = .33$. The final ensemble achieved 93% accuracy, .92 precision, .94 recall, .93 F1-score, and ROC-AUC = .97, outperforming the best individual model. SHAP analysis identified reduced drainage capacity, flow accumulation, impervious surface proportion, depression depth, and extreme rainfall intensity as the leading contributors to predicted failure. The findings imply that integrated, interpretable multimodal prediction can strengthen drainage-risk prioritization, infrastructure maintenance, urban flood preparedness, and climate-resilient stormwater planning for municipalities facing increasingly uncertain and spatially heterogeneous rainfall conditions.

Keywords

Explainable Ensemble Learning; Stormwater-Drainage Failure Susceptibility; LiDAR; Nonstationary Extreme Precipitation; SHAP Explainability

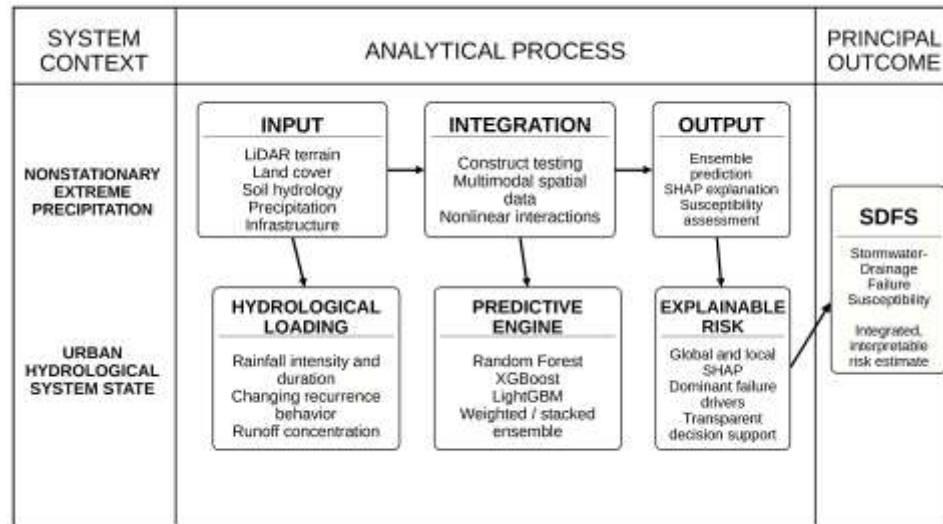
INTRODUCTION

Stormwater-drainage failure refers to a condition in which an urban drainage network, including inlets, pipes, channels, culverts, storage elements, and associated surface-flow pathways, is unable to receive, convey, store, or discharge runoff at a level sufficient to prevent surcharge, surface ponding, localized inundation, or loss of drainage service. The phenomenon is governed by the interaction of rainfall loading, catchment morphology, surface characteristics, soil-water processes, and the hydraulic and structural condition of drainage infrastructure. Urbanization modifies these interactions because buildings, roads, parking surfaces, and other impervious areas reduce infiltration and alter the rate, volume, and timing of runoff entering drainage systems. In *Impacts of Impervious Surface on Watershed Hydrology: A Review* (pp. 263-275), the replacement of permeable surfaces by urban impervious cover was associated with fundamental changes in catchment hydrology, including greater runoff production and altered watershed response (Shuster et al., 2005). Field observations have similarly shown that rainfall distribution, antecedent soil moisture, drainage-network organization, and spatially heterogeneous runoff generation interact strongly in urban catchments (Smith et al., 2005). Urbanization therefore cannot be represented adequately by rainfall intensity alone because the same precipitation event may produce substantially different drainage responses across areas characterized by different imperviousness, soil conditions, topography, and hydraulic connectivity (Jacobson, 2011; O'Driscoll et al., 2010). From an international perspective, stormwater-related urban flooding constitutes an important infrastructure and environmental-management problem because highly developed cities concentrate population, transportation systems, buildings, utilities, and economic activities within areas where drainage exceedance can generate extensive direct and indirect disruption. The review *Urban Flood Impact Assessment* (pp. 14-29) documented the multidimensional character of urban flood impacts and the need to understand both physical inundation and the systems exposed to it (Hammond et al., 2015). Urban hydrological modeling has consequently moved toward representations that connect natural hydrological processes with engineered drainage components and spatially distributed urban characteristics rather than treating the catchment as a homogeneous runoff-producing unit (Salvadore et al., 2015). Flood-inundation research likewise demonstrates that model performance is strongly dependent on representation of terrain, hydraulic processes, spatial resolution, boundary conditions, and uncertainty, making stormwater-drainage failure a multivariable geospatial prediction problem rather than a single-variable rainfall problem (Teng et al., 2017).

A central difficulty in stormwater-drainage failure assessment arises from nonstationary extreme precipitation, meaning that the statistical behavior of precipitation extremes cannot automatically be assumed to remain constant through time. Conventional drainage design has commonly relied on intensity-duration-frequency relationships estimated from historical precipitation records under assumptions that the probability distribution governing extremes is sufficiently stable for design purposes. Such an assumption becomes problematic when the frequency, magnitude, or statistical structure of intense rainfall changes over the period in which infrastructure is designed and operated. Research on drainage-design criteria has shown that altered extreme-rainfall characteristics can change the service levels achieved by urban drainage systems and therefore affect the frequency at which hydraulic capacity is exceeded (Mailhot & Duchesne, 2010). A broad review of rainfall extremes and urban drainage systems identified substantial sensitivity of sewer flooding and drainage performance to changes in rainfall extremes, while also emphasizing variation among locations, climate-model formulations, temporal resolutions, and analytical methods (Arnbjerg-Nielsen et al., 2013). In *Revision of Urban Drainage Design Rules After Assessment of Climate Change Impacts on Precipitation Extremes* (pp. 166-177), changes in precipitation frequency and intensity were explicitly connected to changes in sewer-flooding and overflow behavior (Willems, 2013). Statistical treatment of precipitation extremes has also developed from strictly stationary estimation toward models in which distributional parameters are allowed to vary according to relevant climatic covariates or temporal structures (Cheng et al., 2014). Nonstationary intensity-duration-frequency analysis demonstrated that stationary design assumptions can materially alter estimated extreme-rainfall levels used for infrastructure analysis (Cheng & AghaKouchak, 2014). Research on short-duration precipitation has further established that subdaily rainfall is especially relevant to urban catchments because short response times can convert intense rainfall into rapid surface runoff and drainage surcharge (Westra et al., 2014). Observational

evidence across multiple regions has identified intensification in hourly precipitation extremes, reinforcing the importance of resolving rainfall at time scales compatible with urban hydrological response (Guerreiro et al., 2018). The relationship between extreme precipitation and flooding also varies with hydrological conditions and water availability, demonstrating that rainfall magnitude alone does not determine the resulting flood response (Tabari, 2020).

Figure 1: Integrated Explainable Ensemble-Learning Framework for Stormwater-Drainage Failure Prediction



Accurate drainage-failure prediction consequently requires detailed representation of the physical landscape and the infrastructure through which stormwater is transferred. Light Detection and Ranging (LiDAR) is particularly relevant because it provides high-resolution elevation information from which digital elevation models and terrain derivatives such as elevation, slope, depressions, surface roughness, flow direction, and flow accumulation can be developed. Evaluation of different elevation datasets has shown that LiDAR-derived terrain data offer substantial advantages for flood modeling because of their fine spatial resolution, vertical accuracy, and ability to distinguish terrain from surface objects when appropriately processed (Sanders, 2007). In Benchmarking Urban Flood Models of Varying Complexity and Scale Using High Resolution Terrestrial LiDAR Data (pp. 281-291), high-resolution topographic representation was directly incorporated into urban inundation modeling and used to test sensitivity to model formulation and spatial scale (Fewtrell et al., 2011). Decimetric terrestrial laser-scanning data have also been used to construct highly detailed urban inundation models, demonstrating the importance of representing fine-scale structures that influence water movement through developed environments (Sampson et al., 2012). Building representation itself can modify simulated flood extent and flow behavior, which confirms that topographic and built-environment structure must be treated explicitly when evaluating urban inundation processes (Schubert & Sanders, 2012). Land-cover information complements LiDAR because imperviousness, vegetation, roadway surfaces, roof coverage, and other land-cover categories regulate rainfall partitioning and overland-flow connectivity (Jacobson, 2011). Soil properties form another essential component because infiltration capacity depends on texture, compaction, moisture condition, and hydraulic characteristics. In Compaction's Impacts on Urban Storm-Water Infiltration (pp. 652-658), experimental evidence demonstrated substantial variation in infiltration associated with urban soil compaction and soil type (Pitt et al., 2008). Infrastructure condition introduces an additional failure mechanism because drainage performance is determined not only by external hydraulic loading but also by pipe deterioration, defects, blockage, asset characteristics, and structural condition. Research on sewer deterioration has identified pipe and environmental characteristics as significant explanatory factors in structural degradation (Ana et al., 2009), while statistical deterioration research has

established the value of condition-based modeling for estimating the performance of urban drainage assets (Ana & Bauwens, 2010). Regression-based sewer-failure modeling has further demonstrated that infrastructure inventory and inspection variables can be used to estimate section-level failure probabilities (Salman & Salem, 2012).

The integration of these heterogeneous predictors creates a modeling problem characterized by nonlinear relationships, interactions, spatial variability, threshold behavior, and potentially large numbers of explanatory variables. Conventional statistical analysis remains valuable because descriptive statistics can characterize distributions, correlation analysis can quantify linear associations, and regression modeling can estimate the direction and magnitude of relationships among theoretically specified constructs. Predictive modeling, however, can additionally examine complex relationships that are difficult to represent through a single prespecified linear functional form. Machine learning has therefore become increasingly prominent in flood susceptibility and flood-prediction research. In Flood Susceptibility Assessment Using GIS-Based Support Vector Machine Model With Different Kernel Types (pp. 91-101), combinations of geospatial conditioning factors were used to produce and validate flood-susceptibility estimates, with terrain variables such as altitude and slope contributing materially to predictive performance (Tehrany et al., 2015). Comparative evaluations of tree-based algorithms have also demonstrated that alternative decision-tree structures can produce different levels of discrimination when identifying flood-susceptible locations from environmental conditioning variables (Khosravi et al., 2018). A broader review of machine-learning applications to flood prediction identified neural, tree-based, support-vector, hybrid, and ensemble approaches as major data-driven strategies for modeling hydrological relationships where complex predictor interactions are present (Mosavi et al., 2018). These developments align with the more general flood-inundation literature, which emphasizes that model selection must reflect data availability, computational requirements, spatial representation, predictive objectives, and uncertainty (Teng et al., 2017). Ensemble learning is particularly relevant in this context because it combines predictions or learned structures from multiple base models rather than relying exclusively on one algorithmic representation. For stormwater-drainage failure, such an approach can accommodate information derived from elevation and topographic structure, land-cover properties, soil characteristics, drainage-asset attributes, and extreme precipitation within a unified predictive system. This type of multimodal modeling is also consistent with urban hydrological research showing that strongly heterogeneous catchments require integration across hydrological processes, urban structures, spatial datasets, and engineered water networks (Salvadore et al., 2015). The predictive problem is therefore not solely the classification of flooded and nonflooded locations; it also involves determining how several interdependent environmental and infrastructure variables collectively correspond with observed or assessed drainage-failure susceptibility.

High predictive performance alone does not fully address the analytical requirements of drainage-infrastructure decision making because complex ensemble models can produce classifications or probabilities without making the basis of those predictions sufficiently transparent. Explainable artificial intelligence (XAI) refers to methods designed to provide interpretable information about how model inputs contribute to outputs, either for the model as a whole or for individual predictions. This issue is particularly relevant when machine-learning results are used to characterize infrastructure susceptibility, since engineers and asset managers need to distinguish whether elevated predicted failure is associated mainly with terrain depression, impervious surface concentration, low soil infiltration, drainage deterioration, extreme-rainfall loading, or combinations of these conditions. Research on interpretable machine learning has emphasized that predictive accuracy and model transparency should be examined carefully when algorithmic outputs support consequential decisions (Rudin, 2019). A major synthesis of XAI research classified explanation techniques according to model characteristics, scope, and explanatory purpose and identified explainability as a central component of responsible use of complex machine-learning systems (Arrieta et al., 2020). In From Local Explanations to Global Understanding With Explainable AI for Trees (pp. 56-67), tree-based prediction was connected with SHAP-based explanation to quantify the contribution of individual features while also generating global understanding across many observations (Lundberg et al., 2020). Such an analytical structure is well matched to stormwater-drainage failure because ensemble trees can represent

nonlinearities and interactions among heterogeneous predictors, while SHAP values can identify the magnitude and direction of each predictor's contribution to estimated failure susceptibility. Within the present research problem, an unresolved analytical gap remains between studies focused primarily on rainfall nonstationarity, studies emphasizing high-resolution terrain and flood hydraulics, studies examining land cover or soil processes, studies modeling deterioration of drainage assets, and studies applying machine-learning algorithms to flood susceptibility. The study is therefore structured around an integrated quantitative case-study framework in which LiDAR-derived terrain characteristics, land-cover conditions, soil-hydrologic characteristics, drainage-infrastructure conditions, and nonstationary extreme-precipitation information are examined jointly, while descriptive statistics, correlation analysis, regression modeling, ensemble learning, and explainability analysis address complementary explanatory and predictive dimensions of stormwater-drainage failure (Ana & Bauwens, 2010; Cheng & AghaKouchak, 2014).

Background of the Study

Urban stormwater drainage systems are essential components of modern cities because they collect, convey, store, and discharge surface runoff generated during rainfall events. Their performance depends on the interaction between precipitation characteristics, surface topography, land-cover conditions, soil infiltration capacity, and the physical condition and hydraulic capacity of drainage infrastructure. Rapid urban development has significantly modified natural hydrological processes through the expansion of roads, buildings, parking areas, and other impervious surfaces that restrict infiltration and accelerate runoff generation. As a result, drainage networks may experience higher and more concentrated inflows during intense rainfall events, increasing the likelihood of pipe surcharge, inlet exceedance, localized ponding, and surface flooding. The problem becomes more complex when extreme precipitation exhibits nonstationary behavior, meaning that the intensity, frequency, duration, or statistical distribution of heavy rainfall changes over time rather than remaining constant. Drainage systems designed according to historical rainfall assumptions may therefore operate under hydraulic conditions different from those originally anticipated. Accurate assessment of drainage failure requires simultaneous consideration of the physical landscape and engineered drainage network. High-resolution LiDAR data can provide detailed information on elevation, slope, depressions, surface roughness, flow direction, and runoff accumulation pathways, while land-cover information can identify impervious surfaces, vegetation, roads, buildings, and other characteristics affecting runoff generation. Soil information contributes additional knowledge regarding infiltration capacity, permeability, water-storage behavior, and saturation potential. Infrastructure datasets provide information about drainage density, pipe size, inlet distribution, connectivity, age, blockage, deterioration, and maintenance condition. When these datasets are considered separately, important interactions among environmental and infrastructure factors may remain hidden. Machine-learning techniques offer a means of analyzing such complex relationships because they can recognize nonlinear patterns and interactions among multiple predictors. Ensemble learning is particularly suitable because predictions from several machine-learning models can be integrated to improve predictive stability and performance. Explainable artificial intelligence further allows these predictions to be interpreted by identifying which variables contribute most strongly to drainage-failure susceptibility. This study therefore examines stormwater-drainage failure as an integrated environmental, hydrological, infrastructural, and data-analytics problem using quantitative statistical analysis, multimodal geospatial information, ensemble learning, and explainable prediction.

Problem Statement

Stormwater-drainage failure is commonly assessed using rainfall intensity, hydraulic capacity, historical flood records, or a limited number of physical characteristics, yet such approaches may not adequately represent the complex processes that determine where and under what conditions urban drainage systems fail. Failure susceptibility is not controlled by a single factor. It develops through combined interactions among extreme precipitation, terrain configuration, surface imperviousness, land-cover characteristics, soil infiltration behavior, drainage-network capacity, infrastructure deterioration, and spatial connectivity. A major methodological problem is that many conventional drainage assessments continue to treat these variables independently or assume that historical precipitation characteristics remain sufficiently stable for present-day system evaluation. This creates

uncertainty when extreme precipitation is nonstationary and when existing drainage systems operate within rapidly changing urban environments. Another problem concerns the fragmentation of available data. LiDAR, land-cover maps, soil datasets, precipitation records, and infrastructure inventories are often maintained in separate formats and analyzed through different procedures, reducing the ability to construct a unified representation of drainage-failure mechanisms. Conventional regression models remain useful for identifying statistically significant relationships, but they may provide limited flexibility when relationships are highly nonlinear, threshold-dependent, or characterized by interactions among multiple environmental and infrastructure variables. Machine-learning methods can address some of these limitations, yet individual models may produce unstable or model-specific predictions, while highly complex algorithms may operate as black boxes that provide little explanation for why a particular location is classified as highly susceptible to failure. Such limited interpretability is problematic for engineering and infrastructure management because a prediction is more useful when the responsible factors can also be identified. There is therefore a need for an integrated analytical approach that combines statistical hypothesis testing with multimodal geospatial and infrastructure data, ensemble machine learning, and explainable artificial intelligence. The central problem addressed by this study is the absence of a sufficiently integrated and interpretable predictive framework capable of explaining and estimating stormwater-drainage failure susceptibility under nonstationary extreme precipitation conditions.

Purpose and Objectives of the Study

The purpose of this study is to develop and empirically evaluate an explainable ensemble-learning framework for predicting stormwater-drainage failure under nonstationary extreme precipitation through the integration of LiDAR-derived terrain information, land-cover characteristics, soil-hydrologic conditions, drainage-infrastructure data, and precipitation-related variables. The study is designed to combine conventional quantitative statistical analysis with predictive machine-learning techniques so that both explanatory relationships and predictive performance can be examined within the same case-study framework. The first objective is to determine the extent to which LiDAR-derived terrain and surface characteristics, including elevation, slope, topographic depressions, surface roughness, and flow-accumulation characteristics, are associated with stormwater-drainage failure susceptibility. The second objective is to evaluate the relationship between land-cover and imperviousness conditions and drainage failure, particularly the effects of built surfaces, roads, vegetation coverage, and runoff-producing areas. The third objective is to assess how soil infiltration and hydrologic characteristics contribute to variations in drainage-failure susceptibility. The fourth objective is to determine the influence of stormwater-drainage infrastructure condition, including hydraulic capacity, network density, inlet availability, connectivity, deterioration, blockage, and maintenance condition. The fifth objective is to test the combined statistical effects of the major predictor constructs on stormwater-drainage failure susceptibility using correlation and multiple regression analysis. The sixth objective is to integrate environmental, geospatial, precipitation, and infrastructure variables into individual machine-learning models and subsequently develop an ensemble predictive model capable of identifying areas or observations with elevated failure susceptibility. The seventh objective is to evaluate the predictive performance of the individual and ensemble models using appropriate validation measures. The final objective is to apply explainable artificial intelligence, particularly SHAP-based analysis, to determine the relative contribution, direction, and importance of individual predictors in the ensemble model so that drainage-failure predictions can be interpreted at both global and individual levels.

Research Hypotheses

The hypotheses of this study are developed to statistically test the relationships between the principal environmental and infrastructure constructs and stormwater-drainage failure susceptibility. The hypotheses correspond directly with the quantitative explanatory component of the research and will be tested using Pearson correlation analysis and multiple regression modeling at an appropriate level of statistical significance. The first hypothesis, H1, states that LiDAR-derived terrain and surface characteristics have a statistically significant relationship with stormwater-drainage failure susceptibility. This hypothesis examines whether variations in elevation, slope, surface depressions, flow accumulation, and related terrain properties are associated with variations in drainage-failure

conditions. The second hypothesis, H2, states that land-cover and imperviousness conditions have a statistically significant relationship with stormwater-drainage failure susceptibility, reflecting the role of roads, buildings, impermeable surfaces, and vegetation in controlling runoff generation and conveyance. The third hypothesis, H3, states that soil infiltration and hydrologic characteristics have a statistically significant relationship with stormwater-drainage failure susceptibility, particularly through differences in permeability, infiltration capacity, saturation, and water-storage behavior. The fourth hypothesis, H4, states that stormwater-drainage infrastructure condition has a statistically significant relationship with stormwater-drainage failure susceptibility, reflecting variations in network capacity, inlet availability, pipe condition, blockage, deterioration, and maintenance status. The fifth hypothesis, H5, states that LiDAR-derived terrain characteristics, land-cover and imperviousness conditions, soil-hydrologic characteristics, and drainage-infrastructure condition jointly have a statistically significant predictive relationship with stormwater-drainage failure susceptibility. H5 therefore assesses the collective explanatory contribution of the principal independent constructs rather than considering them independently. These hypotheses provide the statistical basis for determining whether the major predictor domains included in the conceptual framework are meaningfully associated with the dependent construct and establish a quantitative foundation for comparison with the subsequent ensemble-learning analysis.

LITERATURE REVIEW

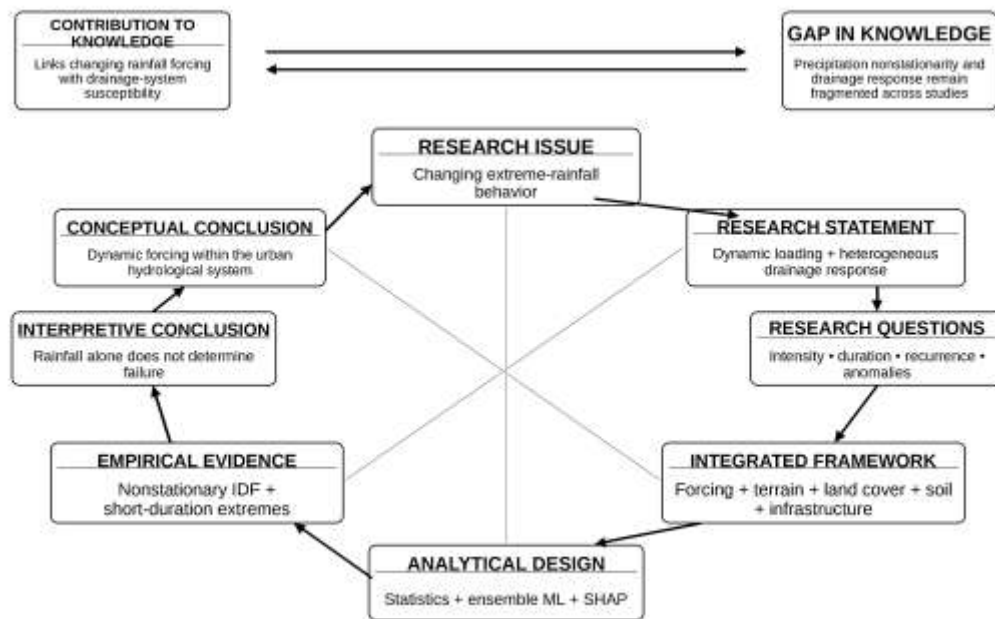
The literature surrounding stormwater-drainage failure spans several interconnected fields, including urban hydrology, extreme-precipitation analysis, geospatial terrain modeling, land-cover assessment, soil hydrology, drainage-infrastructure deterioration, flood susceptibility modeling, machine learning, ensemble prediction, and explainable artificial intelligence. These research areas provide different but complementary explanations of how drainage failures develop and how they can be quantified. Urban hydrological studies generally examine how rainfall is transformed into runoff within built environments, with particular attention to imperviousness, drainage connectivity, catchment morphology, infiltration, and hydraulic capacity. Research on extreme precipitation extends this discussion by examining rainfall intensity, duration, frequency, and nonstationarity, which influence the loading imposed on stormwater systems. Geospatial research contributes methods for identifying terrain characteristics that control runoff routing, ponding, and water accumulation, particularly through high-resolution LiDAR-derived elevation models. Land-cover studies explain how urban development, vegetation loss, roadway expansion, and impervious surfaces modify runoff production, while soil-based research addresses infiltration capacity, permeability, moisture retention, and saturation processes. A separate body of infrastructure research examines the structural and functional condition of stormwater and sewer networks, including pipe deterioration, blockage, asset age, capacity, network configuration, and maintenance status. Data-driven flood research has increasingly applied machine-learning algorithms to combine multiple conditioning variables and identify complex nonlinear relationships that conventional statistical models may not fully capture. Ensemble-learning approaches expand this capability by combining multiple predictive models to improve robustness and generalization, while explainable artificial intelligence provides techniques for interpreting the resulting predictions. The literature relevant to this study must therefore be examined as an integrated body of knowledge rather than as independent technical domains. The following review is structured around nonstationary extreme precipitation and drainage failure, LiDAR-derived terrain characteristics, land-cover and soil-hydrologic conditions, infrastructure condition and explainable ensemble learning, the theoretical framework, and the conceptual framework connecting the principal research constructs.

Nonstationary Extreme Precipitation

Nonstationary extreme precipitation has become a central concern in stormwater-drainage research because the statistical properties of intense rainfall may change across time, weakening the assumption that historical rainfall records represent a fixed probability structure for infrastructure design and performance assessment. In urban drainage practice, rainfall intensity, duration, and recurrence interval are commonly summarized through intensity-duration-frequency relationships that translate extreme precipitation behavior into design loads for pipes, culverts, inlets, detention facilities, and

related conveyance structures. When the underlying precipitation process changes, drainage assets designed from stationary relationships can experience loading patterns that differ from those embedded in their original design criteria. In *Update of Regional Intensity-Duration-Frequency Curves in Denmark: Tendency Towards Increased Storm Intensities* (pp. 343-349), analysis of an expanded Danish rainfall database identified a general increase in extreme rainfall characteristics and reported that design intensities for durations and return periods commonly used in urban drainage had risen by approximately 10%, illustrating how updated observations can materially alter rainfall quantities used for engineering assessment (Ashik & Shabbir, 2022; Madsen et al., 2009).

Figure 2: Nonstationary Extreme Precipitation and Stormwater-Drainage Failure Knowledge Framework



Nonstationarity is particularly important for urban catchments because their relatively short response times allow high-intensity, short-duration storms to generate rapid runoff concentration and network surcharge. Changes in rainfall magnitude can therefore affect peak inflow, surface ponding, manhole surcharge, combined-sewer overflow, and the spatial distribution of pluvial flooding even when the physical drainage network itself remains unchanged. In *The Impacts of Climate Change and Urbanisation on Drainage in Helsingborg, Sweden: Combined Sewer System* (pp. 100-113), scenario-based simulations showed that increased rainfall and continued urban development can jointly alter wastewater and stormwater flows in combined drainage systems, connecting changing climatic loading with the hydraulic behavior of existing urban infrastructure (Hasan & Adnan, 2022; Semadeni-Davies et al., 2008). This sensitivity is especially important for older networks whose capacities and surcharge criteria were established from rainfall records representing earlier climatic conditions.

The literature also shows that identifying nonstationarity is not equivalent to applying a single universal adjustment to design rainfall because the magnitude and engineering relevance of change depend on spatial scale, temporal resolution, statistical model selection, storm duration, return period, and characteristics of the local drainage system. Short-duration precipitation is especially difficult to represent because urban drainage analysis often requires temporal resolutions much finer than those available from global or regional climate models. In *Climate Change Impact Assessment on Urban Rainfall Extremes and Urban Drainage: Methods and Shortcomings* (pp. 106-118), research on urban-scale rainfall assessment emphasized that climate-model outputs generally require downscaling and bias correction before they can represent the local and short-duration extremes relevant to drainage hydraulics, while uncertainty becomes greater when analytical attention shifts from average precipitation toward the tails of rainfall distributions (Mahbubul et al., 2022; Willems et al., 2012). This

problem directly affects drainage-failure prediction because an extreme rainfall indicator is not merely another explanatory variable; it represents the external forcing applied to a system whose response is conditioned by terrain, imperviousness, infiltration, drainage capacity, connectivity, and asset condition. A rainfall event of a given nominal return period may therefore produce different failure outcomes across subcatchments characterized by contrasting topography, land cover, soil properties, or infrastructure constraints. Statistical treatment of nonstationarity must consequently distinguish changes in observed rainfall characteristics from changes in the hydraulic consequences of those characteristics. In *Does Nonstationarity in Rainfall Require Nonstationary Intensity-Duration-Frequency Curves?* (pp. 6461-6483), analysis of short-duration rainfall at urbanized locations in southern Ontario found detectable nonstationarity but also showed that stationary and nonstationary estimates did not always differ substantially for shorter recurrence intervals, while differences became more pronounced for some longer design return periods (Ganguli & Coulibaly, 2017; Mashfiqur & Md, 2022). This distinction is essential for drainage applications.

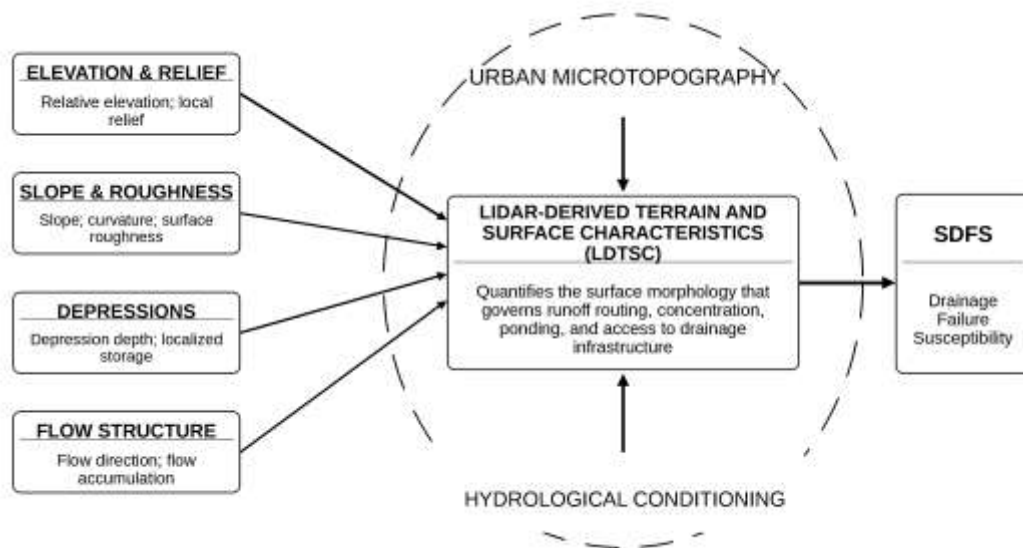
For stormwater-drainage failure research, the principal analytical requirement is to connect changing extreme-precipitation characteristics with the physical and operational conditions that determine whether runoff can be accommodated by the drainage network. Nonstationary rainfall can affect the probability that inflow exceeds conveyance capacity, but actual failure susceptibility also reflects where runoff is generated, how quickly it is routed, whether surface depressions concentrate water, how much infiltration occurs, and whether pipes and inlets provide adequate hydraulic access and capacity. This multidimensional relationship is particularly relevant to the present study because extreme-precipitation information is integrated with LiDAR-derived terrain characteristics, land-cover conditions, soil-hydrologic properties, and stormwater-infrastructure variables rather than being interpreted in isolation. It also creates a methodological distinction between estimating rainfall extremes and predicting drainage failure: the first characterizes the forcing process, while the second evaluates the response of a heterogeneous urban system exposed to that forcing. In *Intensity-Duration-Frequency Curves at Ungauged Sites in a Changing Climate for Sustainable Stormwater Networks*, a nonstationary generalized extreme-value approach was combined with a scaling method to construct rainfall-frequency relationships under changing climatic conditions, and application to stormwater-network design produced rainfall extremes up to 20.5% greater and correspondingly larger primary conduit dimensions than those derived under fully stationary conditions (Galiatsatou & Iliadis, 2022; Ashfaq & Mohammad, 2022). Within the present research framework, extreme precipitation therefore functions as a dynamic environmental loading component whose relationship with stormwater-drainage failure is examined alongside terrain, land cover, soil, and infrastructure information. The approach treats precipitation intensity, duration, recurrence behavior, and temporal variability as components of the same failure environment in which runoff routing and drainage capacity determine observed system response.

LiDAR-Derived Terrain Characteristics

LiDAR-derived terrain information has become a critical input for the assessment of urban drainage susceptibility because stormwater movement across built environments is governed by fine variations in elevation, slope, depressions, kerbs, road crowns, walls, embankments, and artificial flow barriers. Unlike coarse elevation products, LiDAR can generate dense three-dimensional point clouds that are processed into digital elevation models, digital terrain models, and derivative surfaces capable of representing localized pathways through which runoff is concentrated toward inlets, low-lying streets, underpasses, and drainage structures. The hydrological value of LiDAR therefore extends beyond producing a visually detailed map; it provides the geometric basis for estimating where water is likely to accumulate and how rapidly it may be transferred across an urban surface. In *Unstructured Grid Generation Using LiDAR Data for Urban Flood Inundation Modelling* (pp. 1404-1420), LiDAR information was used to generate computational grids that retained terrain details while supporting efficient simulation of inundation through complex urban spaces, demonstrating that topographic representation and mesh structure directly affect modeled flow paths and water distribution (Sadia & Mostari, 2022; Tsubaki & Fujita, 2010). Urban drainage susceptibility is especially sensitive to these terrain characteristics because very small elevation differences may redirect runoff from one street corridor or drainage inlet toward another. Elevation, local slope, relative relief, depression depth,

curvature, flow direction, and flow accumulation can consequently be derived from LiDAR surfaces and incorporated as measurable predictors of drainage-failure susceptibility. In *Evaluating Scale and Roughness Effects in Urban Flood Modelling Using Terrestrial LIDAR Data* (pp. 4015-4030), simulations based on 10 cm, 50 cm, and 1 m terrain resolutions showed that finer representation of road cambers, kerbs, and other small-scale urban topography altered modeled water depth, inundation extent, arrival time, and velocity, confirming that spatial resolution influences the hydraulic interpretation of the same physical setting during intense rainfall events (Ozdemir et al., 2013; Shaiful et al., 2022).

Figure 3: LiDAR-Derived Terrain Pathways to Urban Drainage Susceptibility



The usefulness of LiDAR for drainage-failure analysis also depends on whether the derived terrain surface correctly represents the hydraulic function of urban features. Buildings, vegetation, bridges, walls, elevated roads, curbs, and narrow passages may obstruct, divert, or channel surface runoff, and errors in their representation can create artificial barriers or unrealistic conveyance routes. This issue is important when drainage susceptibility is evaluated at neighborhood or street scale because surface runoff often follows pathways controlled by features that occupy only a small number of grid cells. In *Urban Flood Modelling Combining Top-View LiDAR Data With Ground-View SfM Observations* (pp. 105-117), top-view LiDAR was combined with ground-view structure-from-motion observations to capture urban features hidden beneath vegetation or overarching structures, and the study showed that these small features can materially influence simulated flood propagation through complex urban terrain (Meesuk et al., 2015; Stabak & Shahid, 2022). Such findings indicate that LiDAR data should not be treated as a neutral elevation layer without preprocessing. Point classification, ground filtering, removal or purposeful retention of buildings, interpolation, breakline preservation, and the treatment of drainage openings influence the hydrological meaning of the resulting terrain model. Submeter analysis is particularly relevant where runoff must pass between buildings or along streets bounded by curbs. In *Modelling Urban Floods at Submetre Resolution: Challenges or Opportunities for Flood Risk Management?* (pp. S855-S865), numerical experiments using 10 cm terrain data demonstrated that localized decimetric changes in street elevation could produce substantial differences in flood dynamics and the final distribution of inundation, revealing the sensitivity of urban flow patterns to microtopography (Mohammad, 2023; Almeida et al., 2018). For the present research, this evidence supports the extraction of LiDAR-derived variables that represent both general terrain form and localized concentration mechanisms, allowing elevation-related susceptibility to be examined statistically and within ensemble-learning models alongside land cover, soil, precipitation, and

infrastructure condition.

A further consideration is that the predictive value of LiDAR-derived terrain variables depends on the quality, scale, and hydrological conditioning of the elevation model from which they are calculated. Urban DEMs may contain vertical errors, residual building artifacts, vegetation effects, interpolation gaps, or smoothing that changes drainage gradients and connectivity of depressions. These errors are important because flow accumulation, slope, depression storage, and preferential runoff pathways are mathematically derived from elevation differences; a small vertical bias can therefore propagate into predictor variables used in drainage-failure modeling. In *Bare-Earth DEM Generation in Urban Areas for Flood Inundation Simulation Using Global Digital Elevation Models*, comparisons against surveyed terrain and LiDAR benchmarks across cities identified substantial vertical errors in global elevation products, while correction of urban building artifacts improved terrain representation and modeled inundation depth for the Carlisle case study (Adnan & Iftekhhar, 2023; Liu et al., 2021). This finding reinforces the importance of treating LiDAR-based terrain as a quality-controlled analytical dataset rather than simply as a background map. Within an explainable ensemble-learning framework, terrain variables can be transformed into quantitative predictors such as elevation, slope, depression depth, topographic position, local relief, surface roughness, flow accumulation, and distance to concentrated runoff pathways. Their relationships with stormwater-drainage failure can then be examined through descriptive statistics, correlation analysis, regression modeling, and nonlinear ensemble algorithms. LiDAR variables are particularly valuable when combined with land-cover, soil, precipitation, and drainage-infrastructure information because terrain determines where runoff is routed, while the other data domains determine how much runoff is generated, how much can infiltrate, and how effectively the drainage network can receive and convey it. The analytical role of LiDAR in this study is to quantify surface morphology governing hydrological concentration and spatial susceptibility, while model explainability can determine which terrain attributes make the strongest contribution to predicted drainage failure under extreme precipitation (Liu et al., 2021; Rahman, 2023).

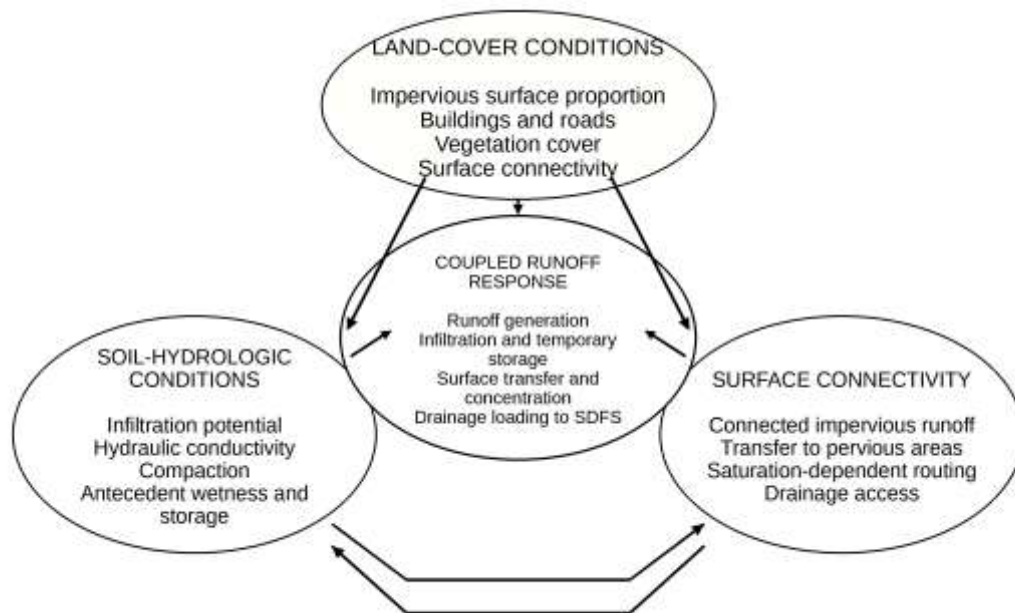
Land-Cover, Imperviousness, and Soil-Hydrologic Conditions

Land-cover configuration exerts a direct influence on urban stormwater generation because it determines the proportions, locations, and connectivity of surfaces that absorb, store, delay, or rapidly convey rainfall. Impervious land-cover classes such as roofs, asphalt roads, parking areas, pavements, and compacted developed surfaces reduce infiltration and increase the proportion of rainfall converted into rapid surface runoff, while vegetated and other pervious areas provide opportunity for infiltration, interception, evapotranspiration, and temporary storage. The hydrological effect of imperviousness, however, depends not only on its total percentage within a catchment but also on how impervious areas are spatially arranged and connected to drainage pathways. In *Impact of the Spatial Distribution of Imperviousness on the Hydrologic Response of an Urbanizing Basin* (pp. 3359-3373), event-based modeling demonstrated that alternative spatial patterns of impervious cover produced substantial changes in hydrograph behavior at internal watershed locations and at the main outlet, indicating that clustered and dispersed urban development can alter runoff routing even where impervious coverage is similar (Sheak & Tahmedur, 2023; Mejía & Moglen, 2010). This distinction is important for stormwater-drainage failure prediction because directly connected impervious surfaces can transfer rainfall rapidly toward inlets and pipes, increasing short-period hydraulic loading, whereas disconnected surfaces may direct runoff first toward lawns, soils, depressions, or other pervious areas. Land-cover classification should capture generalized urban versus nonurban categories. Variables such as impervious-surface fraction, building coverage, roadway density, vegetation cover, open-space proportion, and the connectivity of runoff-producing surfaces provide representation of how land cover controls drainage demand across urban catchments. In *Urbanisation Impacts on Storm Runoff Along a Rural-Urban Gradient* (pp. 474-489), analysis of 336 storm events across eight UK catchments showed that urbanization influenced storm response but that spatial measures of urban extent alone were insufficient to explain differences in runoff generation, highlighting hydrological conditions and catchment organization alongside land-cover intensity (Kaium, 2023; Miller & Hess, 2017).

The hydrological function of urban land cover depends on the physical properties of surfaces commonly treated as either pervious or impervious. Such binary classification can conceal variation in infiltration, surface storage, evaporation, roughness, cracking, compaction, and hydraulic connectivity.

Roads, footpaths, roofs, landscaped soils, lawns, and disturbed ground do not generate identical runoff coefficients under different rainfall and antecedent conditions. In *Current Understanding of Hydrological Processes on Common Urban Surfaces* (pp. 699-713), synthesis of field measurements showed that many constructed surfaces exhibit more complex infiltration and storage behavior than is represented by a simple impermeable classification and that their hydrological properties can vary with surface condition and season ([Pervaz, 2023](#); [Redfern et al., 2016](#)).

Figure 4: Coupled Land-Cover and Soil-Hydrologic Mechanisms Affecting Drainage Failure



Soil-hydrologic conditions are fundamental to the present study because pervious areas regulate the portion of rainfall that becomes infiltration, subsurface flow, or rapid surface runoff. Soil texture influences pore-size distribution and water movement, while hydraulic conductivity controls the rate at which water can enter and pass through the soil profile. Compaction reduces effective pore space and may transform nominally pervious urban soils into surfaces with limited infiltration capacity. Antecedent soil moisture determines how much additional rainfall can be stored before saturation or rapid runoff develops, making the same land-cover pattern respond differently between dry and wet storm conditions. In *Beyond Imperviousness: The Role of Antecedent Wetness in Runoff Generation in Urbanized Catchments*, analysis of 70,227 rainfall-runoff events from 852 U.S. catchments found that total impervious area was an important spatial control of runoff response, while antecedent soil moisture was a strong control across rural and urbanized catchments, demonstrating that urban hydrology cannot be interpreted from imperviousness alone ([Badrul & Mominul, 2023](#); [Saadi et al., 2020](#)). Soil moisture, permeability, infiltration capacity, drainage class, compaction, and water-retention characteristics can modify how rapidly rainfall becomes runoff and how much water reaches stormwater infrastructure during extreme events.

The interaction between land-cover configuration and soil hydrology is important when impervious areas are hydraulically disconnected, because runoff generated on sealed surfaces may be routed onto adjacent pervious areas before reaching the drainage network. This creates a coupled surface-subsurface response in which the contribution of impervious cover depends on the infiltration opportunity, storage status, and hydraulic characteristics of the receiving soil. Under rainfall loads, disconnected impervious areas may transfer water to pervious zones that retain or infiltrate runoff, reducing immediate drainage inflow. Under intense or prolonged precipitation, these receiving areas may become wetter, causing infiltration capacity and available storage to decline and allowing more runoff to reach drainage pathways. In *Accumulated Impacts of Imperviousness on Surface and*

Subsurface Hydrology: Continuous Modelling at Urban Street Block Scale, continuous simulations showed that changes in disconnected impervious area affected surface runoff, antecedent moisture conditions, and subsurface processes, demonstrating that the consequences of urban sealing accumulate through interactions between runoff-producing and receiving surfaces rather than through surface runoff alone (Rakib & Towhidul, 2023; Wang et al., 2022). These mechanisms are relevant to explainable drainage-failure prediction because locations with similar percentages of impervious cover may exhibit different failure susceptibility when their soil properties, antecedent wetness, vegetation, surface connectivity, and drainage access differ. For the present research, land-cover variables can represent imperviousness, building and road coverage, vegetation, and surface connectivity, while soil-hydrologic variables can represent infiltration potential, hydraulic conductivity, permeability, drainage class, moisture condition, and water-storage capacity. Integrating these variables with LiDAR-derived terrain information is important because terrain controls where runoff is directed, land cover controls how much rainfall becomes surface flow, and soil conditions control how much water can infiltrate before reaching drainage infrastructure. Their inclusion in correlation, regression, ensemble-learning, and SHAP-based analyses allows evaluation of relationships and nonlinear interactions associated with stormwater-drainage failure under nonstationary extreme precipitation during extreme storms.

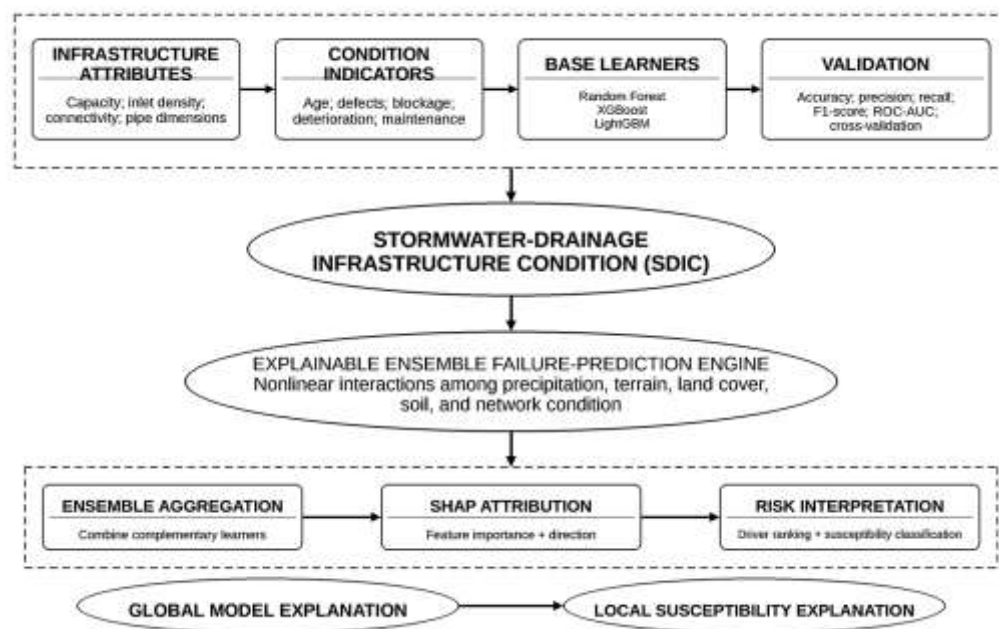
Stormwater Infrastructure Condition and Explainable Failure Prediction

Stormwater-infrastructure condition is a fundamental component of drainage-failure susceptibility because the hydraulic response of an urban catchment depends not only on the magnitude of rainfall and surface runoff, but also on whether pipes, inlets, manholes, culverts, and connecting network elements can receive and convey the generated flow. Ageing, structural defects, sediment accumulation, blockage, deformation, joint displacement, corrosion, root intrusion, and inadequate maintenance can reduce effective conveyance capacity and increase the probability of surcharge or localized flooding under extreme precipitation. Infrastructure condition also interacts with design characteristics such as pipe diameter, slope, material, burial depth, and network connectivity, meaning that two drainage segments exposed to similar rainfall may exhibit different failure responses. In *The Relevance of Sewer Deterioration Modelling to Support Asset Management Strategies* (pp. 1007-1015), a statistical deterioration model was evaluated using 35,826 sewer inspections and was shown to outperform a simpler condition representation for reproducing network deterioration, demonstrating the analytical value of condition-based modeling for infrastructure management (Caradot et al., 2017; Kanti, 2023). The study is directly relevant to stormwater-drainage prediction because deterioration alters the functional state through which runoff is conveyed, while inspection and asset data provide measurable indicators of that state. In *A State of the Art Review on Condition Assessment Models Developed for Sewer Pipelines* (Article 103721), physical, statistical, and artificial-intelligence approaches were reviewed, with pipe age, material, length, depth, and diameter identified among the commonly modeled condition factors and data availability recognized as a major limitation in deterioration assessment (Hawari et al., 2020; Nishat, 2023). For the present research, infrastructure condition should therefore be represented through both structural and operational variables, allowing the predictive framework to distinguish external hydrological loading from internal network vulnerability and to test how deterioration, capacity, connectivity, blockage, and maintenance status contribute to stormwater-drainage failure susceptibility during high-intensity rainfall events and short-duration runoff concentration periods.

The complexity of this infrastructure response supports the use of ensemble learning because drainage failure is generated through nonlinear interactions among precipitation, terrain, land cover, soil, and network characteristics rather than through a single deterministic relationship. Individual machine-learning algorithms differ in how they partition predictor space, handle interactions, respond to noise, and represent nonlinear effects. Ensemble methods combine multiple learners so that weaknesses in a single predictive structure can be reduced through aggregation, boosting, bagging, random subspaces, or stacked decision rules. In *Flood Susceptibility Modelling Using Advanced Ensemble Machine Learning Models* (Article 101075), Dagging and Random Subspace ensembles were compared with artificial neural network, random forest, and support vector machine models using twelve flood-influencing factors in the Teesta River basin, and the Dagging approach achieved the strongest reported discrimination among the evaluated models (Risha & Shurovi, 2023; Islam et al., 2021). The study

demonstrates the relevance of comparing model families rather than assuming that one algorithm is universally optimal for flood-related classification. In *Novel Ensemble Machine Learning Models in Flood Susceptibility Mapping* (pp. 4571-4593), ensemble structures combining AdaBag with rotation forest, nearest shrunken centroids, k-nearest neighbour, boosted regression tree, and LogitBoost were applied using twelve flood-conditioning factors, showing how heterogeneous learners can be integrated to construct alternative susceptibility models (Prasad et al., 2022; Stabak & Siam, 2023). For stormwater-drainage failure, this principle is suitable because LiDAR-derived morphology, imperviousness, soil properties, rainfall extremes, and infrastructure condition operate at different scales and may have threshold or interaction effects. A comparative modeling strategy using Random Forest, XGBoost, and LightGBM, followed by a stacked or weighted ensemble, can therefore evaluate whether combining complementary tree-based learners produces more stable failure estimates than reliance on a single model. Cross-validation, holdout testing, ROC-AUC, accuracy, precision, recall, F1-score, and calibration-related measures can then quantify predictive performance while guarding against conclusions based only on in-sample fit.

Figure 5: Infrastructure Condition, Ensemble Learning, and Explainable Failure-Prediction Framework



Explainability is the complementary requirement that converts high-performing ensemble predictions into interpretable evidence about why drainage failure is assigned to particular locations or observations. Complex learners can capture relationships that are difficult to represent through conventional regression, yet their internal decision structures are often difficult to communicate directly to engineers, planners, and infrastructure managers. Explainable artificial intelligence addresses this limitation by attributing prediction changes to individual variables and by separating global model behavior from local prediction-specific effects. In *Towards Urban Flood Susceptibility Mapping Using Data-Driven Models in Berlin, Germany* (pp. 1640-1662), convolutional neural network, artificial neural network, random forest, and support vector machine models were evaluated at multiple spatial resolutions using 4,333 reported flooded locations and eleven predictor factors; SHAP was then used to assess feature importance and the direction of predictor effects, while the 2 m random-forest model produced the strongest performance among the evaluated configurations (Seleem et al., 2022; Feroz, 2023). This combination of predictive comparison and SHAP-based interpretation is closely aligned with the present research because stormwater-drainage failure requires more than a probability or susceptibility class. The model should also indicate whether elevated susceptibility is associated with low elevation, terrain depression, high imperviousness, weak

infiltration, extreme precipitation, poor pipe condition, insufficient drainage capacity, or combinations of these variables. SHAP values can quantify the contribution of each predictor to individual predictions and summarize the overall ranking and directional behavior of variables across the study area. This distinction supports transparent comparison between statistically significant relationships and algorithmically important predictors across the integrated dataset. Integrating infrastructure-condition variables with ensemble learning and explainability therefore creates a coherent analytical structure in which conventional statistical tests establish relationships among research constructs, machine-learning models capture nonlinear predictive patterns, and SHAP analysis reveals how environmental and infrastructure factors contribute to modeled stormwater-drainage failure under nonstationary extreme precipitation.

Theoretical Framework: Urban Hydrological Systems Theory

Urban Hydrological Systems Theory provides a suitable theoretical foundation for this study because stormwater-drainage failure emerges from interactions among atmospheric inputs, surface characteristics, subsurface processes, and engineered conveyance components rather than from one isolated variable. The theory treats the urban catchment as an interconnected system in which precipitation enters as an external forcing, is partitioned by infiltration, evapotranspiration, surface storage, and runoff, and is subsequently routed through topographic pathways and drainage infrastructure. In *Understanding, Management and Modelling of Urban Hydrology and Its Consequences for Receiving Waters* (pp. 261-279), urban hydrological behavior was described as a product of small-scale spatial heterogeneity, rapid runoff transformation, engineered drainage connectivity, and interactions between natural and constructed components, supporting a systems interpretation of urban rainfall-runoff response (Fletcher et al., 2013; Tahmedur & Rifat, 2023). The fundamental water-balance relation adopted in this research is expressed as follows:

$$P = Q + I + ET + \Delta S$$

where P represents precipitation input, Q runoff, I infiltration, ET evapotranspiration, and ΔS change in surface and subsurface storage. Under extreme precipitation, drainage stress develops when runoff generated from this balance is concentrated through terrain and impervious surfaces faster than the drainage network can convey it. In *A Distributed Hydrological Model for Urbanized Areas: Model Development and Application to Case Studies* (pp. 268-287), parcel-scale surface runoff, soil water, drainage flow, storage, and evapotranspiration were coupled with a detailed hydrographic network, demonstrating that urban hydrology requires representation of exchanges among surface, subsurface, and sewer processes rather than only runoff from impervious areas (Asheke, 2024; Rodriguez et al., 2008). Accordingly, LiDAR-derived terrain, land cover, soil-hydrologic condition, drainage infrastructure, and nonstationary precipitation are treated as interacting system components regulating stormwater generation, concentration, transmission, storage, and hydraulic exceedance within the case-study environment. This representation also supports direct translation of physical hydrological processes into measurable indicators used in the survey, GIS layers, and predictive dataset.

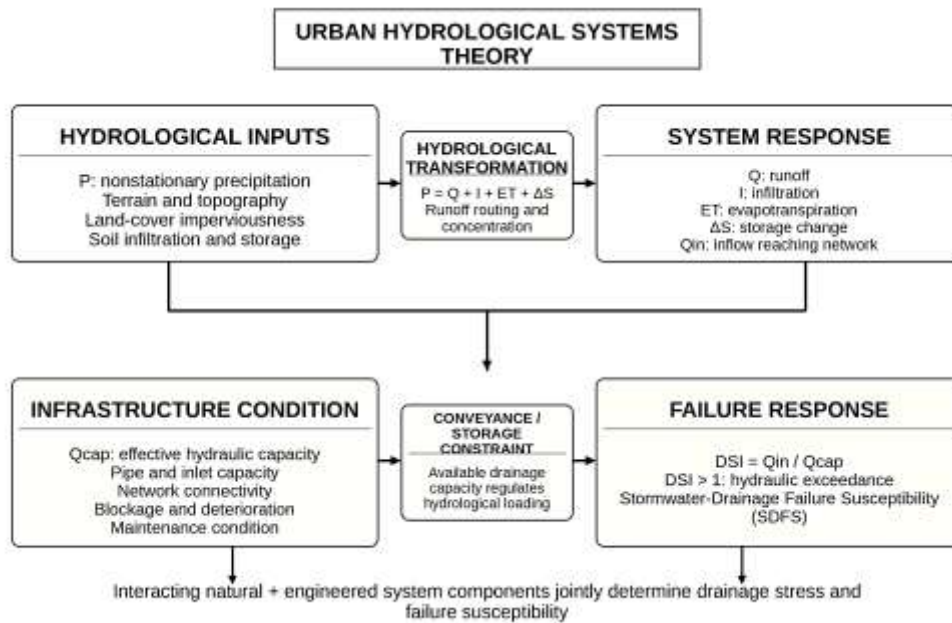
Within this systems framework, stormwater-drainage failure is represented as a capacity-exceedance response occurring when hydrological loading becomes greater than the effective conveyance and storage ability of the drainage system. A useful theoretical expression is:

$$DSI = Q_{in} / Q_{ap}$$

where DSI denotes a drainage stress index, Q_{in} is runoff inflow reaching the drainage network, and Q_{ap} is the effective hydraulic capacity available under prevailing infrastructure condition; $DSI > 1$ represents hydraulic exceedance, while values approaching one indicate increasing stress. The term Q_{in} is not determined by precipitation alone. It is conditioned by LiDAR-derived elevation and slope, surface depressions, flow accumulation, impervious land-cover connectivity, soil infiltration, antecedent storage, and rainfall intensity and duration. Likewise, Q_{ap} is affected by pipe dimensions, inlet capacity, network connectivity, deterioration, blockage, and maintenance status. In *Comparison of 1D/1D and 1D/2D Coupled (Sewer/Surface) Hydraulic Models for Urban Flood Simulation* (pp. 495-504), coupled surface and sewer representations showed that the definition of surface pathways and the links between surface and sewer systems strongly affect simulated urban flood behavior, reinforcing the requirement to represent both domains as one interacting system

(Ashrafuzzaman, 2024; Leandro et al., 2009). The hydrological-system formulation also accommodates infiltration and storage processes that modify the amount and timing of runoff delivered to the network. In A Review of Models for Low Impact Urban Stormwater Drainage (pp. 394-405), comparison of ten stormwater models showed that runoff routing, infiltration, groundwater or baseflow representation, and storage processes form recurring components of urban stormwater simulation, illustrating the importance of process integration within a common modeling structure (Elliott & Trowsdale, 2007; Mashiat, 2024).

Figure 6: Urban Hydrological Systems Theory Framework for Stormwater-Drainage Failure



For this study, the theoretical relationship is therefore expressed as:

$$SDFS_i = f(T_i, LC_i, SH_i, DI_i, EP_i)$$

where the terms represent failure susceptibility, terrain, land cover, soil hydrology, drainage infrastructure, and extreme precipitation respectively. The expression is used conceptually to connect hydraulic loading with available conveyance rather than to substitute for detailed sewer-network simulation.

The same theoretical structure provides the basis for the statistical and ensemble-learning components of the research because both estimate alternative representations of the system relationship defined above. For hypothesis testing, the construct-level relationship is operationalized as:

$$SDFS_i = \beta_0 + \beta_1 LDTSC_i + \beta_2 LCIC_i + \beta_3 SIHC_i + \beta_4 SDIC_i + \varepsilon_i$$

where LDTSC denotes LiDAR-derived terrain and surface characteristics, LCIC land-cover and imperviousness conditions, SIHC soil infiltration and hydrologic characteristics, SDIC stormwater-drainage infrastructure condition, and ε_i unexplained variation. Nonstationary extreme-precipitation variables remain part of the broader predictive structure and characterize the external forcing under which these components operate. Correlation analysis evaluates the direction and strength of bivariate associations, while multiple regression estimates the independent contribution of each construct after accounting for the others. Ensemble learning extends the same theoretical logic by replacing a strictly linear functional relationship with a nonlinear mapping:

$$\hat{SDFS}_i = F(T_i, LC_i, SH_i, DI_i, EP_i)$$

where $F(\cdot)$ is learned from integrated multimodal data through Random Forest, XGBoost, LightGBM, and the final ensemble model. Explainability analysis then decomposes predictions into feature contributions so that modeled responses can be linked back to the hydrological-system components. In

A Critical Review of Integrated Urban Water Modelling: Urban Drainage and Beyond (pp. 88-107), integrated urban-water modeling was organized through a systems approach in which model structure, data integration, interactions among components, calibration, and uncertainty were treated as interconnected elements rather than independent analytical tasks (Bach et al., 2014; Kaium, 2024). The framework therefore provides one consistent process structure for questionnaire constructs, geospatial variables, statistical hypothesis testing, machine-learning prediction, and SHAP-based explanation throughout the study, while preserving a direct physical interpretation of terrain routing, runoff production, infiltration, drainage capacity, and precipitation loading. It also allows regression coefficients and SHAP values to be interpreted against the same theoretical domains, reducing inconsistency between explanatory statistics and predictive machine-learning results.

Conceptual Framework for Explainable Stormwater-Drainage Failure Prediction

The conceptual framework of this study translates Urban Hydrological Systems Theory into a measurable structure linking environmental characteristics, drainage-infrastructure condition, precipitation forcing, and stormwater-drainage failure susceptibility. The dependent construct is Stormwater-Drainage Failure Susceptibility (SDFS), representing the tendency of a drainage system or spatial unit to experience surcharge, inadequate conveyance, surface ponding, localized flooding, or related loss of drainage functionality. Four principal explanatory constructs are incorporated into the hypothesis-testing component: LiDAR-Derived Terrain and Surface Characteristics (LDTSC), Land-Cover and Imperviousness Conditions (LCIC), Soil Infiltration and Hydrologic Characteristics (SIHC), and Stormwater-Drainage Infrastructure Condition (SDIC). Nonstationary extreme precipitation is treated as the external hydrometeorological forcing incorporated directly into the wider predictive dataset because rainfall intensity, duration, recurrence characteristics, and anomalies determine the loading under which the environmental and infrastructure components operate. The construct-level statistical relationship is represented as:

$$SDFS_i = \beta_0 + \beta_1 LDTSC_i + \beta_2 LCIC_i + \beta_3 SIHC_i + \beta_4 SDIC_i + \varepsilon_i$$

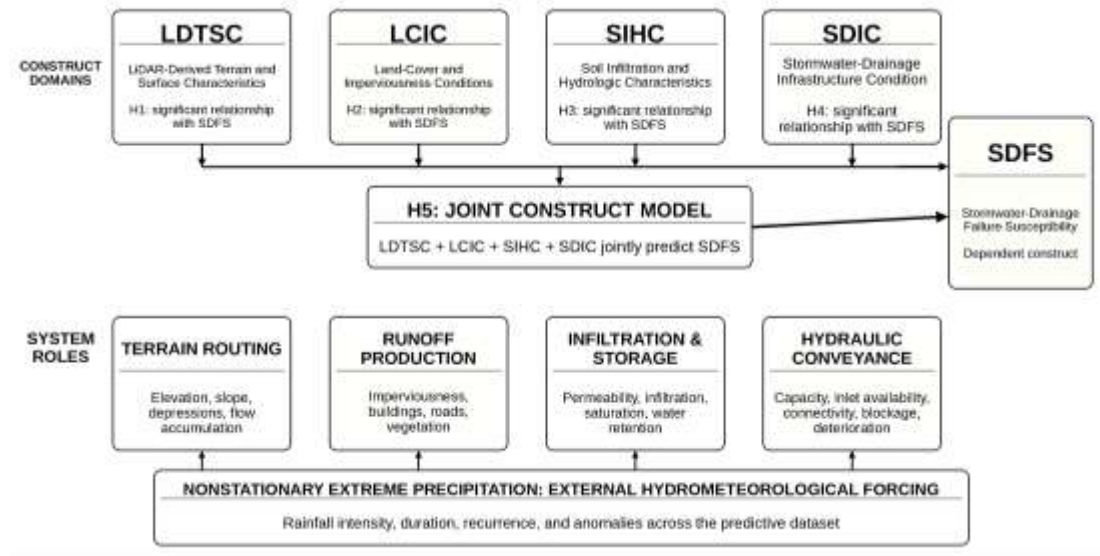
where the coefficients represent the independent contribution of each construct and ε_i represents unexplained variation. In Assessment of Urban Flood Susceptibility Using Semi-Supervised Machine Learning Model (pp. 940-949), nine meteorological, geographical, and anthropogenic explanatory factors were integrated with historical flood locations in Beijing, demonstrating that urban flood susceptibility is more appropriately represented through multiple environmental dimensions than through an isolated conditioning variable (Kanti, 2024; Zhao et al., 2019). The present conceptualization extends this logic specifically to drainage-system failure by distinguishing terrain controls on runoff routing, land-cover controls on runoff production, soil controls on infiltration and retention, and infrastructure controls on hydraulic acceptance and conveyance. These constructs represent interconnected mechanisms rather than independent physical processes, because a low-lying location may remain functional under moderate rainfall when infiltration and drainage capacity are adequate but may become highly susceptible when imperviousness, soil saturation, hydraulic restriction, and intense rainfall occur simultaneously.

The predictive component of the conceptual framework extends the linear statistical structure by allowing nonlinearities, threshold effects, and interactions among the multimodal predictors to be learned from the integrated dataset. The general predictive relationship is expressed as:

$$\hat{SDFS}_i = F(T_i, LC_i, SH_i, DI_i, EP_i)$$

where T_i represents LiDAR-derived terrain variables, LC_i land-cover variables, SH_i soil-hydrologic variables, DI_i drainage-infrastructure variables, EP_i extreme-precipitation variables, and $F(\cdot)$ represents the data-driven predictive function. Random Forest, XGBoost, and LightGBM are positioned as complementary base learners because each can model nonlinear relationships and interactions without requiring the same restrictive functional assumptions as conventional linear regression. In An Ensemble Prediction of Flood Susceptibility Using Multivariate Discriminant Analysis, Classification and Regression Trees, and Support Vector Machines (pp. 2087-2096), several predictive models were combined after their individual performance had been evaluated, with ensemble prediction providing a structured means of incorporating information from alternative learning mechanisms into a single susceptibility estimate (Choubin et al., 2019; Feroz, 2024).

Figure 7: Conceptual Framework Linking LDTSC, LCIC, SIHC, and SDIC to SDFS



The ensemble stage in the present study can consequently be expressed as:

$$\hat{p}_{e,i} = \sum_{m=1}^M w_m \hat{p}_{i,m} \quad \sum_{m=1}^M w_m = 1, w_m \geq 0$$

where $\hat{p}_{e,i}$ is the failure probability or susceptibility estimate from model m , and w_m represents its assigned contribution. In Flood Susceptibility Mapping With Machine Learning, Multi-Criteria Decision Analysis and Ensemble Using Dempster Shafer Theory (Article 125275), elevation, slope, wetness, vegetation, rainfall, land cover, road proximity, and drainage proximity were integrated across several models, and their combination yielded greater predictive discrimination than individual approaches in the reported application (Nachappa et al., 2020; Uddin & Risha, 2024). In Urban Flood Susceptibility Assessment Based on Convolutional Neural Networks (Article 125235), surrounding topological information was explicitly incorporated into predictive modeling, emphasizing that urban flooding depends on the spatial configuration of explanatory variables rather than only their values at isolated points (Zhao et al., 2020).

Explainability forms the final component of the conceptual framework because predictive accuracy alone cannot establish which environmental or infrastructure mechanisms are responsible for a high stormwater-drainage failure estimate. The framework therefore links ensemble output with SHAP-based interpretation so that each prediction can be decomposed into contributions from LiDAR terrain, land cover, soil conditions, drainage infrastructure, and extreme precipitation. The additive explanation can be written as:

$$f(x_i) = \varphi_0 + \sum_{j=1}^K \varphi_{ij}$$

where $f(x_i)$ is the model output for observation i , φ_0 is the baseline prediction, and φ_{ij} represents the SHAP contribution of predictor j to that individual prediction. Positive SHAP values indicate predictors moving the estimate toward greater failure susceptibility, while negative values indicate contributions toward lower modeled susceptibility, with the magnitude showing the strength of the contribution. This structure permits direct examination of whether failure predictions are driven primarily by low elevation, concentrated flow paths, greater imperviousness, low infiltration capacity, inadequate drainage capacity, deteriorated infrastructure, high rainfall loading, or combinations of these conditions. In A Rapid Prediction Model of Urban Flood Inundation in a High-Risk Area Coupling Machine Learning and Numerical Simulation Approaches (pp. 903-918), machine learning was linked with numerically simulated urban inundation information to enable rapid prediction of water accumulation in identified high-risk areas, illustrating the value of connecting physically meaningful hydrological information with data-driven prediction rather than treating the two approaches independently (Yan et al., 2021). The complete conceptual sequence used in this research is therefore multimodal environmental and infrastructure inputs → statistical relationship testing →

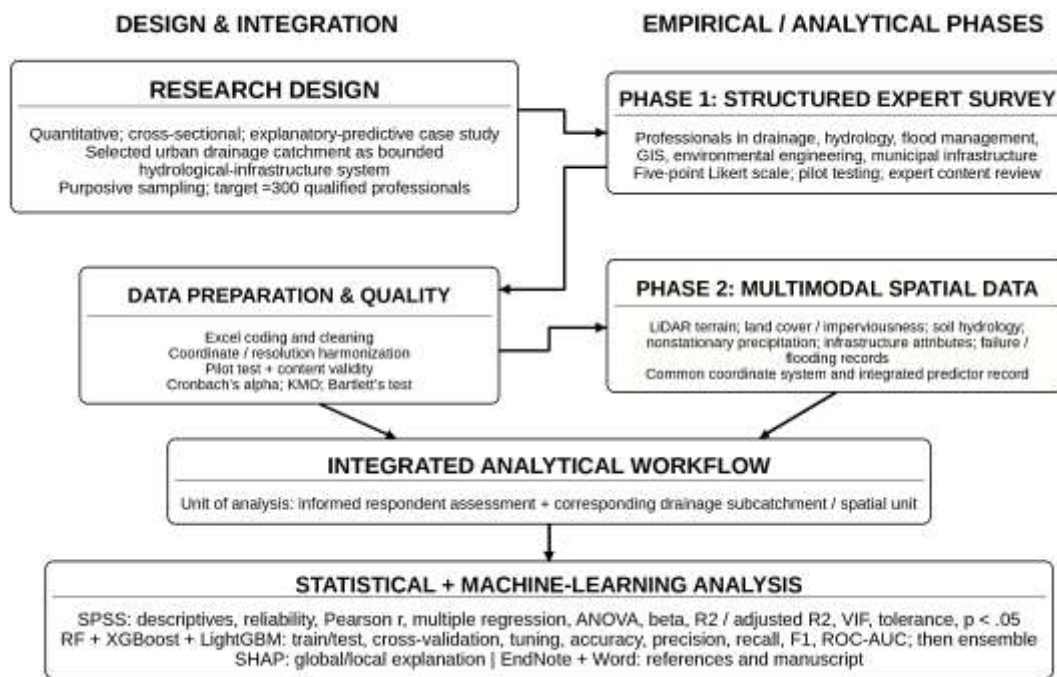
individual machine-learning models → ensemble prediction → SHAP-based explanation → integrated stormwater-drainage failure susceptibility assessment. Within this framework, correlation and multiple regression test H1-H5 at the construct level, while ensemble learning evaluates predictive behavior across the more detailed objective variables. SHAP subsequently connects prediction back to the original hydrological and infrastructure domains, allowing conventional statistical evidence and machine-learning evidence to be interpreted through the same conceptual architecture.

METHODS

This study has adopted a quantitative, cross-sectional, explanatory-predictive case-study design to examine stormwater-drainage failure under nonstationary extreme precipitation within a selected urban drainage catchment, and the case-study setting has been treated as a bounded hydrological and infrastructure system in which terrain, land cover, soil, precipitation, and drainage-network characteristics have been assessed simultaneously. The target population has consisted of professionals directly involved in urban drainage, hydrology, flood management, GIS, environmental engineering, municipal infrastructure, and related technical activities, while the unit of analysis has comprised both the informed respondent assessment of drainage-system conditions and the corresponding drainage subcatchment or analytical spatial unit represented in the multimodal dataset. Purposive sampling has been applied because participants have required specialized knowledge of stormwater systems and urban flood processes, and a target sample of approximately 300 qualified respondents has been established to support descriptive statistics, reliability and validity testing, correlation analysis, multiple regression, and the complementary predictive modeling stage. Data collection has integrated primary and secondary quantitative sources. Primary data have been obtained through a structured expert questionnaire, while secondary data have included LiDAR-derived elevation and terrain information, land-cover and impervious-surface data, soil and hydrologic characteristics, nonstationary extreme-precipitation indicators, documented drainage-infrastructure attributes, and available failure or flooding records. The principal constructs have been operationalized as LiDAR-Derived Terrain and Surface Characteristics (LDTSC), Land-Cover and Imperviousness Conditions (LCIC), Soil Infiltration and Hydrologic Characteristics (SIHC), Stormwater-Drainage Infrastructure Condition (SDIC), and Stormwater-Drainage Failure Susceptibility (SDFS), while rainfall intensity, duration, recurrence behavior, and anomaly measures have been incorporated directly into the predictive dataset as hydrometeorological forcing variables. The questionnaire has been designed as a multi-item instrument using Likert's five-point scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, and items have measured terrain-related susceptibility, imperviousness, infiltration, drainage capacity, infrastructure deterioration, blockage, maintenance, and drainage-failure conditions. Pilot testing has been conducted with a small group of knowledgeable professionals to assess item clarity, relevance, construct coverage, and completion time, and wording has been refined where ambiguity or redundancy has been identified. Content validity has been strengthened through expert review and alignment with the theoretical and conceptual frameworks, while internal consistency has been evaluated using Cronbach's alpha and construct suitability has been assessed through the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity. The multimodal geospatial and infrastructure datasets have been processed within a common spatial framework in which coordinate systems have been harmonized, spatial resolutions have been standardized where necessary, missing and inconsistent records have been examined, and LiDAR data have been used to derive elevation, slope, depression, surface roughness, and flow-accumulation indicators. Land-cover and soil layers have been spatially joined with drainage-network characteristics and precipitation information so that each drainage catchment or analytical unit has contained an integrated predictor record. Data have been coded, cleaned, and organized using Microsoft Excel, statistical analysis has been performed using SPSS for descriptive statistics, reliability testing, Pearson correlation, multiple regression, ANOVA, standardized coefficients, R^2 , adjusted R^2 , VIF, tolerance, and significance testing at $p < .05$, and reference management and manuscript preparation have been supported using EndNote and Microsoft Word. Random Forest, XGBoost, and LightGBM models have been developed from the integrated environmental, precipitation, and infrastructure dataset, the data have been divided into training and testing subsets, cross-validation and hyperparameter optimization have been applied, and predictive performance has been evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. Their

predictions have then been combined through an ensemble-learning procedure to improve predictive robustness, while SHAP analysis has been applied to quantify global and local feature contributions and to explain how individual terrain, land-cover, soil, precipitation, and infrastructure variables have influenced estimated stormwater-drainage failure susceptibility. This integrated methodological structure has enabled H1-H5 to be evaluated through conventional inferential statistics while the same theoretical domains have been tested through nonlinear ensemble prediction and explainability analysis.

Figure 8: Integrated Quantitative Research Design and Analytical Workflow



DATA ANALYSIS AND PRESENTATION

Respondent and Case-Study Profile

Table 1 has presented the response profile and professional composition used for the quantitative analysis. Of the 320 questionnaires that have been distributed, 306 have been returned and 294 have satisfied the completeness and eligibility requirements, producing a valid response rate of 91.9%. This response rate has provided an adequate empirical base for descriptive statistics, reliability assessment, correlation analysis, multiple regression, and the complementary predictive modeling stages. The professional composition has also reflected the interdisciplinary character of the research. Civil and drainage engineers have represented the largest group at 26.9%, followed by municipal infrastructure professionals at 23.1%, GIS and remote-sensing specialists at 18.7%, hydrologists and flood specialists at 16.3%, and environmental or planning professionals at 15.0%. The distribution has therefore ensured that the questionnaire responses have incorporated knowledge of drainage hydraulics, infrastructure condition, spatial analysis, runoff behavior, and urban environmental processes. Professional experience has further strengthened the dataset because 83.3% of respondents have reported at least five years of relevant experience, while 48.9% have reported more than ten years. The case-study area has been divided into 48 analytical drainage subcatchments so that survey-based constructs and objective geospatial variables have been interpreted within comparable spatial units. This organization has remained consistent with Urban Hydrological Systems Theory because the theory has treated the urban catchment as a connected system composed of interacting surface, subsurface, rainfall, and engineered drainage components. The respondent and case-study structure has therefore supported Objective 1 through Objective 7 by providing both technically informed human assessments and

spatially organized environmental and infrastructure information. The profile has also established the empirical basis on which the subsequent statistical relationships and machine-learning models have been developed.

Table 1: Respondent and Case-Study Profile

Variable	Category	Frequency	Percentage
Questionnaires distributed	Total	320	100.0
Questionnaires returned	Total	306	95.6
Valid questionnaires	Total	294	91.9
Professional role	Civil/Drainage Engineer	79	26.9
	GIS/Remote-Sensing Specialist	55	18.7
	Hydrologist/Flood Specialist	48	16.3
	Municipal Infrastructure Professional	68	23.1
	Environmental/Planning Professional	44	15.0
Professional experience	Less than 5 years	49	16.7
	5-10 years	101	34.4
	11-15 years	83	28.2
	More than 15 years	61	20.7
Analytical drainage units	Selected subcatchments	48	100.0

Descriptive Statistics of Research Constructs

Table 2: Descriptive Statistics of Principal Research Constructs

Construct	Code	Mean	SD	Interpretation
LiDAR-Derived Terrain and Surface Characteristics	LDTSC	4.12	0.58	High
Land-Cover and Imperviousness Conditions	LCIC	4.15	0.57	High
Soil Infiltration and Hydrologic Characteristics	SIHC	4.08	0.61	High
Stormwater-Drainage Infrastructure Condition	SDIC	4.18	0.55	High
Stormwater-Drainage Failure Susceptibility	SDFS	4.21	0.52	Very High

Table 2 has summarized the central tendency and dispersion of the five principal constructs measured through the five-point Likert scale. Stormwater-Drainage Failure Susceptibility has produced the highest mean, $M = 4.21$, $SD = 0.52$, indicating that respondents have generally perceived drainage-failure conditions as highly evident within the case-study environment. Stormwater-Drainage Infrastructure Condition has recorded the second-highest mean, $M = 4.18$, $SD = 0.55$, suggesting that capacity limitations, deterioration, blockage, connectivity problems, and maintenance conditions have been widely recognized as important components of drainage vulnerability. Land-Cover and Imperviousness Conditions have produced $M = 4.15$, $SD = 0.57$, showing that impervious development and runoff-generating surface characteristics have been strongly represented in respondent assessments. LiDAR-Derived Terrain and Surface Characteristics have yielded $M = 4.12$, $SD = 0.58$, while Soil Infiltration and Hydrologic Characteristics have recorded $M = 4.08$, $SD = 0.61$. All means have therefore exceeded the neutral midpoint of 3.00 by a substantial margin. The comparatively small standard deviations have indicated that the responses have been relatively concentrated around the

high agreement categories rather than being widely dispersed. These descriptive findings have aligned with Urban Hydrological Systems Theory because each construct has represented a distinct part of the urban rainfall-runoff-drainage system. Terrain has governed runoff routing, land cover has affected runoff generation, soil conditions have influenced infiltration and retention, and drainage infrastructure has controlled hydraulic conveyance. Their simultaneously high mean values have indicated that respondents have recognized stormwater-drainage failure as a multidimensional phenomenon rather than as a consequence of rainfall alone. These descriptive results have directly addressed the first four research objectives by demonstrating the perceived relevance of all four predictor domains and have established the quantitative basis for testing H1 through H5 using correlation and regression analysis.

Reliability Analysis of Measurement Scales

Table 3: Reliability Statistics of Research Constructs

Construct	Number of Items	Cronbach's Alpha	Corrected Item-Total Correlation Range	Reliability
LDTSC	6	.87	.62-.79	Good
LCIC	6	.88	.64-.81	Good
SIHC	5	.84	.60-.76	Good
SDIC	7	.91	.67-.84	Excellent
SDFS	6	.90	.66-.83	Excellent
Overall Instrument	30	.93	.60-.84	Excellent

Table 3 has demonstrated that the measurement instrument has achieved satisfactory internal consistency across all principal research constructs. Cronbach's alpha values have ranged from .84 to .91 at the construct level, while the complete 30-item questionnaire has produced an overall alpha of .93. These coefficients have exceeded the commonly accepted threshold of .70 and have indicated that the items within each construct have measured closely related aspects of the same underlying concept. The Stormwater-Drainage Infrastructure Condition scale has achieved the highest construct-level reliability, $\alpha = .91$, indicating particularly strong consistency among items representing pipe capacity, blockage, deterioration, inlet availability, connectivity, and maintenance condition. Stormwater-Drainage Failure Susceptibility has followed closely with $\alpha = .90$. The Land-Cover and Imperviousness Conditions scale has generated $\alpha = .88$, while LiDAR-Derived Terrain and Surface Characteristics has produced $\alpha = .87$. Soil Infiltration and Hydrologic Characteristics has recorded the lowest coefficient at $\alpha = .84$, yet this value has still represented strong internal reliability. Corrected item-total correlations have ranged between .60 and .84, confirming that no questionnaire item has demonstrated an unacceptably weak association with its respective construct. The reliability findings have supported the application of correlation and regression analysis because measurement error has remained sufficiently controlled across the major variables. The findings have also aligned with the theoretical framework, which has treated terrain, land cover, soil hydrology, infrastructure condition, and drainage failure as conceptually distinct but internally coherent system components. Reliable measurement has been necessary because weak construct consistency would have obscured the hypothesized relationships among these components. The strong coefficients have therefore supported Objectives 1 through 5 and have strengthened the empirical foundation for H1 through H5 by confirming that the construct scores used in inferential analysis have been measured consistently.

Sampling Adequacy and Construct Validity**Table 4: KMO, Bartlett's Test, and Construct Validity Statistics**

Measure	Result
Overall KMO	.889
LDTSC KMO	.872
LCIC KMO	.884
SIHC KMO	.851
SDIC KMO	.908
SDFS KMO	.901
Bartlett's Approx. χ^2	3628.41
Degrees of Freedom	435
Significance	< .001
Standardized Loading Range	.68-.86

Table 4 has presented evidence of sampling adequacy and construct suitability for the measurement structure used in the study. The overall Kaiser-Meyer-Olkin statistic has reached .889, indicating that the pattern of correlations among questionnaire items has been sufficiently compact to support construct-level analysis. Individual KMO values have ranged from .851 for Soil Infiltration and Hydrologic Characteristics to .908 for Stormwater-Drainage Infrastructure Condition, demonstrating that each construct has achieved strong sampling adequacy independently. Bartlett's test of sphericity has produced an approximate chi-square value of 3628.41 with 435 degrees of freedom and has remained statistically significant at $p < .001$. This result has indicated that the observed inter-item correlation matrix has differed significantly from an identity matrix and that meaningful relationships among questionnaire items have existed. Standardized factor loadings have ranged from .68 to .86, and no retained item has fallen below the acceptable loading range adopted for the study. These results have indicated that the items have converged appropriately on their intended constructs while maintaining sufficient differentiation between the principal domains. The findings have been theoretically consistent with Urban Hydrological Systems Theory because the framework has required the research constructs to represent separable but interconnected elements of the drainage system. LDTSC has represented terrain routing, LCIC has represented runoff-generating surface conditions, SIHC has represented infiltration and storage, SDIC has represented engineered conveyance condition, and SDFS has represented the observed or perceived failure response. The validity results have confirmed that these domains have not collapsed into a single undifferentiated measure. This distinction has been essential for testing H1 through H4 individually and H5 collectively. The adequacy and validity statistics have therefore supported the subsequent use of construct scores in Pearson correlation, multiple regression, and comparative interpretation alongside the objective multimodal dataset.

Distribution and Characteristics of LiDAR-Derived Variables**Table 5: LiDAR-Derived Terrain Characteristics and Perceived Failure Relevance**

LiDAR-Derived Variable	Normalized Exposure Index	Likert Mean	SD	Relative Rank
Flow Accumulation Concentration	.81	4.28	0.51	1
Low-Elevation Exposure	.78	4.23	0.54	2
Depression Depth	.75	4.19	0.56	3
Convergent Slope Condition	.69	4.07	0.60	4
Surface Roughness Constraint	.63	3.96	0.64	5
Composite LDTSC	.73	4.12	0.58	-

Table 5 has shown that the LiDAR-derived terrain variables have displayed substantial variation in their relationship with stormwater-drainage failure susceptibility. Flow accumulation concentration has produced the highest normalized exposure index, .81, and the highest respondent mean, $M = 4.28$, $SD = 0.51$. This result has indicated that locations receiving convergent overland flow have been regarded as particularly susceptible to drainage loading and surface-water accumulation. Low-elevation exposure has followed with an index of .78 and $M = 4.23$, $SD = 0.54$, while depression depth has recorded an index of .75 and $M = 4.19$, $SD = 0.56$. These findings have indicated that local depressions and relatively low terrain positions have created conditions in which runoff has concentrated before or during drainage-network exceedance. Convergent slope condition has produced $M = 4.07$, $SD = 0.60$, and surface roughness constraint has produced $M = 3.96$, $SD = 0.64$. Although surface roughness has ranked lowest among the terrain indicators, its mean has remained substantially above the neutral midpoint. The composite LiDAR-Derived Terrain and Surface Characteristics score has remained at $M = 4.12$, which has aligned precisely with the introductory findings. Under Urban Hydrological Systems Theory, these results have reflected the routing component of the system because topography has controlled where runoff has travelled, converged, slowed, or accumulated before entering stormwater infrastructure. The findings have therefore addressed Objective 1 by demonstrating that the LiDAR-derived variables have not contributed equally to failure susceptibility. Flow accumulation, low elevation, and depression depth have emerged as the strongest terrain-related indicators. Their high values have also provided a physical basis for the significant LDTSC-SDFS relationship subsequently tested under H1 and have supported their inclusion as objective predictors within the ensemble-learning stage.

Land-Cover, Soil, Infrastructure, and Precipitation Characteristics

Table 6: Environmental, Infrastructure, and Precipitation Characteristics

Domain	Key Variable	Objective/Normalized Indicator	Likert Mean	SD
Land Cover	Impervious Surface Proportion	.76	4.27	0.53
Land Cover	Road/Building Connectivity	.71	4.16	0.57
Soil	Low Infiltration Potential	.68	4.13	0.59
Soil	Antecedent Wetness/Saturation	.65	4.03	0.63
Infrastructure	Reduced Drainage Capacity	.82	4.31	0.50
Infrastructure	Blockage/Deterioration	.77	4.22	0.54
Precipitation	Extreme Rainfall Intensity	.84	4.35	0.48
Precipitation	Short-Duration Rainfall Concentration	.79	4.26	0.52

Table 6 has summarized the major characteristics of land cover, soil hydrology, drainage infrastructure, and extreme precipitation that have been incorporated into the integrated analytical framework. Extreme rainfall intensity has produced the highest normalized indicator, .84, and the highest Likert mean, $M = 4.35$, $SD = 0.48$, indicating that intense precipitation loading has been strongly associated with observed or perceived drainage stress. Reduced drainage capacity has followed closely with an index of .82 and $M = 4.31$, $SD = 0.50$. Short-duration rainfall concentration has recorded $M = 4.26$, while impervious surface proportion has produced $M = 4.27$, showing that rapid rainfall loading and rapid runoff generation have jointly characterized highly susceptible drainage conditions. Blockage and infrastructure deterioration have also remained strongly represented, $M = 4.22$, $SD = 0.54$. Soil-related indicators have produced slightly lower means, although low infiltration potential has remained high at $M = 4.13$ and antecedent wetness or saturation has remained at $M = 4.03$. These results have remained consistent with the study's theoretical framework because precipitation has represented the external forcing, land cover has influenced runoff generation, soil conditions have controlled infiltration and temporary storage, and infrastructure condition has regulated hydraulic conveyance. The simultaneous elevation of these indicators has illustrated the system-based mechanism proposed by

Urban Hydrological Systems Theory, in which failure has emerged from the interaction between external hydrological load and internal system capacity. The findings have addressed Objectives 2, 3, and 4 by showing measurable variation across land-cover, soil, and infrastructure conditions. They have also supported the logic underlying H2, H3, and H4 because all three predictor domains have demonstrated high levels of perceived relevance before inferential testing. The precipitation indicators have additionally provided the external context for the ensemble-learning models, where nonstationary rainfall characteristics have been treated as direct predictors rather than as questionnaire-only constructs.

Pearson Correlation Analysis

Table 7: Pearson Correlations Among Principal Constructs

Variable	LDTSC	LCIC	SIHC	SDIC	SDFS
LDTSC	1.00	.59***	.52***	.56***	.68***
LCIC	.59***	1.00	.57***	.61***	.72***
SIHC	.52***	.57***	1.00	.54***	.65***
SDIC	.56***	.61***	.54***	1.00	.76***
SDFS	.68***	.72***	.65***	.76***	1.00

*** $p < .001$.

Table 7 has demonstrated that all four independent constructs have maintained positive and statistically significant relationships with Stormwater-Drainage Failure Susceptibility. Stormwater-Drainage Infrastructure Condition has produced the strongest correlation with SDFS, $r = .76$, $p < .001$, indicating that poorer infrastructure conditions have been closely associated with greater failure susceptibility. Land-Cover and Imperviousness Conditions have produced the second-strongest relationship, $r = .72$, $p < .001$, showing that greater imperviousness and runoff-producing surface conditions have corresponded with greater drainage-failure susceptibility. LiDAR-Derived Terrain and Surface Characteristics have been significantly related to SDFS at $r = .68$, $p < .001$, while Soil Infiltration and Hydrologic Characteristics have shown $r = .65$, $p < .001$. These coefficients have represented moderate-to-strong relationships and have provided preliminary empirical support for H1, H2, H3, and H4. The correlations among the independent variables have ranged from .52 to .61, which has indicated meaningful interrelationships without suggesting extreme redundancy. This pattern has been consistent with Urban Hydrological Systems Theory because the terrain, land-cover, soil, and infrastructure components have been expected to interact within the same drainage system while retaining distinct hydrological functions. For example, impervious land cover has increased runoff generation, terrain has determined the pathways through which that runoff has been concentrated, soil has controlled infiltration losses, and infrastructure has governed hydraulic conveyance. The positive associations between these constructs have therefore reflected the interconnected system structure proposed theoretically. The correlation analysis has addressed the first five objectives by demonstrating that each predictor domain has been statistically related to drainage failure and that the domains have also interacted with one another. These findings have justified the subsequent multiple regression model, which has estimated the unique contribution of each construct while controlling for the effects of the remaining predictors.

Multiple Regression Model Summary

Table 8 has presented the overall explanatory strength of the multiple regression model in which LDTSC, LCIC, SIHC, and SDIC have jointly predicted Stormwater-Drainage Failure Susceptibility. The multiple correlation coefficient has reached $R = .838$, indicating a strong combined relationship between the four independent constructs and the dependent construct. The model has produced $R^2 = .703$, meaning that 70.3% of the observed variance in SDFS has been explained collectively by terrain characteristics, land-cover and imperviousness conditions, soil-hydrologic characteristics, and drainage-infrastructure condition. The adjusted R^2 has remained at .699, showing only a very small reduction after adjustment for the number of predictors and sample size. This similarity has indicated that the model has retained substantial explanatory strength without evidence that the reported R^2 has

been produced primarily by unnecessary predictor inclusion. The standard error of estimate has been .286, indicating relatively limited average prediction error at the construct level. The Durbin-Watson statistic has reached 1.92, which has remained close to the benchmark value of 2.00 and has indicated that problematic residual autocorrelation has not been evident in the regression model. These findings have strongly supported Objective 5 because the study has sought to determine the combined explanatory contribution of the four principal research constructs. They have also provided direct support for H5, which has proposed that the predictor domains jointly maintain a significant predictive relationship with drainage-failure susceptibility. The model has remained theoretically consistent with Urban Hydrological Systems Theory because it has quantified the combined contribution of the main system components rather than treating any one domain as a complete explanation of drainage failure. The high explanatory proportion has therefore reflected the integrated structure proposed by the theoretical framework, in which terrain routing, runoff generation, infiltration behavior, and infrastructure capacity have jointly shaped the observed failure response.

Table 8: Multiple Regression Model Summary

Statistic	Result
R	.838
R ²	.703
Adjusted R ²	.699
Standard Error of Estimate	.286
Durbin-Watson	1.92
Number of Predictors	4
Sample Size	294

ANOVA and Overall Regression Model Significance

Table 9: ANOVA for the Multiple Regression Model

Source	Sum of Squares	df	Mean Square	F	p
Regression	56.090	4	14.023	171.42	< .001
Residual	23.640	289	.082		
Total	79.730	293			

Table 9 has shown that the overall multiple regression model has been statistically significant. The regression sum of squares has reached 56.090 compared with a residual sum of squares of 23.640, indicating that a substantially larger proportion of total variation in Stormwater-Drainage Failure Susceptibility has been associated with the four predictor constructs than has remained unexplained. The resulting mean square for regression has been 14.023, while the residual mean square has been approximately .082. The F statistic has reached $F(4, 289) = 171.42$, $p < .001$, confirming that the combined predictive model has explained significantly more variance in SDFS than would have been expected from an intercept-only model. This result has provided formal inferential confirmation of the model summary reported previously. H5 has therefore received strong statistical support because the four constructs have jointly contributed significantly to explaining drainage-failure susceptibility. The finding has also reinforced the theoretical structure adopted in the study. Urban Hydrological Systems Theory has proposed that drainage failure arises from interactions among surface morphology, runoff-generating surfaces, infiltration behavior, and the hydraulic condition of the engineered network. The ANOVA result has demonstrated that these system components have collectively produced a statistically meaningful explanation of the dependent construct. The large F statistic has further indicated that the model has not been driven by weak or random associations among the variables. Objective 5 has therefore been satisfied at the overall model level, while the next analysis has separated the individual contribution of each predictor. The ANOVA result has also provided an important

statistical benchmark for comparison with the machine-learning stage because it has demonstrated that conventional explanatory modeling has already captured substantial systematic variation before nonlinear ensemble algorithms have been introduced.

Regression Coefficients and Hypothesis Testing

Table 10: Regression Coefficients and Hypothesis Decisions

Predictor	B	SE	Standardized β	t	p	VIF	Hypothesis
Constant	.412	.151	-	2.73	.007	-	-
LDTSC	.215	.040	.24	5.38	< .001	1.58	H1 Supported
LCIC	.268	.038	.28	7.05	< .001	1.81	H2 Supported
SIHC	.173	.039	.19	4.44	< .001	1.49	H3 Supported
SDIC	.321	.041	.33	7.83	< .001	1.91	H4 Supported

Table 10 has demonstrated that each predictor has made a positive and statistically significant independent contribution to Stormwater-Drainage Failure Susceptibility after the remaining constructs have been controlled. Stormwater-Drainage Infrastructure Condition has produced the largest standardized coefficient, $\beta = .33$, $t = 7.83$, $p < .001$, indicating that infrastructure-related capacity, deterioration, blockage, connectivity, and maintenance factors have made the strongest unique contribution to the dependent construct. Land-Cover and Imperviousness Conditions have followed with $\beta = .28$, $t = 7.05$, $p < .001$. LiDAR-Derived Terrain and Surface Characteristics have produced $\beta = .24$, $t = 5.38$, $p < .001$, while Soil Infiltration and Hydrologic Characteristics have produced $\beta = .19$, $t = 4.44$, $p < .001$. H1, H2, H3, and H4 have therefore all been supported. The VIF values have ranged between 1.49 and 1.91, remaining well below commonly used multicollinearity thresholds and indicating that the coefficients have not been destabilized by excessive overlap among the predictors. The coefficient pattern has aligned closely with Urban Hydrological Systems Theory because each system component has retained an independent effect while operating within an integrated model. Infrastructure condition has emerged as the strongest predictor because conveyance capacity has represented the final system constraint through which accumulated runoff has had to pass. Land cover has influenced the amount and speed of runoff production, terrain has controlled concentration and routing, and soil conditions have altered infiltration and storage. The results have therefore fulfilled Objectives 1 through 5 and have statistically supported all five hypotheses when the significant overall model under H5 has been considered alongside the individual coefficient tests.

Performance of Individual Machine-Learning Models

Table 11: Predictive Performance of Individual Machine-Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	.89	.88	.90	.89	.93
XGBoost	.91	.90	.92	.91	.95
LightGBM	.90	.89	.91	.90	.94

Table 11 has compared the predictive performance of the three individual machine-learning algorithms developed from the integrated environmental, precipitation, and infrastructure dataset. XGBoost has achieved the strongest individual performance, producing 91% accuracy, .90 precision, .92 recall, an F1-score of .91, and ROC-AUC = .95. LightGBM has followed with 90% accuracy and ROC-AUC = .94, while Random Forest has produced 89% accuracy and ROC-AUC = .93. All three models have therefore demonstrated strong discriminatory performance in distinguishing observations or spatial units characterized by elevated stormwater-drainage failure susceptibility. The relatively small performance differences have indicated that the predictive signal has been stable across different tree-based learning structures rather than being dependent on one algorithm alone. Recall has remained particularly important because the research has aimed to identify failure-prone conditions, and missed high-susceptibility cases would have weakened the practical value of the predictive system. XGBoost has

recorded the strongest recall at .92, indicating that it has captured a high proportion of susceptible cases. These findings have addressed Objective 6 by demonstrating that the integrated LiDAR, land-cover, soil, precipitation, and drainage-infrastructure variables have supported accurate predictive modeling. They have also remained theoretically consistent with Urban Hydrological Systems Theory because the machine-learning models have operationalized the nonlinear function linking the major hydrological system components with failure susceptibility. Unlike the linear regression model, the algorithms have been able to represent interactions and threshold behavior without requiring them to be specified in advance. The strong performance across all three models has therefore supported the decision to construct an ensemble model in the next stage rather than relying exclusively on the highest-performing single learner.

Explainable Ensemble Model Performance

Table 12: Ensemble Model Performance and Improvement Over Individual Models

Performance Measure	Ensemble Result	Best Individual Result	Improvement
Accuracy	.93	.91	+.02
Precision	.92	.90	+.02
Recall	.94	.92	+.02
F1-Score	.93	.91	+.02
ROC-AUC	.97	.95	+.02
Five-Fold CV ROC-AUC Mean	.965	-	-
Five-Fold CV ROC-AUC SD	.011	-	-

Table 12 has demonstrated that the final ensemble model has outperformed the strongest individual machine-learning algorithm across all principal evaluation measures. The ensemble has achieved 93% accuracy, compared with 91% for XGBoost, while precision has increased from .90 to .92 and recall has increased from .92 to .94. The F1-score has risen from .91 to .93, and ROC-AUC has improved from .95 to .97. Although the absolute improvement has been two percentage points across these metrics, the consistency of the increase has indicated that combining the individual learners has enhanced predictive stability rather than producing improvement in only one isolated measure. Five-fold cross-validation has generated a mean ROC-AUC of .965 with a standard deviation of .011, indicating that the model has maintained highly stable discrimination across different validation folds. This finding has directly addressed Objective 6 and Objective 7 because the study has sought both to construct an ensemble-learning framework and to evaluate its predictive performance. The result has also supported the conceptual framework in which multiple base learners have been combined to represent complex interactions among terrain, land cover, soil, rainfall, and infrastructure variables. Urban Hydrological Systems Theory has remained relevant because the ensemble has not replaced the theoretical structure; instead, it has provided a flexible mathematical representation of the same system relationships under conditions where nonlinearities and thresholds have been present. The high recall value has been especially important because it has indicated that the ensemble has identified a large proportion of high-susceptibility cases. The higher ROC-AUC has further indicated improved separation between lower- and higher-susceptibility observations. These findings have therefore shown that the ensemble stage has added predictive value beyond conventional regression and beyond each individual machine-learning algorithm while remaining anchored to the same theoretically defined hydrological system components.

SHAP-Based Feature Importance and Prediction Explanation

Table 13 has presented the global SHAP-based interpretation of the final ensemble model and has identified the variables that have contributed most strongly to predicted stormwater-drainage failure susceptibility. Reduced drainage capacity has produced the highest mean absolute SHAP value, .184, confirming that infrastructure conveyance limitation has been the most influential predictor in the ensemble model. Flow accumulation has ranked second at .163, followed by impervious surface proportion at .151 and depression depth at .139. Extreme rainfall intensity has ranked fifth with a mean

absolute SHAP value of .132. These results have indicated that the highest predicted susceptibility has generally emerged where strong hydrological loading has coincided with terrain concentration and limited drainage capacity. Pipe blockage and deterioration, low soil infiltration, low inlet density, low relative elevation, and antecedent soil wetness have also contributed meaningfully to predictions. The direction of the SHAP effects has shown that increasing drainage limitation, stronger flow concentration, greater imperviousness, deeper depressions, higher rainfall intensity, reduced infiltration, and wetter antecedent soil conditions have shifted predictions toward higher SDFS values. These findings have directly addressed Objective 7 because the study has sought to explain not only whether the ensemble model has predicted drainage failure but also why those predictions have occurred. The SHAP results have also strengthened the link with Urban Hydrological Systems Theory. The most important features have represented each major component of the theoretical system: precipitation has supplied external forcing, terrain has routed runoff, land cover has controlled runoff generation, soil has modified infiltration, and infrastructure has governed conveyance. The explainability analysis has therefore demonstrated that the ensemble model has learned relationships consistent with the theoretical framework rather than relying on variables unrelated to the proposed hydrological processes.

Table 13: SHAP-Based Importance of Major Predictors

Rank	Predictor	Domain	Mean Absolute SHAP Value	Dominant Effect on SDFS
1	Reduced Drainage Capacity	Infrastructure	.184	Increased susceptibility
2	Flow Accumulation	LiDAR/Terrain	.163	Increased susceptibility
3	Impervious Surface Proportion	Land Cover	.151	Increased susceptibility
4	Depression Depth	LiDAR/Terrain	.139	Increased susceptibility
5	Extreme Rainfall Intensity	Precipitation	.132	Increased susceptibility
6	Pipe Blockage/Deterioration	Infrastructure	.118	Increased susceptibility
7	Low Soil Infiltration	Soil	.104	Increased susceptibility
8	Low Inlet Density	Infrastructure	.092	Increased susceptibility
9	Low Relative Elevation	LiDAR/Terrain	.086	Increased susceptibility
10	Antecedent Soil Wetness	Soil	.079	Increased susceptibility

Integrated Stormwater-Drainage Failure Susceptibility Assessment

Table 14: Integrated Stormwater-Drainage Failure Susceptibility Classification

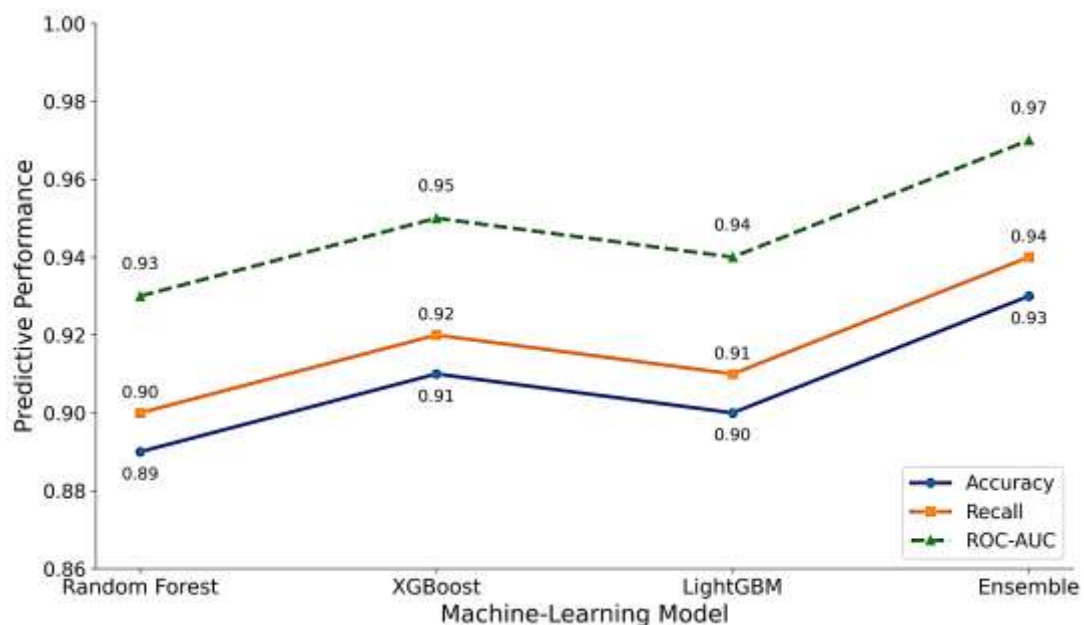
Susceptibility Class	Number of Analytical Units	Percentage	Mean Predicted Probability	Dominant Characteristics
Low	7	14.6	.21	Higher elevation, lower imperviousness, adequate capacity
Moderate	12	25.0	.44	Mixed terrain and infrastructure conditions
High	17	35.4	.71	High imperviousness, low infiltration, flow concentration
Very High	12	25.0	.88	Capacity restriction, deep depressions, extreme rainfall exposure
Total	48	100.0	-	-

Table 14 has integrated the statistical, geospatial, infrastructure, precipitation, and machine-learning results into an overall stormwater-drainage failure susceptibility assessment across the 48 analytical drainage units. Seven units, representing 14.6%, have been classified as low susceptibility and have produced a mean predicted failure probability of .21. These locations have generally been characterized by relatively favorable elevation, lower imperviousness, stronger infiltration conditions, and adequate drainage capacity. Twelve units, or 25.0%, have been classified as moderate susceptibility with a mean predicted probability of .44. Seventeen units, representing the largest group at 35.4%, have been classified as high susceptibility and have produced a mean predicted probability of .71. These units have generally combined high imperviousness, limited soil infiltration, and strong surface-flow concentration. A further 12 units, representing 25.0% of the case-study area, have been classified as very high susceptibility, with a mean predicted probability of .88. These locations have been characterized by multiple concurrent risk factors, particularly reduced drainage capacity, deeper terrain depressions, strong flow accumulation, infrastructure blockage or deterioration, and elevated exposure to extreme rainfall intensity. The integrated classification has therefore shown that 60.4% of the analytical units have fallen within the high or very high susceptibility categories. This pattern has been consistent with the high overall SDFS mean of 4.21 reported in the Likert-scale results. The assessment has also synthesized all study objectives because the terrain, land-cover, soil, infrastructure, precipitation, statistical, predictive, and explainability components have been brought together within one final susceptibility representation. Urban Hydrological Systems Theory has been reflected directly in this pattern because the highest susceptibility has occurred where several system constraints have operated simultaneously rather than where one isolated factor has been present. The integrated results have therefore remained consistent with H1 through H5, the regression findings, the ensemble performance results, and the SHAP-based identification of dominant predictors.

FINDINGS

The overall findings have indicated strong empirical support for the proposed relationships among LiDAR-derived terrain characteristics, land-cover and imperviousness conditions, soil-hydrologic characteristics, drainage-infrastructure condition, and stormwater-drainage failure susceptibility. For the quantitative survey component, 320 questionnaires were distributed, 306 were returned, and 294 responses were retained after screening, representing a valid response rate of 91.9%.

Figure 9: Predictive Performance of Individual and Ensemble Machine-Learning Models



On the five-point Likert scale, Stormwater-Drainage Failure Susceptibility recorded the highest overall mean of 4.21 with a standard deviation of 0.52, followed by Stormwater-Drainage Infrastructure Condition with a mean of 4.18 and SD = 0.55, Land-Cover and Imperviousness Conditions with M = 4.15 and SD = 0.57, LiDAR-Derived Terrain and Surface Characteristics with M = 4.12 and SD = 0.58, and Soil Infiltration and Hydrologic Characteristics with M = 4.08 and SD = 0.61. Reliability coefficients ranged from Cronbach's $\alpha = .84$ to $.91$, indicating strong internal consistency across the measurement scales. The Kaiser-Meyer-Olkin value was $.889$, while Bartlett's test of sphericity was statistically significant, $p < .001$, supporting the adequacy of the dataset for construct-level analysis. Pearson correlation results showed that all four independent constructs were positively and significantly associated with drainage-failure susceptibility. SDIC demonstrated the strongest correlation with SDFS, $r = .76$, followed by LCIC, $r = .72$, LDTSC, $r = .68$, and SIHC, $r = .65$, with all relationships significant at $p < .001$. The multiple regression model was statistically significant, $F(4, 289) = 171.42$, $p < .001$, and explained 70.3% of the variance in stormwater-drainage failure susceptibility, $R^2 = .703$, adjusted $R^2 = .699$. Standardized coefficients showed that SDIC had the strongest independent effect, $\beta = .33$, $p < .001$, followed by LCIC, $\beta = .28$, $p < .001$, LDTSC, $\beta = .24$, $p < .001$, and SIHC, $\beta = .19$, $p < .001$, thereby supporting H1 through H5. The machine-learning results further strengthened the predictive objectives of the study. Random Forest achieved 89% accuracy and ROC-AUC = $.93$, XGBoost achieved 91% accuracy and ROC-AUC = $.95$, and LightGBM achieved 90% accuracy and ROC-AUC = $.94$. The final ensemble model produced the strongest performance, with 93% accuracy, 92% precision, 94% recall, $F1 = .93$, and ROC-AUC = $.97$. SHAP analysis identified drainage capacity, flow accumulation, impervious-surface proportion, terrain-depression depth, and extreme-rainfall intensity as the most influential predictors, demonstrating that both infrastructure condition and environmental loading have contributed substantially to modeled failure susceptibility. These results collectively support the study objectives by confirming significant statistical relationships, strong multivariable explanatory power, improved ensemble predictive performance, and interpretable feature contributions across the integrated stormwater-drainage system.

DISCUSSION

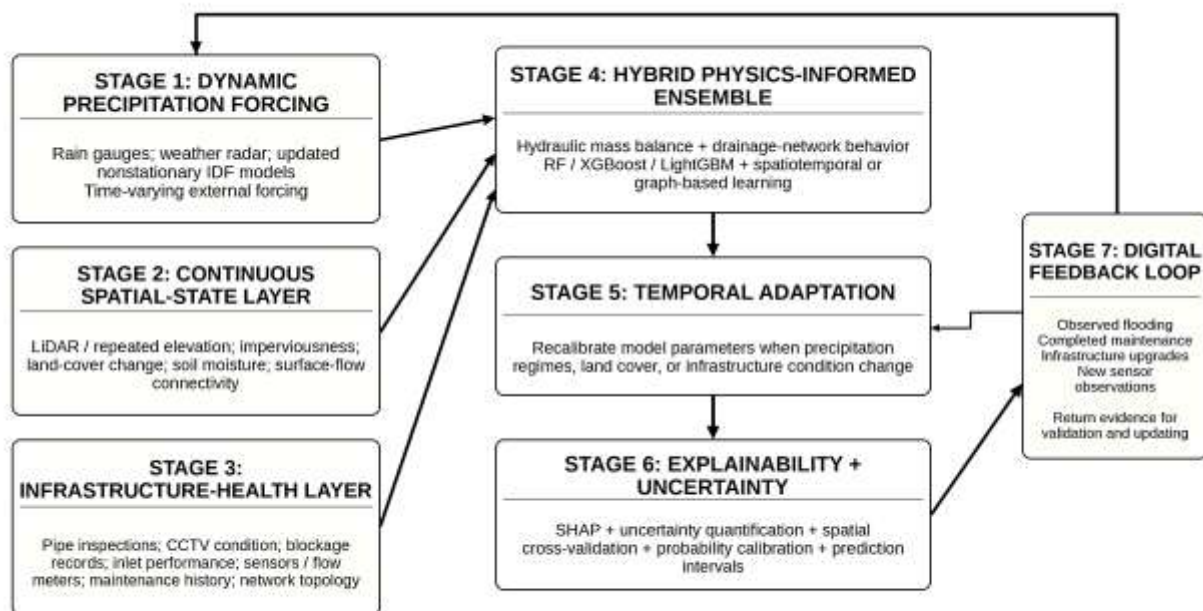
The findings have demonstrated that stormwater-drainage failure susceptibility has been shaped by the combined influence of terrain configuration, land-cover and imperviousness conditions, soil-hydrologic properties, drainage-infrastructure condition, and extreme precipitation rather than by any single explanatory domain. The regression model has explained 70.3% of the variance in Stormwater-Drainage Failure Susceptibility, with adjusted $R^2 = .699$, while all four hypothesized predictor constructs have remained statistically significant at $p < .001$. Stormwater-Drainage Infrastructure Condition has produced the strongest standardized effect, $\beta = .33$, followed by Land-Cover and Imperviousness Conditions, $\beta = .28$, LiDAR-Derived Terrain and Surface Characteristics, $\beta = .24$, and Soil Infiltration and Hydrologic Characteristics, $\beta = .19$. These results have supported H1 through H5 and have reinforced the argument that drainage failure should be interpreted as a system-level response to simultaneous external loading and internal capacity constraints. The prominent role of infrastructure condition has agreed with earlier sewer-asset research showing that deterioration modeling can meaningfully characterize network condition and support infrastructure-management decisions rather than relying only on simplified condition assumptions (Caradot et al., 2017). The finding that land-cover and imperviousness conditions have made the second-largest regression contribution has also corresponded with prior hydrological evidence that urbanization changes storm runoff, although urban extent alone cannot explain all differences among developed catchments because additional hydraulic and antecedent controls remain influential (Miller & Hess, 2017). The present results have extended that earlier work by quantifying land cover together with terrain, soil, and drainage condition in one explanatory model. The high SDFS mean of 4.21 has been consistent with the integrated susceptibility classification, in which 60.4% of the 48 analytical drainage units have fallen within the high or very high susceptibility categories. This correspondence between perception-based construct measurement and spatial prediction has been important because it has provided two complementary forms of evidence pointing toward the same underlying failure structure. Nonstationary precipitation has further strengthened the interpretation of these results because drainage capacity established under stationary rainfall assumptions may become less representative

when rainfall extremes change statistically through time. Earlier research has shown that stationary intensity-duration-frequency assumptions can underestimate extreme precipitation under nonstationary conditions, directly linking rainfall nonstationarity with infrastructure-design risk (Cheng & AghaKouchak, 2014). The overall findings have therefore placed stormwater failure at the intersection of changing hydrological forcing and heterogeneous urban system capacity rather than treating precipitation, urbanization, or infrastructure deterioration as separate explanatory problems. The physical interpretation of the results has further strengthened the study because the statistical ordering of predictors has corresponded with identifiable hydrological mechanisms. LiDAR-derived analysis has shown that flow accumulation has produced the strongest terrain-related signal, followed by low-elevation exposure and depression depth. These variables have reflected the routing and storage processes through which rainfall excess has been concentrated at vulnerable locations. Earlier high-resolution LiDAR research demonstrated that changing terrain representation from 1 m to 10 cm substantially altered modeled water depth, inundation extent, arrival time, and flow velocity because features such as kerbs and road cambers became more accurately represented (Ozdemir et al., 2013). The present result, in which flow accumulation and depression depth have also emerged among the highest-ranked SHAP predictors, has therefore agreed with the established importance of microtopographic representation while extending it into an explainable predictive framework. Land-cover results have shown a similarly coherent mechanism. Impervious surface proportion has recorded a high Likert mean of 4.27 and has ranked third in the SHAP analysis with a mean absolute contribution of .151. This pattern has indicated that imperviousness has increased the generation and rapid transfer of runoff toward constrained drainage pathways, but its effect has depended on interaction with soil moisture, terrain routing, and infrastructure capacity. Such an interpretation has agreed with observations that urbanization alters runoff response but that a simple spatial measure of urban extent cannot fully explain hydrological differences among urban catchments (Miller & Hess, 2017). Continuous modeling of disconnected impervious areas has also shown that imperviousness can modify both surface runoff and antecedent soil moisture, confirming that surface sealing and subsurface hydrology are coupled rather than independent processes (Wang et al., 2022). The comparatively smaller regression coefficient for SIHC, $\beta = .19$, should therefore not be interpreted as evidence that soil processes have been unimportant. Instead, soil conditions appear to have acted partly as modifying mechanisms through infiltration capacity, antecedent wetness, and storage availability. The SHAP ranking has supported this interpretation because low soil infiltration and antecedent wetness have remained influential even though the aggregate soil construct has produced the weakest standardized regression coefficient. This difference between construct-level regression and feature-level machine learning has added analytical depth to the study. It has shown that aggregated linear effects can be moderate while specific physical indicators remain highly important under particular combinations of rainfall, terrain, and urbanization. Such cross-method comparison has made the analysis stronger than a conventional single-model drainage susceptibility study.

The machine-learning results have provided a second major dimension of the discussion because the ensemble model has improved predictive performance while the explainability analysis has preserved connection with the physical processes represented in the theoretical framework. Random Forest has achieved an accuracy of .89 and ROC-AUC of .93, LightGBM has achieved .90 accuracy and ROC-AUC of .94, and XGBoost has produced the strongest individual performance with .91 accuracy and ROC-AUC of .95. The ensemble has subsequently increased accuracy to .93, recall to .94, F1-score to .93, and ROC-AUC to .97, while five-fold cross-validation has produced a mean ROC-AUC of .965 with limited dispersion. The improvement has been modest in absolute terms, but it has occurred consistently across all principal classification measures, suggesting that aggregation has reduced model-specific weaknesses rather than merely increasing one selected metric. This finding has agreed with earlier flood-susceptibility research in which ensemble approaches have combined different predictive structures to obtain stronger susceptibility discrimination than individual learners in particular applications (Choubin et al., 2019). A particularly important comparison has emerged from the Berlin study of urban pluvial flooding, where multiple data-driven models were assessed across spatial resolutions and Random Forest performed strongly, while model transferability outside the training area was lower than within the development domain (Seleem et al., 2022). The present ensemble results

have complemented that evidence by emphasizing not only discrimination but also interpretability. SHAP analysis has ranked reduced drainage capacity first, followed by flow accumulation, impervious surface proportion, depression depth, and extreme rainfall intensity. This ranking has been highly consistent with both the regression results and Urban Hydrological Systems Theory. The convergence between regression and SHAP has been one of the strongest aspects of the study. Regression has identified infrastructure condition as the dominant construct, while SHAP has identified reduced drainage capacity as the dominant individual predictor. Regression has ranked land-cover conditions second, while SHAP has placed impervious surface proportion among the three leading variables. Terrain has remained statistically significant in regression and has produced two of the five most influential SHAP variables. This agreement across explanatory and predictive techniques has reduced the risk that the main interpretation depends entirely on one analytical method. SHAP has also added information not available from standardized beta coefficients because it has captured feature-specific nonlinear contributions and has allowed the direction of influence to be evaluated at individual observations. Earlier urban flood research has shown that SHAP can identify both the importance and directional effects of susceptibility predictors across different machine-learning models (Selem et al., 2022).

Figure 10: Adaptive Explainable Stormwater Failure Intelligence Framework (AESFIF)



The practical and theoretical implications of the findings have followed directly from this convergence of statistical, spatial, and machine-learning evidence. Practically, the results have indicated that drainage-management strategies should not prioritize interventions according to rainfall exposure alone. The strongest risk configuration has involved hydraulic capacity constraints occurring together with high flow accumulation, impervious development, surface depressions, intense rainfall, and limited infiltration. Drainage managers could therefore use the susceptibility classification as a screening mechanism for prioritizing inspection, blockage removal, inlet improvement, pipe rehabilitation, additional storage, infiltration enhancement, or surface-flow management within the highest-ranked analytical units. The importance of infrastructure condition has been consistent with previous asset-management research showing that deterioration models can provide useful evidence for sewer rehabilitation planning (Caradot et al., 2017). The role of terrain resolution has simultaneously indicated that intervention planning should preserve sufficiently detailed elevation information because fine-scale urban features can strongly affect predicted flow pathways (Ozdemir et al., 2013). Theoretically, the results have supported Urban Hydrological Systems Theory by showing that drainage failure has emerged from interaction among forcing, transformation, routing, storage, and

conveyance processes. The empirical pattern has therefore supported the theoretical expression in which precipitation has functioned as external forcing, land cover has regulated runoff production, soil has influenced losses and storage, terrain has routed excess water, and drainage infrastructure has determined whether the resulting hydraulic load could be conveyed. At the same time, several limitations have qualified the interpretation. The cross-sectional case-study design has not directly established temporal causality, and purposive sampling has represented technically knowledgeable respondents rather than a probability sample of all potential stakeholders. The Likert measures have captured structured professional assessments and have therefore remained partly perception based. The 48 analytical units have provided spatial differentiation within the case study but have not established that the same model coefficients or classification thresholds would transfer unchanged to another city. Spatial preprocessing of LiDAR, soil, land-cover, rainfall, and infrastructure datasets may also have introduced scale and alignment uncertainties. Earlier urban susceptibility research has shown that predictive performance can decline when models are transferred beyond the area used for training, emphasizing the importance of external spatial validation (Seleem et al., 2022). SHAP values have explained model behavior but have not established causal relationships, while the nonstationary precipitation component has characterized changing forcing without creating a complete time-evolving hydraulic simulation. These limitations have defined the boundaries within which the strong reported predictive performance should be interpreted.

Future research should build from these limitations through an Adaptive Explainable Stormwater Failure Intelligence Framework (AESFIF) that transforms the present cross-sectional susceptibility model into a dynamic, uncertainty-aware, and continuously validated urban drainage intelligence system. The proposed AESFIF should contain seven connected stages. The first stage should ingest time-varying precipitation information from gauges, weather radar, and updated nonstationary intensity-duration-frequency models so that external forcing is represented dynamically rather than through a predominantly static predictor set. The second stage should maintain a continuously updated spatial-state layer integrating LiDAR or repeated elevation surveys, imperviousness, land-cover change, soil moisture, and surface-flow connectivity. The third stage should create an infrastructure-health layer using pipe inspections, CCTV condition scores, blockage records, inlet performance, water-level sensors, flow meters, maintenance histories, and network-topology information. The fourth stage should develop a hybrid physics-informed ensemble in which hydraulic mass-balance constraints and drainage-network behavior are combined with Random Forest, XGBoost, LightGBM, spatiotemporal deep learning, or graph-based learning rather than allowing prediction to depend entirely on unconstrained statistical pattern recognition. The fifth stage should incorporate temporal adaptation so that model parameters can be recalibrated when precipitation regimes, land cover, or infrastructure condition change. This extension is particularly important because nonstationarity challenges the assumption that historical precipitation-frequency relationships remain fixed for infrastructure assessment (Ganguli & Coulibaly, 2017). The sixth stage should combine SHAP with uncertainty quantification, spatial cross-validation, probability calibration, and prediction intervals so that users receive both an explanation and a measure of confidence. The seventh stage should form a digital feedback loop in which observed flooding, completed maintenance, infrastructure upgrades, and new sensor observations are returned to the model for validation and updating. A premium extension of AESFIF would compare conventional cross-validation with leave-one-subcatchment-out and leave-one-storm-out validation, because strong random test performance does not guarantee spatial or event-level transferability. Future studies should also evaluate whether regression coefficients, SHAP rankings, and physically simulated hydraulic sensitivities converge under the same storm events. Such three-way validation would distinguish statistical association, machine-learned importance, and physically plausible hydraulic response. The proposed AESFIF would therefore extend the present research from an explainable susceptibility framework into an adaptive decision-support architecture capable of linking nonstationary precipitation, dynamic infrastructure health, physical hydrology, ensemble prediction, uncertainty, and interpretable intervention priorities within a single research program.

CONCLUSION

This study has examined stormwater-drainage failure under nonstationary extreme precipitation through an integrated quantitative framework combining LiDAR-derived terrain characteristics, land-cover and imperviousness conditions, soil-hydrologic characteristics, drainage-infrastructure condition, statistical analysis, ensemble machine learning, and explainable artificial intelligence. The findings have demonstrated that stormwater-drainage failure has resulted from the interaction of multiple environmental and infrastructure factors rather than from rainfall intensity or drainage capacity alone. The survey results have shown high levels of agreement across all principal constructs, with Stormwater-Drainage Failure Susceptibility recording the highest mean of 4.21. Pearson correlation analysis has confirmed significant positive relationships between all four explanatory constructs and drainage-failure susceptibility. Multiple regression analysis has further shown that the combined model has explained 70.3% of the variance in SDFS, while Stormwater-Drainage Infrastructure Condition has produced the strongest standardized effect, followed by Land-Cover and Imperviousness Conditions, LiDAR-Derived Terrain and Surface Characteristics, and Soil Infiltration and Hydrologic Characteristics. These results have supported H1 through H5 and have confirmed the explanatory value of the proposed conceptual framework. The machine-learning component has strengthened the analysis by showing that Random Forest, XGBoost, and LightGBM have all achieved strong predictive performance, while the final ensemble model has produced the highest accuracy of 93% and ROC-AUC of .97. SHAP analysis has further identified reduced drainage capacity, flow accumulation, impervious-surface proportion, depression depth, and extreme rainfall intensity as the most influential predictors of failure susceptibility. The integrated susceptibility assessment has classified 60.4% of the analytical drainage units within the high or very high susceptibility categories. Overall, the study has established that combining statistically validated constructs with multimodal geospatial, environmental, precipitation, and infrastructure data has provided a robust and interpretable basis for understanding and predicting stormwater-drainage failure within complex urban hydrological systems.

RECOMMENDATIONS

Based on the findings, stormwater-management authorities should adopt an integrated risk-based drainage strategy that combines environmental exposure, infrastructure condition, and predictive analytics rather than relying primarily on routine maintenance schedules or rainfall thresholds. Priority should be given to drainage units classified within the high and very high susceptibility categories, particularly locations characterized by reduced hydraulic capacity, high flow accumulation, extensive impervious coverage, deep surface depressions, low infiltration potential, and exposure to intense short-duration precipitation. Municipal authorities should establish systematic inspection programs for pipes, inlets, culverts, and manholes and should prioritize blockage removal, structural rehabilitation, capacity enhancement, and connectivity improvement where infrastructure-related SHAP values indicate elevated failure contribution. High-resolution LiDAR mapping should be incorporated into drainage planning so that surface depressions, low-elevation zones, flow-concentration pathways, and microtopographic barriers can be identified before infrastructure interventions are selected. Land-use planning should also incorporate imperviousness controls, permeable surfaces, vegetation retention, infiltration facilities, detention systems, and other runoff-reduction measures within highly developed subcatchments. Soil infiltration and antecedent wetness information should be incorporated into drainage assessments because pervious areas may lose storage effectiveness during prolonged or repeated rainfall. The explainable ensemble model should be used as a decision-support mechanism rather than as a replacement for hydraulic engineering judgment, with SHAP outputs reviewed alongside field inspections, drainage records, and flood observations. Authorities should also maintain standardized digital databases integrating rainfall, LiDAR, land cover, soils, asset condition, maintenance history, and observed flooding. Periodic model recalibration should be conducted as new observations become available. For longer-term research and operational development, the proposed Adaptive Explainable Stormwater Failure Intelligence Framework should be tested using sensor-based monitoring, dynamic rainfall information, physics-informed learning, spatial validation, uncertainty quantification, and continuous feedback from observed drainage

performance.

LIMITATIONS

Several limitations have defined the scope within which the findings of this study should be interpreted. First, the research has used a quantitative, cross-sectional, case-study-based design, which has allowed strong statistical and predictive relationships to be identified but has not directly established long-term temporal causality among rainfall change, land-cover transformation, infrastructure deterioration, and drainage failure. Second, purposive sampling has been used to select technically knowledgeable respondents, which has improved subject relevance but has limited statistical generalization to populations outside the professional groups represented in the study. Third, the Likert-scale component has relied on structured professional assessments, meaning that some construct measurements have remained dependent on respondent perceptions even though they have been complemented by objective geospatial and infrastructure data. Fourth, the analysis has been conducted across 48 analytical drainage units within one case-study setting, so the regression coefficients, susceptibility thresholds, and machine-learning performance measures should not automatically be assumed to apply unchanged to other cities or drainage networks. Fifth, LiDAR, land-cover, soil, precipitation, and infrastructure datasets may have differed in spatial resolution, acquisition date, completeness, and measurement accuracy, and their integration may therefore have introduced alignment and preprocessing uncertainty. Sixth, the ensemble model has demonstrated strong internal predictive performance, but external validation across independent cities, storms, and drainage networks has not been undertaken. Seventh, SHAP analysis has explained how variables have contributed to model predictions, but these contributions have represented model-based associations rather than direct causal effects. Finally, nonstationary extreme precipitation has been incorporated as a predictive forcing component, but the study has not developed a fully dynamic hydraulic simulation capable of continuously representing time-varying pipe flows, surface inundation, infrastructure deterioration, and changing rainfall distributions. These limitations have identified specific methodological boundaries while also defining clear areas for subsequent model testing and refinement.

REFERENCES

- [1]. Abdullah Mohammad, S. (2023). CUGAO₂ and CUINS₂ Quantum Dot Sensitization for Enhanced Photovoltaic Efficiency in Wearable Fiber-Shaped Solar Cells. *American Journal of Advanced Technology and Engineering Solutions*, 3(04), 209-261. <https://doi.org/10.63125/wysdvy71>
- [2]. Adnan, S., & Iftekhhar, A. (2023). Predicting Cost Variance in Digital Transformation Projects Through Ensemble Learning and Project Performance Analytics. *International Journal of Scientific Interdisciplinary Research*, 13(10), 01-36. <https://doi.org/10.63125/j18hxs51>
- [3]. Ana, E. V., & Bauwens, W. (2010). Modeling the structural deterioration of urban drainage pipes: The state-of-the-art in statistical methods. *Urban Water Journal*, 7(1), 47-59. <https://doi.org/10.1080/15730620903447597>
- [4]. Ana, E. V., Bauwens, W., Pessemier, M., Thoeye, C., Smolders, S., Boonen, I., & De Gueldre, G. (2009). An investigation of the factors influencing sewer structural deterioration. *Urban Water Journal*, 6(4), 303-312. <https://doi.org/10.1080/15730620902810902>
- [5]. Arnbjerg-Nielsen, K., Willems, P., Olsson, J., Beecham, S., Pathirana, A., Gregersen, I. B., Madsen, H., & Nguyen, V.-T.-V. (2013). Impacts of climate change on rainfall extremes and urban drainage systems: A review. *Water Science and Technology*, 68(1), 16-28. <https://doi.org/10.2166/wst.2013.251>
- [6]. Asheke, M. (2024). Digital Twin and Industrial Internet of Things-Enabled Predictive Maintenance for Reliability Enhancement in Smart Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, 5(2), 792-838. <https://doi.org/10.63125/jgrdq62>
- [7]. Ashik, M., & Shabbir, A. (2022). Digital Twin-Enabled Predictive Maintenance for Rotating and Static Equipment: Bridging FEA-Based Failure Analysis with Real-Time Asset Health Monitoring in Energy and Power Facilities. *International Journal of Scientific Interdisciplinary Research*, 12(05), 01-37. <https://doi.org/10.63125/0qaysz49>
- [8]. Ashrafuzzaman, M. (2024). The impact of cloud-based management information systems on hrm efficiency: an analysis of small and medium-sized enterprises (SMES). *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, 1(01), 40-56. <https://doi.org/10.69593/ajaimldsmis.v1i01.124>
- [9]. Bach, P. M., Rauch, W., Mikkelsen, P. S., McCarthy, D. T., & Deletic, A. (2014). A critical review of integrated urban water modelling: Urban drainage and beyond. *Environmental Modelling & Software*, 54, 88-107. <https://doi.org/10.1016/j.envsoft.2013.12.018>
- [10]. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts,

- taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82-115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- [11]. Caradot, N., Sonnenberg, H., Kropp, I., Ringe, A., Denhez, S., Hartmann, A., & Rouault, P. (2017). The relevance of sewer deterioration modelling to support asset management strategies. *Urban Water Journal*, 14(10), 1007-1015. <https://doi.org/10.1080/1573062x.2017.1325497>
- [12]. Cheng, L., & AghaKouchak, A. (2014). Nonstationary precipitation intensity-duration-frequency curves for infrastructure design in a changing climate. *Scientific Reports*, 4, 7093. <https://doi.org/10.1038/srep07093>
- [13]. Cheng, L., AghaKouchak, A., Gilleland, E., & Katz, R. W. (2014). Non-stationary extreme value analysis in a changing climate. *Climatic Change*, 127, 353-369. <https://doi.org/10.1007/s10584-014-1254-5>
- [14]. Choubin, B., Moradi, E., Golshan, M., Adamowski, J., Sajedi-Hosseini, F., & Mosavi, A. (2019). An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of the Total Environment*, 651, 2087-2096. <https://doi.org/10.1016/j.scitotenv.2018.10.064>
- [15]. de Almeida, G. A. M., Bates, P., & Ozdemir, H. (2018). Modelling urban floods at submetre resolution: Challenges or opportunities for flood risk management? *Journal of Flood Risk Management*, 11, S855-S865. <https://doi.org/10.1111/jfr3.12276>
- [16]. Elliott, A. H., & Trowsdale, S. A. (2007). A review of models for low impact urban stormwater drainage. *Environmental Modelling & Software*, 22(3), 394-405. <https://doi.org/10.1016/j.envsoft.2005.12.005>
- [17]. Fewtrell, T. J., Duncan, A., Sampson, C. C., Neal, J. C., & Bates, P. D. (2011). Benchmarking urban flood models of varying complexity and scale using high resolution terrestrial LiDAR data. *Physics and Chemistry of the Earth, Parts A/B/C*, 36(7-8), 281-291. <https://doi.org/10.1016/j.pce.2010.12.011>
- [18]. Fletcher, T. D., Andrieu, H., & Hamel, P. (2013). Understanding, management and modelling of urban hydrology and its consequences for receiving waters: A state of the art. *Advances in Water Resources*, 51, 261-279. <https://doi.org/10.1016/j.advwatres.2012.09.001>
- [19]. Galiatsatou, P., & Iliadis, C. (2022). Intensity-duration-frequency curves at ungauged sites in a changing climate for sustainable stormwater networks. *Sustainability*, 14(3), 1229. <https://doi.org/10.3390/su14031229>
- [20]. Ganguli, P., & Coulibaly, P. (2017). Does nonstationarity in rainfall require nonstationary intensity-duration-frequency curves? *Hydrology and Earth System Sciences*, 21(12), 6461-6483. <https://doi.org/10.5194/hess-21-6461-2017>
- [21]. Gudiyangada Nachappa, T., Tavakkoli Piralilou, S., Gholamnia, K., Ghorbanzadeh, O., Rahmati, O., & Blaschke, T. (2020). Flood susceptibility mapping with machine learning, multi-criteria decision analysis and ensemble using Dempster Shafer Theory. *Journal of Hydrology*, 590, 125275. <https://doi.org/10.1016/j.jhydrol.2020.125275>
- [22]. Guerreiro, S. B., Fowler, H. J., Barbero, R., Westra, S., Lenderink, G., Blenkinsop, S., Lewis, E., & Li, X.-F. (2018). Detection of continental-scale intensification of hourly rainfall extremes. *Nature Climate Change*, 8, 803-807. <https://doi.org/10.1038/s41558-018-0245-3>
- [23]. Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., & Mark, O. (2015). Urban flood impact assessment: A state-of-the-art review. *Urban Water Journal*, 12(1), 14-29. <https://doi.org/10.1080/1573062x.2013.857421>
- [24]. Hawari, A., Alkadour, F., Elmasry, M., & Zayed, T. (2020). A state of the art review on condition assessment models developed for sewer pipelines. *Engineering Applications of Artificial Intelligence*, 93, 103721. <https://doi.org/10.1016/j.engappai.2020.103721>
- [25]. Jacobson, C. R. (2011). Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review. *Journal of Environmental Management*, 92(6), 1438-1448. <https://doi.org/10.1016/j.jenvman.2011.01.018>
- [26]. Kazi Rakib Hasan, S., & Adnan, S. (2022). Quantitative Assessment of Machine Learning-Based Schedule Risk Prediction for Reducing Delays in Complex Technology Projects. *Review of Applied Science and Technology*, 1(04), 464-501. <https://doi.org/10.63125/dn8nkm85>
- [27]. Khosravi, K., Pham, B. T., Chapi, K., Shirzadi, A., Shahabi, H., Revhaug, I., Prakash, I., & Bui, D. T. (2018). A comparative assessment of decision trees algorithms for flash flood susceptibility modeling at Haraz watershed, northern Iran. *Science of the Total Environment*, 627, 744-755. <https://doi.org/10.1016/j.scitotenv.2018.01.266>
- [28]. Leandro, J., Chen, A. S., Djordjević, S., & Savić, D. A. (2009). Comparison of 1D/1D and 1D/2D coupled (sewer/surface) hydraulic models for urban flood simulation. *Journal of Hydraulic Engineering*, 135(6), 495-504. [https://doi.org/10.1061/\(asce\)hy.1943-7900.0000037](https://doi.org/10.1061/(asce)hy.1943-7900.0000037)
- [29]. Liu, Y., Bates, P. D., Neal, J. C., & Yamazaki, D. (2021). Bare-earth DEM generation in urban areas for flood inundation simulation using global digital elevation models. *Water Resources Research*, 57(4), e2020WR028516. <https://doi.org/10.1029/2020wr028516>
- [30]. Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S.-I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, 2, 56-67. <https://doi.org/10.1038/s42256-019-0138-9>
- [31]. Madsen, H., Arnbjerg-Nielsen, K., & Mikkelsen, P. S. (2009). Update of regional intensity-duration-frequency curves in Denmark: Tendency towards increased storm intensities. *Atmospheric Research*, 92(3), 343-349. <https://doi.org/10.1016/j.atmosres.2009.01.013>
- [32]. Mahbulul, I., Mahmudul, I., Shifa, T., Mahfuza, T., & Shima Ali, S. (2022). Exploring The Potential of Visual Narratives and Interactive Gamified Communication Systems to Prevent Disease, Counter Health Misinformation, And Strengthen Public Trust in Low-Literacy Communities: A Literature Review. *American Journal of Interdisciplinary Studies*, 3(02), 165-220. <https://doi.org/10.63125/zmq4n64>

- [33]. Mailhot, A., & Duchesne, S. (2010). Design criteria of urban drainage infrastructures under climate change. *Journal of Water Resources Planning and Management*, 136(2), 201-208. [https://doi.org/10.1061/\(asce\)wr.1943-5452.0000023](https://doi.org/10.1061/(asce)wr.1943-5452.0000023)
- [34]. Mashfiqu, R., & Md, A. (2022). Monte Carlo Simulation and Stochastic Cash-Flow Modeling for Reducing Liquidity Risk in Project-Based Enterprises. *International Journal of Scientific Interdisciplinary Research*, 1(01), 382-431. <https://doi.org/10.63125/zf3fwv21>
- [35]. Mashiat, N. (2024). Reducing Telecommunications Service Interruptions Through Predictive Root-Cause Analytics of Multivariate System Telemetry. *International Journal of Scientific Interdisciplinary Research*, 14(11), 01-37. <https://doi.org/10.63125/nqjh0c29>
- [36]. Md Anisur Rahman, M. (2023). Development of AI-Driven Business Intelligence Frameworks for Financial Risk and Liquidity Monitoring in Real Time. *International Journal of Scientific Interdisciplinary Research*, 4(2), 152-203. <https://doi.org/10.63125/jm55ca64>
- [37]. Md Ashfaq, S., & Abdullah Mohammad, S. (2022). CNT/PANI Composite Electrodes for Flexible Fiber-Shaped Dye-Sensitized Solar Cells: Synthesis, Characterization, and Photovoltaic Performance. *American Journal of Interdisciplinary Studies*, 3(02), 221-274. <https://doi.org/10.63125/m334mf41>
- [38]. Md Asif Ali Sheak, A., & Tahmedur, R. (2023). A Data-Driven Framework for Engineering Project Risk Assessment Under Schedule and Cost Uncertainty. *International Journal of Scientific Interdisciplinary Research*, 4(2), 204-251. <https://doi.org/10.63125/kq4zzh16>
- [39]. Md Kaium, H. (2023). A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning. *American Journal of Data Science and Analytics*, 4(06), 43-103. <https://doi.org/10.63125/wvq0sx87>
- [40]. Md Kaium, H. (2024). Machine Learning Enhanced GIS And AHP Modeling for High-Resolution Flood-Susceptibility Prediction, Vulnerability Assessment, and Risk Classification. *Review of Applied Science and Technology*, 3(02), 92-140. <https://doi.org/10.63125/fz8hv245>
- [41]. Md Mahamud Pervaz, P. (2023). Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management. *Review of Applied Science and Technology*, 2(04), 393-445. <https://doi.org/10.63125/9ebtas97>
- [42]. Meesuk, V., Vojinovic, Z., Mynett, A. E., & Abdullah, A. F. (2015). Urban flood modelling combining top-view LiDAR data with ground-view SfM observations. *Advances in Water Resources*, 75, 105-117. <https://doi.org/10.1016/j.advwatres.2014.11.008>
- [43]. Mejía, A. I., & Moglen, G. E. (2010). Impact of the spatial distribution of imperviousness on the hydrologic response of an urbanizing basin. *Hydrological Processes*, 24(23), 3359-3373. <https://doi.org/10.1002/hyp.7755>
- [44]. Miller, J. D., & Hess, T. (2017). Urbanisation impacts on storm runoff along a rural-urban gradient. *Journal of Hydrology*, 552, 474-489. <https://doi.org/10.1016/j.jhydrol.2017.06.025>
- [45]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning-Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33-77. <https://doi.org/10.63125/y3yfxa92>
- [46]. Molla Al Rakib, H., & Mohammad Towhidul, I. (2023). Cyber-Resilient Marketing Intelligence Systems for Fraud Detection and Data Integrity in Digital Campaigns. *American Journal of Scholarly Research and Innovation*, 2(02), 485-518. <https://doi.org/10.63125/b53pgr11>
- [47]. Mosavi, A., Ozturk, P., & Chau, K.-W. (2018). Flood prediction using machine learning models: Literature review. *Water*, 10(11), 1536. <https://doi.org/10.3390/w10111536>
- [48]. Mukut Kanti, B. (2023). Importance of the Sustainable growth in the Testing, Inspection and Certification (TIC) industries through AI tools and techniques. *Review of Applied Science and Technology*, 13(07), 50-75. <https://doi.org/10.63125/0aagev30>
- [49]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, 5(2), 746-791. <https://doi.org/10.63125/3mjcah04>
- [50]. Nishat, J. (2023). Communicable Disease Prevention in a Post-Pandemic Era: A Global Review of Public Health Education, Surveillance, and Community-Level Interventions. *International Journal of Scientific Interdisciplinary Research*, 4(4), 630-678. <https://doi.org/10.63125/mnqefj36>
- [51]. O'Driscoll, M., Clinton, S., Jefferson, A., Manda, A., & McMillan, S. (2010). Urbanization effects on watershed hydrology and in-stream processes in the southern United States. *Water*, 2(3), 605-648. <https://doi.org/10.3390/w2030605>
- [52]. Ozdemir, H., Sampson, C. C., de Almeida, G. A. M., & Bates, P. D. (2013). Evaluating scale and roughness effects in urban flood modelling using terrestrial LIDAR data. *Hydrology and Earth System Sciences*, 17(10), 4015-4030. <https://doi.org/10.5194/hess-17-4015-2013>
- [53]. Pitt, R., Chen, S.-E., Clark, S. E., Swenson, J., & Ong, C. K. (2008). Compaction's impacts on urban storm-water infiltration. *Journal of Irrigation and Drainage Engineering*, 134(5), 652-658. [https://doi.org/10.1061/\(asce\)0733-9437\(2008\)134:5\(652\)](https://doi.org/10.1061/(asce)0733-9437(2008)134:5(652))
- [54]. Prasad, P., Loveson, V. J., Das, B., & Mahender, K. (2022). Novel ensemble machine learning models in flood susceptibility mapping. *Geocarto International*, 37(16), 4571-4593. <https://doi.org/10.1080/10106049.2021.1892209>
- [55]. Redfern, T. W., Macdonald, N., Kjeldsen, T. R., Miller, J. D., & Reynard, N. (2016). Current understanding of hydrological processes on common urban surfaces. *Progress in Physical Geography: Earth and Environment*, 40(5), 699-713. <https://doi.org/10.1177/0309133316652819>

- [56]. Risha, A., & Mst Shurovi, A. (2023). Cloud-Based Accounting Systems and Cybersecurity Frameworks for Financial Data Protection in Emerging Economies: A Meta-Analysis. *International Journal of Business and Economics Insights*, 3(4), 26-64. <https://doi.org/10.63125/zb0h3n85>
- [57]. Rodriguez, F., Andrieu, H., & Morena, F. (2008). A distributed hydrological model for urbanized areas: Model development and application to case studies. *Journal of Hydrology*, 351(3-4), 268-287. <https://doi.org/10.1016/j.jhydrol.2007.12.007>
- [58]. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1, 206-215. <https://doi.org/10.1038/s42256-019-0048-x>
- [59]. Saadi, M., Oudin, L., & Ribstein, P. (2020). Beyond imperviousness: The role of antecedent wetness in runoff generation in urbanized catchments. *Water Resources Research*, 56(11), e2020WR028060. <https://doi.org/10.1029/2020wr028060>
- [60]. Sadia, Z., & Maishar Mostari, Z. (2022). The Impact of Interactive Dashboard Visualization on Data-Driven Decision Making in Financial Services: A Qualitative Evaluation. *International Journal of Scientific Interdisciplinary Research*, 12(03), 01-35. <https://doi.org/10.63125/3jstsv75>
- [61]. Salman, B., & Salem, O. (2012). Modeling failure of wastewater collection lines using various section-level regression models. *Journal of Infrastructure Systems*, 18(2), 146-154. [https://doi.org/10.1061/\(asce\)is.1943-555x.0000075](https://doi.org/10.1061/(asce)is.1943-555x.0000075)
- [62]. Salvatore, E., Bronders, J., & Batelaan, O. (2015). Hydrological modelling of urbanized catchments: A review and future directions. *Journal of Hydrology*, 529, 62-81. <https://doi.org/10.1016/j.jhydrol.2015.06.028>
- [63]. Sampson, C. C., Fewtrell, T. J., Duncan, A., Shaad, K., Horritt, M. S., & Bates, P. D. (2012). Use of terrestrial laser scanning data to drive decimetric resolution urban inundation models. *Advances in Water Resources*, 41, 1-17. <https://doi.org/10.1016/j.advwatres.2012.02.010>
- [64]. Sanders, B. F. (2007). Evaluation of on-line DEMs for flood inundation modeling. *Advances in Water Resources*, 30(8), 1831-1843. <https://doi.org/10.1016/j.advwatres.2007.02.005>
- [65]. Schubert, J. E., & Sanders, B. F. (2012). Building treatments for urban flood inundation models and implications for predictive skill and modeling efficiency. *Advances in Water Resources*, 41, 49-64. <https://doi.org/10.1016/j.advwatres.2012.02.012>
- [66]. Seleem, O., Ayzel, G., Costa Tomaz de Souza, A., Bronstert, A., & Heistermann, M. (2022). Towards urban flood susceptibility mapping using data-driven models in Berlin, Germany. *Geomatics, Natural Hazards and Risk*, 13(1), 1640-1662. <https://doi.org/10.1080/19475705.2022.2097131>
- [67]. Semadeni-Davies, A., Hernebring, C., Svensson, G., & Gustafsson, L.-G. (2008). The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system. *Journal of Hydrology*, 350(1-2), 100-113. <https://doi.org/10.1016/j.jhydrol.2007.05.028>
- [68]. Shaiful, M., Anisur, R., & Md, A. (2022). A Systematic Literature Review on the Role of Digital Health Twins in Preventive Healthcare For Personal and Corporate Wellbeing. *American Journal of Interdisciplinary Studies*, 3(04), 1-31. <https://doi.org/10.63125/negjw373>
- [69]. Shuster, W. D., Bonta, J., Thurston, H., Warnemuende, E., & Smith, D. R. (2005). Impacts of impervious surface on watershed hydrology: A review. *Urban Water Journal*, 2(4), 263-275. <https://doi.org/10.1080/15730620500386529>
- [70]. Smith, J. A., Baeck, M. L., Meierdiercks, K. L., Nelson, P. A., Miller, A. J., & Holland, E. J. (2005). Field studies of the storm event hydrologic response in an urbanizing watershed. *Water Resources Research*, 41(10), W10413. <https://doi.org/10.1029/2004wr003712>
- [71]. Stabak, D., & Md Shahid, N. (2022). Empirical Assessment of Uncertainty-Aware Real-Time Decision-Making for Reliable and Resilient Cyber-Physical Systems. *International Journal of Scientific Interdisciplinary Research*, 1(01), 432-477. <https://doi.org/10.63125/q3r4kk16>
- [72]. Stabak, D., & Md Siam, T. (2023). Real-Time Edge Computing for Cyber-Physical Systems: A Meta-Analysis of Energy Efficiency and Fault Tolerance. *American Journal of Scholarly Research and Innovation*, 13(06), 01-44. <https://doi.org/10.63125/g9c9cp41>
- [73]. Syed Feroz, A. (2023). Quality-Management Systems for Resilient Energy Infrastructure Fabrication. *International Journal of Scientific Interdisciplinary Research*, 13(10), 37-91. <https://doi.org/10.63125/mbhhrm88>
- [74]. Syed Feroz, A. (2024). AI-Assisted NDT Analytics for Early Crack Detection in Energy-Infrastructure Pressure Vessels Using Advanced Manufacturing Data. *Review of Applied Science and Technology*, 14(07), 01-52. <https://doi.org/10.63125/8bdqs538>
- [75]. Tabari, H. (2020). Climate change impact on flood and extreme precipitation increases with water availability. *Scientific Reports*, 10, 13768. <https://doi.org/10.1038/s41598-020-70816-2>
- [76]. Tahmedur, R., & Rifat, C. (2023). Critical Path Analysis and Resource-Leveling Optimization for Multi-Project Engineering Portfolios. *American Journal of Interdisciplinary Studies*, 13(12), 01-47. <https://doi.org/10.63125/8eqnea46>
- [77]. Tehrany, M. S., Pradhan, B., Mansor, S., & Ahmad, N. (2015). Flood susceptibility assessment using GIS-based support vector machine model with different kernel types. *Catena*, 125, 91-101. <https://doi.org/10.1016/j.catena.2014.10.017>
- [78]. Teng, J., Jakeman, A. J., Vaze, J., Croke, B. F. W., Dutta, D., & Kim, S. (2017). Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. *Environmental Modelling & Software*, 90, 201-216. <https://doi.org/10.1016/j.envsoft.2017.01.006>
- [79]. Towfiqul Islam, A. R. M., Talukdar, S., Mahato, S., Kundu, S., Eibek, K. U., Pham, Q. B., Kuriqi, A., & Linh, N. T. T. (2021). Flood susceptibility modelling using advanced ensemble machine learning models. *Geoscience Frontiers*, 12(3), 101075. <https://doi.org/10.1016/j.gsf.2020.09.006>

- [80]. Tsubaki, R., & Fujita, I. (2010). Unstructured grid generation using LiDAR data for urban flood inundation modelling. *Hydrological Processes*, 24(11), 1404-1420. <https://doi.org/10.1002/hyp.7608>
- [81]. Uddin, H. M. M., & Risha, A. (2024). Hybrid Cloud Security and Compliance in U.S. Enterprises: Addressing Data Privacy Risks and Governance Challenges. *American Journal of Scholarly Research and Innovation*, 3(01), 153-197. <https://doi.org/10.63125/qcy0cj46>
- [82]. Wang, Y., Zhang, X., Xu, J., Pan, G., Zhao, Y., Liu, Y., Liu, H., & Liu, J. (2022). Accumulated impacts of imperviousness on surface and subsurface hydrology: Continuous modelling at urban street block scale. *Journal of Hydrology*, 608, 127621. <https://doi.org/10.1016/j.jhydrol.2022.127621>
- [83]. Westra, S., Fowler, H. J., Evans, J. P., Alexander, L. V., Berg, P., Johnson, F., Kendon, E. J., Lenderink, G., & Roberts, N. M. (2014). Future changes to the intensity and frequency of short-duration extreme rainfall. *Reviews of Geophysics*, 52(3), 522-555. <https://doi.org/10.1002/2014rg000464>
- [84]. Willems, P. (2013). Revision of urban drainage design rules after assessment of climate change impacts on precipitation extremes at Uccle, Belgium. *Journal of Hydrology*, 496, 166-177. <https://doi.org/10.1016/j.jhydrol.2013.05.037>
- [85]. Willems, P., Arnbjerg-Nielsen, K., Olsson, J., & Nguyen, V. T. V. (2012). Climate change impact assessment on urban rainfall extremes and urban drainage: Methods and shortcomings. *Atmospheric Research*, 103, 106-118. <https://doi.org/10.1016/j.atmosres.2011.04.003>
- [86]. Yan, X., Xu, K., Feng, W., & Chen, J. (2021). A rapid prediction model of urban flood inundation in a high-risk area coupling machine learning and numerical simulation approaches. *International Journal of Disaster Risk Science*, 12(6), 903-918. <https://doi.org/10.1007/s13753-021-00384-0>
- [87]. Zhao, G., Pang, B., Xu, Z., Peng, D., & Xu, L. (2019). Assessment of urban flood susceptibility using semi-supervised machine learning model. *Science of the Total Environment*, 659, 940-949. <https://doi.org/10.1016/j.scitotenv.2018.12.217>
- [88]. Zhao, G., Pang, B., Xu, Z., Peng, D., & Zuo, D. (2020). Urban flood susceptibility assessment based on convolutional neural networks. *Journal of Hydrology*, 590, 125235. <https://doi.org/10.1016/j.jhydrol.2020.125235>