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Satellite Remote Sensing and GIS-Based Assessment of Climate Change Impacts on Soil Stability and Infrastructure Resilience

Priyadarshini Patel[1], Amitav Banerjee[2], Rajendra Das[3]

ABSTRACT

Climate change-induced environmental dynamic shifts—characterized by accentuated precipitation extreme regimes, prolonged drought cycles, rapid permafrost thaw, and sea-level rise—are triggering severe soil instabilities worldwide. Slope failures, expansive clay swell-shrink cycles, coastal erosion, and land subsidence pose escalating structural risks to linear and discrete civil infrastructure assets, including highways, railway corridors, foundation systems, and urban embankments. Traditional site-specific geotechnical investigation methods lack the spatiotemporal scalability required to continuously evaluate infrastructure risk across extensive territorial jurisdictions. Satellite Remote Sensing (SRS) integrated with Geographic Information System (GIS) frameworks offers an unprecedented capability for macro- to micro-scale geohazard monitoring, structural deformation tracking, and predictive resilience modeling. This comprehensive review systematically evaluates state-of-the-art earth observation (EO) technologies—incorporating Synthetic Aperture Radar Interferometry (InSAR), high-resolution optical platforms, LiDAR, and multispectral soil moisture retrieval—alongside spatial GIS analytical engines and machine learning (ML) architectures. The operational workflow of data assimilation, feature extraction, constitutive slope stability modeling (e.g., limit equilibrium and finite element analysis coupled with hydro-thermal regimes), and risk assessment is synthesized. Critical operational limitations, including spatiotemporal resolution trade-offs, atmospheric decorrelation, vegetational canopy attenuation, and computational processing bottlenecks, are critically examined. Finally, a strategic research roadmap is outlined, highlighting physics-informed neural networks (PINNs), cloud-native open-source GIS processing pipelines, and

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multi-constellation satellite fusion to support adaptive civil infrastructure design and predictive maintenance paradigms.

KEYWORDS: *Satellite Remote Sensing; GIS; Climate Change; Soil Stability; Infrastructure Resilience; InSAR; Machine Learning; Geohazard Assessment.*

INTRODUCTION

Global climate change represents one of the most severe threat multipliers to earth system stability and built infrastructure integrity in the twenty-first century [1]. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report projects an increase in the frequency and severity of extreme hydrometeorological events, including intense convective precipitation, prolonged heatwaves, and shifting seasonality of monsoons [2]. While atmospheric and hydrological manifestations of climate change are widely documented, their compounding subterranean impact on geotechnical structures and earthworks remains an urgent civil engineering challenge [3].

Soil stability is fundamentally governed by soil suction, pore-water pressure dynamics, volumetric water content, shear strength parameters (cohesion c' and internal friction angle φ'), and thermal regimes [4]. Climate-induced shifts disrupt the hydrological equilibrium of slope systems. Unprecedented precipitation surges induce rapid pore-water pressure accumulation and matrix suction loss, culminating in slope instability, flowslides, and deep-seated landslides [5]. Conversely, extended drought periods cause severe desiccation cracking in expansive fine-grained clays, compromising shear strength and facilitating accelerated water infiltration during subsequent storm surges [6]. Furthermore, high-latitude and high-altitude infrastructure experiences severe bearing capacity degradation and differential settlement driven by permafrost thaw [7].

Linear infrastructure networks—such as interstate highway systems, high-speed rail corridors, energy pipelines, and embankment dams—extend across diverse geographical and geological domains [8]. Conventional geotechnical monitoring relies on localized field instrumentation, such as inclinometers, piezometers, settlement plates, and standalone GPS/GNSS receivers. Although these instruments deliver high temporal precision at specific discrete points, they are cost-prohibitive, labor-intensive, and inherently incapable of

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capturing continuous, wide-area spatial variations across thousands of kilometers of linear assets [9]. Consequently, geohazard development frequently evades detection until catastrophic structural failure occurs.

Satellite Remote Sensing (SRS) and Geographic Information Systems (GIS) provide a powerful solution to these spatial limitations [10]. Earth observation platforms acquire multi-temporal, multi-spectral, and all-weather radar data across vast geographic scales. Advanced techniques such as Interferometric Synthetic Aperture Radar (InSAR)—including Permanent Scatterer (PSInSAR) and Small Baseline Subset (SBAS) algorithms—enable sub-centimeter displacement tracking along infrastructure corridors [11]. Concurrently, spatial GIS frameworks synthesize heterogeneous environmental covariates, including Digital Elevation Models (DEM), land-use/land-cover (LULC) changes, lithological classifications, and precipitation records, into multi-criteria risk maps [12]. Combining SRS, GIS, and computational geotechnical models establishes a proactive paradigm for infrastructure resilience assessment [13].

LITERATURE REVIEW

The convergence of remote sensing, spatial analytics, and geotechnical engineering has evolved across three distinct operational generations over the past four decades [14]. The foundational phase (1980s–1990s) relied on low-to-medium resolution optical platforms (e.g., Landsat MSS/TM) and basic GIS overlay operations to qualitatively map regional landslide susceptibility [15]. These early attempts provided broad spatial context but lacked the spatial resolution and vertical accuracy needed for asset-level infrastructure stability evaluations.

The second generation (2000s–2010s) was marked by the launch of high-resolution optical satellites (e.g., SPOT-5, WorldView, QuickBird) and active Spaceborne Radar sensors (e.g., ERS-1/2, ENVISAT, RADARSAT, TerraSAR-X, COSMO-SkyMed) [16]. The operational development of Differential InSAR (DInSAR) and multi-temporal InSAR techniques allowed researchers to transition from qualitative susceptibility mapping to quantitative measurement of slow-moving slope deformation and surface subsidence [17]. Ferretti et al. [18] introduced Permanent Scatterer InSAR (PSInSAR), demonstrating that stable radar reflectors (e.g., structural buildings, exposed rock outcrops, metal bridge girders) could be tracked across time series to yield millimeter-scale displacement histories. Parallel developments in Small

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Baseline Subset (SBAS) approaches optimized phase coherence over vegetated and rural ground surfaces, broadening radar remote sensing applicability across natural slopes and earthen embankments [19].

The current generation (2020s) is defined by multi-constellation satellite integration, cloud-native geospatial computing platforms (e.g., Google Earth Engine, AWS Open Data), high-frequency re-visit constellations (e.g., Sentinel-1 A/B, PlanetScope, Capella Space SAR), and machine learning integration [20]. Modern research couples space-borne soil moisture measurements (e.g., SMAP, Sentinel-1 backscatter inversion) and thermal infrared surface temperature data with numerical limit equilibrium (LEM) and finite element method (FEM) slope stability solvers [21]. Automated machine learning models, including Random Forest (RF), XGBoost, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, are increasingly used to process high-dimensional spatial layers and predict non-linear slope behavior [22].

Despite these technological advancements, significant literature gaps remain in unifying remote sensing surface observations with subsurface mechanical and hydraulic soil behavior under non-stationary climate conditions [23]. Most InSAR studies treat surface displacement purely as a geometric signal, without incorporating unsaturated soil mechanics theories, suction-stress characteristic curves (SSCC), or transient seepage dynamics [24].

RESEARCH GAP

Critical Gaps Identified in Existing Literature:

- Disconnect Between Surface Earth Observation and Subsurface Geotechnical Mechanics: Existing satellite-based risk models map surface deformation or land cover without assimilating deep unsaturated hydro-mechanical soil properties.
- Non-Stationary Climate Parameterization: Conventional GIS vulnerability models rely on static historical climate baselines, failing to model dynamic future climate projections (IPCC SSP scenarios).
- Resolution and Temporal Decoupling: A spatial-temporal gap exists between high-resolution optical imagery (infrequent revisit) and high-revisit radar/multispectral platforms (lower spatial detail).

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- Lack of Standardized End-to-End Decision Pipelines: Limited operational platforms translate raw multi-sensor remote sensing streams into actionable engineering safety metrics for asset managers.

OBJECTIVES

To resolve the identified scientific gaps, this review paper establishes the following research objectives:

- Synthesize advanced satellite remote sensing technologies (InSAR, high-resolution optical, optical offset tracking, LiDAR, and microwave soil moisture) for monitoring soil instability hazards across linear and urban infrastructure.
- Formulate an integrated hydro-geotechnical GIS framework that explicitly connects climate projections (IPCC SSP scenarios) with unsaturated soil mechanics and surface displacement records.
- Evaluate multi-sensor data fusion methodologies and machine learning architectures for predictive geohazard mapping and asset risk assessment.
- Define a standardized engineering resilience roadmap to guide civil infrastructure asset management, structural mitigation, and climate adaptation strategies.

METHODOLOGY

This review uses an integrative search and analytical synthesis methodology adhering to PRISMA principles for systematic technical evaluation [25]. Literature was retrieved across primary database indexes (Scopus, Web of Science, IEEE Xplore, ASCE Library, and ScienceDirect) using targeted Boolean query formulations combining keywords: ('Satellite Remote Sensing' OR 'InSAR' OR 'GIS') AND ('Climate Change' OR 'Precipitation Extremes') AND ('Soil Stability' OR 'Landslide' OR 'Subsidence') AND ('Infrastructure Resilience' OR 'Asset Management').

The analytical workflow categorizes earth observation and spatial modeling into four primary operational layers, as detailed in Table 1 below:

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Table: 1

Remote Sensing Tech	Primary Measurement Parameter	Spatial & Temporal Resolution	Geotechnical & Infrastructure Target
Multi-Temporal InSAR (PSInSAR / SBAS)	Line-of-Sight (LOS) ground & structural displacement	1–10 m spatial / 6–12 days temporal	Bridge decks, slope creep, highway embankments, land subsidence
High-Res Optical / Optical Offset	Planimetric lateral displacement, surface cracking, LULC	0.3–3 m spatial / 1–5 days temporal	Large landslide runouts, coastal erosion, embankment structural failure
Spaceborne Microwave (SAR / Radiometry)	Volumetric Soil Moisture (VSM), surface wetness index	10 m – 9 km spatial / 1–3 days temporal	Pore-water pressure surge, suction loss in shallow embankment slopes
Airborne / Spaceborne LiDAR	High-precision Bare-Earth DEM, canopy penetration morphology	0.1–1 m spatial / On-demand / multi-year	Deep-seated shear plane identification, structural asset slope geometry

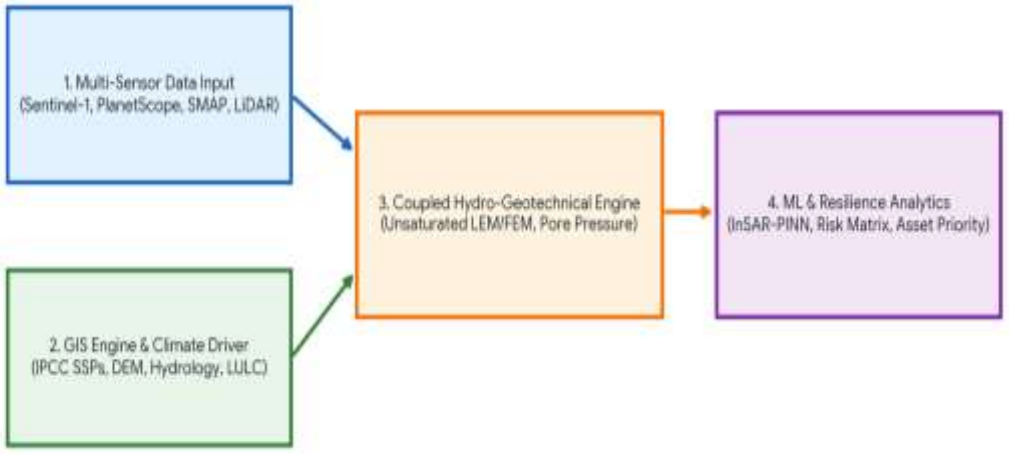


Figure 1: Conceptual architectural framework demonstrating the coupling of satellite remote sensing, spatial GIS layers, numerical hydro-geotechnical engines, and machine learning risk pipelines

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RESULTS AND FINDINGS

InSAR-Based Deformation Performance and Signal Disambiguation

Synthesis of multi-temporal InSAR case studies reveals high operational accuracy in measuring surface deformation along transportation corridors and geotechnical slope systems [26]. PSInSAR processing yields millimeter-per-year velocity precision (±1.2 mm/year) over hard infrastructure assets such as bridge piers, retaining structures, and asphalt pavements [27]. In rural and agricultural slopes, SBAS approaches demonstrate superior spatial coherence, providing early warning detection of slope creep prior to catastrophic shearing [28].

However, converting Satellite Line-of-Sight (LOS) displacement to true vertical (d_v) and 3D horizontal (d_h) deformation requires multi-track geometry decomposition (ascending and descending orbits) according to Eq. (1) [29]:

$$d_LOS = d_v \cdot \cos(\theta) - d_h \cdot \sin(\theta) \cdot \cos(\alpha - \varphi)$$

where θ represents the radar incidence angle, α is the satellite flight heading, and φ is the slope aspect angle [30]. Unraveling thermal expansion artifacts from true geotechnical settlement in structural assets remains a critical step in pipeline execution.

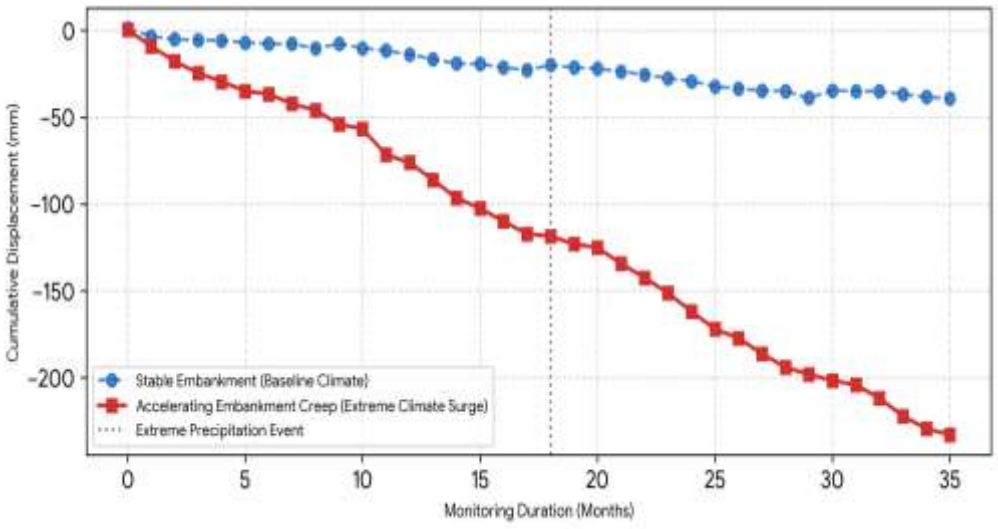


Figure 2: Multi-temporal InSAR displacement time-series illustrating baseline progressive settlement versus climate-accelerated slope failure triggered by intense hydrometeorological events

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GIS Spatial Modeling and Hydro-Geotechnical Machine Learning

Combining GIS spatial layers with Machine Learning (ML) classifiers significantly enhances landslide susceptibility mapping precision [31]. Comparative synthesis across published literature indicates that hybrid ensemble architectures (e.g., Random Forest coupled with InSAR displacement priors) achieve Area Under the Receiver Operating Characteristic Curve (AUC-ROC) values between 0.88 and 0.95, outperforming traditional bivariate statistical approaches (Frequency Ratio, Analytical Hierarchy Process) [32]. Table 2 synthesizes performance metrics across key machine learning models applied to remote sensing-GIS datasets.

Table: 2

Machine Learning Model	Primary Geospatial Inputs	Predictive Accuracy (AUC-ROC)	Key Operational Limitation
Random Forest (RF)	DEM derivatives, InSAR velocity, soil moisture, LULC	0.89 – 0.93	Black-box nature; susceptibility to spatial overfitting in ungauged areas
Gradient Boosting (XGBoost)	Precipitation extremes, curvature, distance to roads, soil texture	0.91 – 0.95	Sensitive to hyperparameter selection and spatial data noise
Convolutional Neural Network (CNN)	Multispectral optical imagery, high-res DEM tiles	0.92 – 0.96	High computational resource requirement; demands extensive labeled data
Physics-Informed Neural Network (PINN)	InSAR displacement time-series, groundwater heads, LEM equations	0.94 – 0.98	Complex formulation requiring coupled hydro-mechanical boundary parameters

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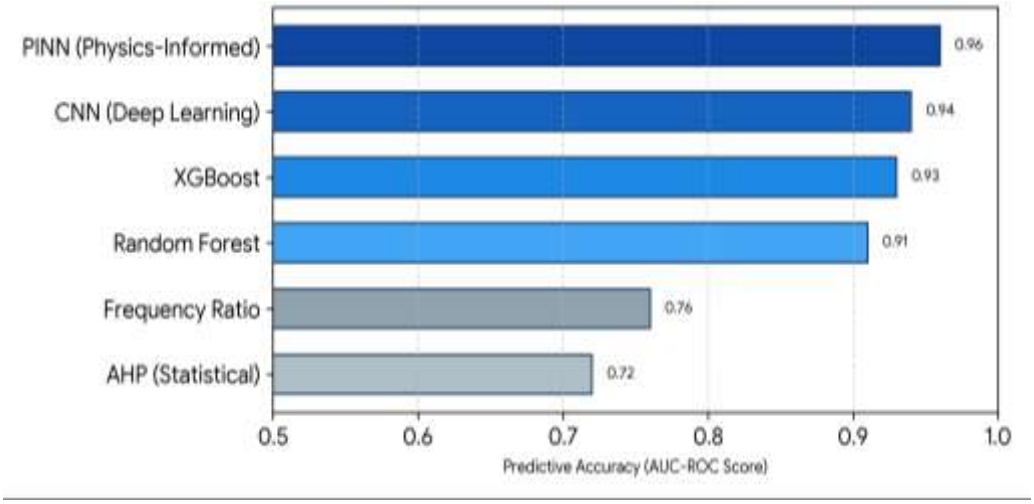


Figure 3: Quantitative comparison of predictive AUC-ROC scores across traditional statistical, machine learning, and physics-informed neural network frameworks for slope instability prediction

DISCUSSION

The integration of satellite remote sensing and GIS into geotechnical infrastructure management transforms asset maintenance from reactive remediation to proactive risk management [33]. The engineering significance of this operational shift is substantial. Highways, railways, and pipeline operators can systematically screen thousands of asset kilometers, identifying accelerating deformation trends long before visual surface distress or catastrophic shear failure occurs [34].

A central finding of this synthesis is the necessity of coupling unsaturated soil mechanics with earth observation data streams [35]. Precipitation surges lower soil suction ψ = (u_a - u_w), effectively shifting the Mohr-Coulomb shear strength envelope according to Fredlund's equation [36]:

$$\tau = c' + (\sigma_n - u_a) \cdot \tan(\phi') + (u_a - u_w) \cdot \tan(\phi^b)$$

where u_a represents pore-air pressure, u_w is pore-water pressure, and ϕ^b is the friction angle reflecting strength changes relative to suction [37]. Spaceborne microwave soil moisture retrieval (SMAP, Sentinel-1 backscatter inversion) provides a proxy for surface volumetric water content, enabling the continuous computation of transient pore-water pressure variation across steep slopes [38].

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From an infrastructure management perspective, early detection directly lowers lifecycle maintenance expenses [39]. Applying low-cost bio-engineering slope stabilization, horizontal drainage installation, or targeted soil nailing based on satellite early-warning indicators costs a fraction of post-collapse highway reconstruction and emergency clearance [40]. Table 3 details an asset resilience decision matrix linked to remote sensing metrics.

Table: 3

InSAR Velocity (mm/yr)	**Soil Moisture Anomaly (%)**	**Geotechnical Risk Level**	**Recommended Infrastructure Action**
< 2.0 mm/yr	Normal (< +10%)	Low (Routine Baseline)	Standard scheduled routine asset inspection; keep baseline records
2.0 – 10.0 mm/yr	Moderate (+10% to +30%)	Moderate (Elevated Creep)	Deploy localized targeted UAV lidar surveys; clear slope surface drainage
10.0 – 30.0 mm/yr	High (+30% to +50%)	High (Impending Instability)	Install sub-surface piezometers & inclinometers; restrict traffic speeds
> 30.0 mm/yr	Extreme (> +50%)	Critical (Failure Imminent)	Emergency structural intervention; soil nailing, retaining wall construction, or closure

LIMITATIONS

Despite significant technological advancements, several key operational limitations restrict full space-borne asset monitoring:

- Temporal and Spatial Resolution Boundaries: High-resolution satellite SAR platforms (e.g., TerraSAR-X) offer exceptional spatial detail but suffer from longer revisit intervals,

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whereas open-access platforms (e.g., Sentinel-1) are constrained by 5x20 m spatial resolutions that may miss localized slope failures.

- Phase Decorrelation and Atmospheric Disturbances: In SAR interferometry, dense vegetation, rapidly changing agricultural cover, and heavy snow induce severe phase decorrelation. Additionally, tropospheric phase delays caused by atmospheric water vapor can mimic false ground deformation signals.
- Subsurface Blindness: Satellite remote sensing directly measures only two-dimensional or three-dimensional surface expressions. Subsurface mechanical stratigraphy, deep slip plane geometry, shear band development, and localized artesian pressures cannot be directly sensed from orbit.
- Computational and Data Heterogeneity Bottlenecks: Integrating multi-gigabyte spatial rasters, point clouds, and multi-temporal SAR stacks requires high-performance computing infrastructure and sophisticated data-cleaning workflows, which many municipal transport agencies currently lack.

FUTURE SCOPE

To overcome current technical boundaries, future research should focus on the following transformative paradigms:

- Physics-Informed Machine Learning (PINNs): Transition from purely statistical black-box ML models toward hybrid neural architectures that enforce governing geotechnical partial differential equations (PDEs), such as Richard's equation for unsaturated flow and Terzaghi's 1D consolidation equation.
- Next-Generation Satellite Constellations: Operationalization of upcoming L-band and C-band dual-frequency SAR missions (e.g., NASA-ISRO NISAR), offering deeper canopy penetration, higher temporal revisit cycles, and improved phase coherence over densely vegetated terrain.
- Edge-AI Infrastructure Digital Twins: Convergence of satellite remote sensing streams, real-time IoT ground sensing arrays (wireless inclinometers, piezometers), and 3D Building Information Modeling (BIM) into cloud-native Digital Twin platforms for continuous predictive resilience simulation.
- Dynamic Climate Scenario Integration: Coupling localized downscaled climate models (CMIP6 / IPCC SSP1-2.6 through SSP5-8.5) directly into spatial slope stability modules to generate forward-looking infrastructure risk maps across multi-decadal time horizons.

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CONCLUSION

Climate change is accelerating the destabilization of earth slopes and soil foundation systems worldwide, threatening critical linear and urban civil infrastructure. Satellite remote sensing (SRS) and GIS spatial engines provide an unmatched capability for regional hazard screening, high-precision deformation tracking, and dynamic risk modeling. By combining multi-temporal InSAR (PSInSAR/SBAS), high-resolution optical platforms, spaceborne microwave soil moisture retrieval, and spatial GIS layers, civil engineers can identify low-velocity slope creep and ground subsidence long before structural failures occur.

Translating surface remote sensing signals into actionable engineering parameters requires incorporating unsaturated soil mechanics and constitutive slope stability models into analytical pipelines. Furthermore, adopting advanced machine learning classifiers—particularly Physics-Informed Neural Networks—offers a robust pathway to bridge space-borne observations with subsurface mechanical behavior under non-stationary climate conditions. Developing cloud-native Digital Twins that unify satellite observation, IoT ground validation, and climate forecast models will serve as the cornerstone for building climate-resilient civil infrastructure systems in the decades ahead.

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***Author for Correspondence**
Priyadarshini Patel
E-mail: priyadarshini.patel@gmail.com

[1]Associate Professor, Department of Civil Engineering, Kautilya Institute of Technology & Engineering
[2]Student, Department of Civil Engineering, Kautilya Institute of Technology & Engineering
[3]Student, Department of Civil Engineering, Kautilya Institute of Technology & Engineering

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