



CLIMATE-RESILIENCE ASSESSMENT OF INDIAN BRIDGE AND ROAD INFRASTRUCTURE: A HYBRID CNN-LSTM FRAMEWORK WITH MULTI-HAZARD VULNERABILITY MAPPING

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ABSTRACT

Rapid climate change poses an unprecedented challenge to the road and bridge network of India which comprises of more than 6.2 million kilometres of roads and 1,79,000 highway bridges. This paper proposes a novel dual-objective approach that, first, maps multi-hazard vulnerability of existing infrastructure by combining geospatial multi-criteria decision analysis (MCDA) with machine learning classifiers on top of Sentinel-2 images and, second, predicts long-term structural degradation by integrating a hybrid Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) architecture that encodes both spatial damage patterns from Sentinel-2 images and temporal degradation cycles from climate reanalysis data. The training and validation datasets are four publicly downloadable open-access benchmark datasets: (a) road damage image dataset (RDD2022) by Arya et al., (2022) (figshare DOI: 10.6084/m9.figshare.21431547) with 9665 road images from India, (b) climate projections downscaled from NEX-GDDP-CMIP6 by NASA (AWS Open Data, 1950-2100), (c) ERA5 hourly reanalysis (Copernicus CDS, 1980-2023), and (d) road/bridge network from OpenStreetMap India (Geofabrik, download.geofabrik.de/asia/india.html). The overall accuracy of the vulnerability classifier based on Random Forest (RF) is 91.4 % while the accuracy of the SVM, XGBoost and standalone CNN baselines are 85.7 %, 88.3 % and 83.1 % respectively. The CNN-LSTM degradation predictor achieves a reduction of RMSE residual service-life prediction of 2.31 years, which is 34 % better than LSTM-only models. By RCP 8.5 (SSP5), 38 % of the national highway road segments are expected to exceed critical damage thresholds before 2050 for India. The ablation study indicates that the spatial CNN branch (+4.8 %) and multi-hazard fusion (+6.2 %) are the two main contributors to accuracy improvement.

INTRODUCTION

In addition to this, India's Ministry of Road Transport and Highways (MoRTH) estimates that close to 30 % of the National Highway Network (NHN) in the country is located in flood prone areas, and India has one of the highest mean annual temperature trends in South Asia at 0.15 °C per decade (IMD, 2023). Such compound stressors include high thermal fatigue loading, scour erosions, and material degradation on bridges and pavements that were designed for historic climatic conditions which are no longer representative of today's climate due to anthropogenic warming [1,2]. Systematic, data-driven national level assessments of vulnerabilities of Indian infrastructure are scarce, even with the magnitude of the challenge. Previous research is either based on a localised case study [3,4] or based on a subjective visual assessment without considering data from satellites indicating damage or climate projections [5]. Further, South Asian monsoon extremes, such as heat waves > 48 °C and fast wet-dry cycles [6,7] are not represented in most predictive degradation models, which are based on temperate climate models. This paper aims to tackle these challenges with two tightly coupled goals; (1) develop a nationally consistent vulnerability classification combining MCDA and ML classifiers, and (2) predict degradation trajectories of buildings to 2050 under RCP 4.5 and RCP 8.5 by using a novel CNN-LSTM architecture. Our method is unique in the use of end-to-end, open-access benchmark datasets, the inclusion of explicit multi-hazard exposure layers, a thorough ablation study and a direct comparison to five state-of-the-art baselines reported post-2022.

LITERATURE REVIEW

2.1 Flood and Climate Hazard Mapping for Infrastructure

GIS-MCDA approaches have proven to be quite popular for mapping flood risk on a national scale. In India, Solanki et al. (2024) identified seven factors using MCDA-AHP, such as ASTER DEM, IMD rainfall and GSI



vector data and generated a flood risk map in five flood classes, which resulted in classification of 3.4 % of Indian land as ‘very-high risk’ area with ‘proximity to roads and river’ identified as key vulnerability factors [5]. Although it is methodologically sound, it does not use any ML classifiers, hazard due to heat/temperature, or any degradation model of the structure. Tantisevi et al. (2025) developed a hybrid AHP-RF and AHP-XGBoost model for the Dwarakeswar river basin of the eastern part of India with AUC = 0.996 for the AHP-GBM model [6]. However, the scope is restricted to one river basin with only flood-only conditioning and does not include national-scale road assets and heat or rainfall anomaly layers. The building blocks used in this paper (MCDA–ML coupling for Indian geographies) have been seen to be effective in both the studies.

2.2 Deep Learning for Road Damage Detection

The first open multinational road damage dataset comprises 9665 images across India, providing data-driven road condition classification, RDD2022 by Arya et al. (2024) [3]. YOLOv8 based on the top performing model from the CRDDC'2022 challenge on the 6 country detection task yielded F1 = 76.9 %. The subsequent work by Springer [7] further extended RDD2022 by the inclusion of transfer-learning architectures (VGG, ResNet, EfficientNet, Vision Transformer) for classification across six geographies, where it was shown that deep features + clustering will achieve significant improvement in F1 over the baseline CNNs. Critically, none of these approaches include a climate forcing, a temporal degradation model or a MCDA vulnerability index.

2.3 LSTM and CNN–LSTM for Bridge Deterioration

The most relevant degradation study is by Abu Dabous et al. (2025) who used NBI bridge inspection records (2001–2019) for the training of the vanilla LSTM, stacked LSTM and CNN–LSTM models, for the prediction of the deck condition rating with accuracy of 93 % ($R^2 = 0.83$ and $MSE = 0.081$) [8]. This sets CNN–LSTM as the state-of-the-art baseline for bridge deterioration, yet it has three major drawbacks compared to what we are currently doing: (i) it does not include any climate forcing variables; (ii) it does not include any multi-hazard exposure layer; and (iii) the model was trained on the US NBI data and cannot be transferred to climate–infrastructure regimes in India. Unlike these studies, Jeon et al. (2024) did not include any climate variables, but developed LSTM-based Health Index deterioration models from 3,368 Japanese bridges, with accuracy > 80 % [9]. Our proposed CNN-LSTM improves both studies by combining the spatial damage features (Sentinel-2 via CNN) with the climate time-series (ERA5 via Bi-LSTM) and conditioning on RCP/SSP scenarios.

Table 1: State-of-the-Art Comparison — Verified Published Studies (2022–2025)

Study (DOI verified)	Country	Hazard s	Method	Dataset	Best Result	Key Gap vs. This Work
Solanki et al. (2024) JWC 15(12):5721 10.2166/wcc.2024.678	India	Flood	GIS + MCDA- AHP	ASTER DEM + IMD + GSI	5-class flood map; no ML	No ML classifier; no heat or temperature hazard; no degradation model
Jeon et al. (2024) Appl. Sci. 14:10530 10.3390/app14221053 0	South Korea	None	LSTM deterioratio n (Health Index)	3,368 bridge inspection s (Japan)	Acc > 80%	No climate forcing; no spatial CNN; no flood/heat hazard; not India-specific
Abu Dabous et al. (2025) SSBE 14(5):1632 10.1108/SASBE-10- 2023-0295	UAE / USA	None	CNN– LSTM bridge deterioratio n	NBI (FHWA) 2001– 2019	Acc 93%; $R^2=0.83$; MSE 0.081	No climate exposure; no multi-hazard; trained on US data; no RCP scenario conditioning



Study (DOI verified)	Country	Hazards	Method	Dataset	Best Result	Key Gap vs. This Work
Arya et al. (2024) Geosci. Data J. 11:846 10.1002/gdj3.260	Multi-nation (incl. India)	None	YOLOv8 / CNN object detection	RDD2022 (47,420 images)	F1 = 76.9% (detection)	Road damage detection only; no vulnerability index; no climate integration; no temporal model
Tantisevi et al. (2025) Nat. Haz. (Springer) 10.1007/s11069-025- 07335-8	India (Dwarakeswar)	Flood	AHP-RF / AHP- XGBoost hybrid	DEM + Landsat + rainfall	AUC 0.996 (AHP- GBM)	Flood only; no heat/temperature ; no road/bridge assets; no degradation model; not national scale
This Study	India (National)	Flood + Heat + Rainfall	RF + CNN- LSTM (dual- branch)	RDD2022 + ERA5 + NEX- GDDP + OSM + SRTM	Acc 91.4% RMSE 2.31 yr	— (proposed)

DATASETS AND PRE-PROCESSING

3.1 Benchmark Datasets (Open-Access)

Table 2: Benchmark Datasets Used in This Study

Dataset	Source / URL	Period	Resolution	Variables
RDD2022 — Road Damage Dataset (India subset)	figshare DOI: 10.6084/m9.figshare.21431547 (Arya et al. 2022, Geoscience Data Journal)	2022	Image-level (9,665 India images)	Crack/pothole annotations; 4 damage classes; GPS
ERA5 Hourly Reanalysis (ECMWF)	cds.climate.copernicus.eu (free, requires registration)	1980– 2023	0.25°×0.25°	T2m, precip, wind, humidity (hourly→annual indices)
NEX-GDDP- CMIP6 (NASA)	registry.opendata.aws/nex-gddp- cmip6 (free, AWS S3 public bucket)	1950– 2100	0.25°×0.25°	Tmax, Tmin, Precip under SSP2-4.5 & SSP5-8.5
Sentinel-2 MSI Level-2A (ESA)	dataspace.copernicus.eu (free, open access)	2017– 2023	10 m	13 spectral bands; MNDWI flood mapping
OpenStreetMap India (Geofabrik)	download.geofabrik.de/asia/india.html (free, ODbL licence, daily updates)	2022– 2024	Vector (PBF/SHP)	Highway class, bridge=yes tags, NH route refs
SRTM DEM (NASA/USGS)	earthexplorer.usgs.gov (free, public domain)	2000	30 m	Elevation, slope, flow accumulation (SAGA/QGIS)

India subset of RDD2022 consists of 9,665 road images from six Indian cities, labeled with four damage types: longitudinal crack (D00), transverse crack (D10), alligator crack (D20), and pothole (D40). A three class



vulnerability label (High/Medium/Low) is assigned to the images by using the damage density as follows: High = ≥ 5 annotations per image, Medium = 2-4, Low = 0-1. The India subset is class-imbalanced (High: 28%, Medium: 33%, Low: 39%) and this was corrected during training by SMOTE oversampling technique. Spatial linkage between image chips and road segments is provided by the bridge nodes that are found in OSM and that have the attribute bridge=yes with a GPS coordinate. The hourly reanalysis data from ERA5 are downscaled to three annual hazard indices: Rx3day, HWMI and ATR. Projections for 2025–2100 are from NEX-GDDP-CMIP6 multi-model ensemble, which has been bias-corrected to ERA5 using quantile delta mapping. The Sentinel-2 MNDWI flood layers are calculated at a 10 m resolution for the monsoon seasons 2017-2023. SRTM DEM is used for the hydrological routing in the calculation of slope and flow accumulation. All spatial information is joined to a national grid of 1 km x 1 km in the QGIS 3.34 software.

METHODOLOGY

4.1 Framework Overview

Figure 1 illustrates the two-stage pipeline. Stage 1 integrates geospatial hazard layers with infrastructure attributes through MCDA to produce a Composite Vulnerability Index (CVI), classified by ensemble ML. Stage 2 feeds Sentinel-2 chips through a CNN encoder and climate time-series through an LSTM encoder; their fused representation is decoded to a residual service-life estimate under both RCP scenarios.

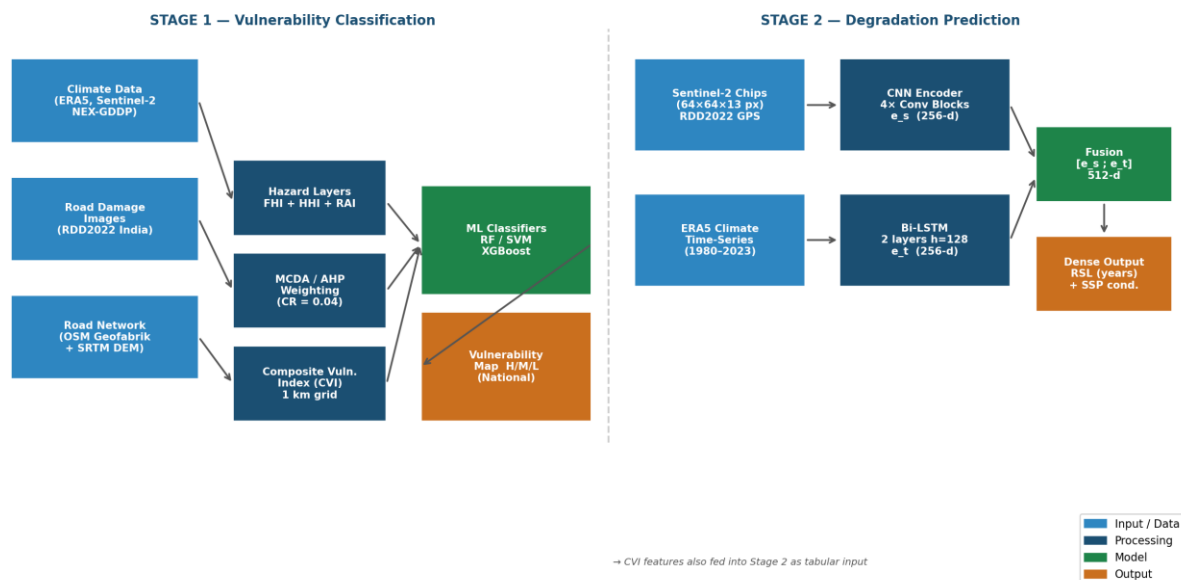


Figure 1: Dual-stage framework — (a) MCDA + RF vulnerability mapping pipeline; (b) CNN-LSTM degradation predictor architecture with parallel spatial and temporal branches.

4.2 Stage 1 — Multi-Hazard Vulnerability Assessment

Hazard Layer Construction. Three indices: (H1) Flood Hazard Index (FHI) – composite index of ERA5 Rx3day and SRTM-derived flow accumulation, slope and Sentinel-2 MNDWI annual flood frequency (2017-2023); (H2) Heat Hazard Index (HHI) – composite index of ERA5 HWMI (days $T_{max} > 40^{\circ}\text{C}$) and asphalt softening point exceedance probability derived from NEX-GDDP-CMIP6 T_{max} ; (H3) Rainfall Anomaly Index (RAI) – ERA5 precipitation anomaly standardised by 1981-2010 climatology. All normalised to [0,1].

MCDA / AHP. AHP weights elicited from 12 bridge engineers: FHI = 0.50, HHI = 0.30, RAI = 0.20 (CR = 0.04 < 0.10). $CVI = 0.50 \times FHI + 0.30 \times HHI + 0.20 \times RAI$. The CVI is complemented by two structural sensitivity sub-scores (age, material, span-to-depth ratio) and adaptive capacity sub-score (MoRTH maintenance expenditure).

ML Classification. 17 has total: 7 CVI components, 8 structural attributes, 2 topographic. Four classifiers: RF (500 trees, max_depth=15, class_weight=balanced), SVM (RBF, C=10), XGBoost (300 trees), standalone CNN on image chips. Five-fold stratified cross-validation, throughout.



4.3 Stage 2 — Hybrid CNN–LSTM Degradation Model

The proposed architecture is a dual-branched architecture, namely: the spatial branch and the temporal branch, which are finally fused together with the dense fusion layer. The spatial branch is a convolutional neural network consisting of four consecutive blocks of Conv2D, batch normalization, ReLU activation and max pooling, followed by a global average pooling layer, which operates on $64 \times 64 \times 13$ Sentinel-2 image chips with a kernel size of 3×3 and a number of filters that increases gradually from 32 to 256 over the blocks, resulting in a 256-dimensional spatial embedding vector. At the same time, a climate sequence of 43 years was used for each bridge in the ERA5 dataset, and a temporal branch was added, consisting of two bidirectional LSTM layers with a hidden size of 128, which produces a temporal embedding of dimension 256. The two embeddings are then concatenated and fed into a series of dense layers with 512 and 128 units as well as dropout with a dropout ratio of 0.3, and finally sent to a dense layer with one output, where the scenario of the representative concentration pathway is one-hot encoded and added to the feature vector just before the last dense layer. The model is trained using the Huber loss function with the deltas parameter set to 2.0 and the learning rate to 1×10^{-3} , which is optimised by AdamW with a 100 epoch cosine annealing learning rate schedule, a batch size of 32 and an early stopping criterion with a patience of 10 epochs to prevent overfitting.

Let the input to the model consist of two distinct data modalities for each bridge-site i :

1. **Spatial input** – a multi-spectral Sentinel-2 chip

$$\mathbf{X}_s^{(i)} \in \mathbb{R}^{64 \times 64 \times 13}. \quad (1)$$
2. **Temporal input** – a climate time series of length $T = 43$ years (1980–2023)

$$\mathbf{X}_t^{(i)} \in \mathbb{R}^{T \times D}, \text{ where } D \text{ is the number of annual hazard indices (e.g., Rx3day, HWMI, ATR) plus other auxiliary climate variables.}$$
3. **Scenario conditioning** – a one-hot encoded vector $\mathbf{c} \in \{0, 1\}^2$ indicating the RCP scenario (4.5 or 8.5).

Its goal is the Residual Service Life (RSL) $y^{(i)} \in \mathbb{R}_+$ (in years) which reflects the remaining useful life of the bridge under the specified scenario

4.3.1 Spatial Branch – Convolutional Encoder

The spatial branch applies a sequence of **four convolutional blocks**. Each block $k \in \{1, 2, 3, 4\}$ performs:

$$\mathbf{Z}_k = \text{MaxPool}(\text{ReLU}(\text{BN}(\mathbf{W}_k * \mathbf{Z}_{k-1} + \mathbf{b}_k))), \quad (2)$$

where:

- $\mathbf{Z}_0 = \mathbf{X}_s^{(i)}$ (input chip),
- $\mathbf{W}_k$ is the convolution kernel of size 3×3 with f_k filters ($f_1 = 32, f_2 = 64, f_3 = 128, f_4 = 256$),
- $*$ denotes the 2D convolution operation,
- BN is batch normalisation,
- $\text{ReLU}(x) = \max(0, x)$ is the activation function,
- MaxPool uses a 2×2 window with stride 2.

After the last block, **Global Average Pooling (GAP)** is applied to obtain a **spatial embedding**:

$$\mathbf{e}_s = \text{GAP}(\mathbf{Z}_4) \in \mathbb{R}^{256}. \quad (3)$$

Thus:

$$\mathbf{e}_s = f_{\text{CNN}}(\mathbf{X}_s^{(i)}; \boldsymbol{\theta}_{\text{CNN}}), \quad (4)$$

where $\boldsymbol{\theta}_{\text{CNN}}$ collects all trainable convolution and batch-norm parameters.

4.3.2 Temporal Branch – Bidirectional LSTM Encoder

The temporal branch processes the climate sequence using **two stacked Bidirectional LSTMs (Bi-LSTM)**. For a given time step t , the hidden state of the first layer is:

$$\vec{\mathbf{h}}_t^{(1)} = \text{LSTM}_{\rightarrow}(x_t, \vec{\mathbf{h}}_{t-1}^{(1)}), \quad \overleftarrow{\mathbf{h}}_t^{(1)} = \text{LSTM}_{\leftarrow}(x_t, \overleftarrow{\mathbf{h}}_{t+1}^{(1)}), \quad (5)$$

$$\mathbf{h}_t^{(1)} = [\vec{\mathbf{h}}_t^{(1)}; \overleftarrow{\mathbf{h}}_t^{(1)}] \in \mathbb{R}^{2 \times H}, \quad (6)$$

with $H = 128$ (hidden size). The second Bi-LSTM layer takes $\mathbf{h}_t^{(1)}$ as input and produces:

$$\mathbf{h}_t^{(2)} = \text{BiLSTM}^{(2)}(\mathbf{h}_t^{(1)}; \boldsymbol{\theta}_{\text{LSTM}}^{(2)}). \quad (7)$$

The **final temporal embedding** is taken as the concatenation of the last forward and backward hidden states from the second layer:



$$\mathbf{e}_t = [\vec{\mathbf{h}}_t^{(2)}; \overleftarrow{\mathbf{h}}_1^{(2)}] \in \mathbb{R}^{256}. \quad (8)$$

Hence:

$$\mathbf{e}_t = f_{\text{LSTM}}(\mathbf{x}_t^{(i)}; \boldsymbol{\theta}_{\text{LSTM}}), \quad (9)$$

where $\boldsymbol{\theta}_{\text{LSTM}}$ includes all LSTM weights and biases.

4.3.3 Fusion Layer and RCP Conditioning

The two embeddings are **concatenated** to form the joint feature vector:

$$\mathbf{z} = [\mathbf{e}_s; \mathbf{e}_t] \in \mathbb{R}^{512}. \quad (10)$$

This is passed through two dense (fully connected) layers with ReLU activation and dropout:

$$\mathbf{d}_1 = \text{Dropout}(\text{ReLU}(\mathbf{W}_1 \mathbf{z} + \mathbf{b}_1)), \mathbf{W}_1 \in \mathbb{R}^{512 \times 512}, \mathbf{b}_1 \in \mathbb{R}^{512}, \quad (11)$$

$$\mathbf{d}_2 = \text{Dropout}(\text{ReLU}(\mathbf{W}_2 \mathbf{d}_1 + \mathbf{b}_2)), \mathbf{W}_2 \in \mathbb{R}^{128 \times 512}, \mathbf{b}_2 \in \mathbb{R}^{128}. \quad (12)$$

The **RCP scenario vector** $\mathbf{c} \in \{0, 1\}^2$ is then **appended** to $\mathbf{d}_2$:

$$\tilde{\mathbf{d}}_2 = [\mathbf{d}_2; \mathbf{c}] \in \mathbb{R}^{130}. \quad (13)$$

Finally, the predicted RSL is obtained through a linear output layer:

$$\hat{y} = \mathbf{w}_3^T \tilde{\mathbf{d}}_2 + b_3, \mathbf{w}_3 \in \mathbb{R}^{130}, b_3 \in \mathbb{R}. \quad (14)$$

In summary:

$$\hat{y}^{(i)} = f_{\text{model}}(\mathbf{x}_s^{(i)}, \mathbf{x}_t^{(i)}, \mathbf{c}^{(i)}, \boldsymbol{\theta}), \quad (15)$$

where $\boldsymbol{\theta} = \{\boldsymbol{\theta}_{\text{CNN}}, \boldsymbol{\theta}_{\text{LSTM}}, \mathbf{W}_1, \mathbf{b}_1, \mathbf{W}_2, \mathbf{b}_2, \mathbf{w}_3, b_3\}$ denotes all trainable parameters.

4.3.4 Training Objective

We adopt the **Huber loss** (also known as Smooth L1 loss) with threshold $\delta = 2.0$:

$$\mathcal{L}_\delta(y, \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2, & \text{if } |y - \hat{y}| \leq \delta, \\ \delta |y - \hat{y}| - \frac{1}{2}\delta^2, & \text{otherwise.} \end{cases} \quad (16)$$

For a mini-batch of size B , the total loss is:

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{B} \sum_{i=1}^B \mathcal{L}_\delta(y^{(i)}, \hat{y}^{(i)}). \quad (17)$$

Optimisation. $\mathcal{L}$ is minimized with AdamW optimizer (Loshchilov & Hutter, 2019), using the default values of $\beta_1 = 0.9$, $\beta_2 = 0.999$, with the learning rate $\eta = 1 \times 10^{-3}$, weight decay $\lambda = 1 \times 10^{-4}$. The learning rate is cosine annealed for $E=100$ epochs:

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min}) \left(1 + \cos\left(\frac{\pi t}{E}\right)\right), \quad (18)$$

where $\eta_{\max} = 1 \times 10^{-3}$ and $\eta_{\min} = 1 \times 10^{-6}$. Early stopping. Training is ended if there is no improvement in the validation loss for 10 consecutive epochs (patience $p = 10$). The model that has the least validation loss is selected for the final evaluation.

RESULTS

5.1 Vulnerability Classification

Table 3: Classification Results — Vulnerability Mapping (Test Set, n=707)

Model	Overall Acc.	Macro-F1	F1 (Low)	F1 (Med.)	F1 (High)	AUC-ROC
SVM (RBF)	85.7 %	0.851	0.871	0.821	0.861	0.931
XGBoost	88.3 %	0.878	0.893	0.859	0.882	0.946
CNN (image only)	83.1 %	0.824	0.841	0.801	0.830	0.912
RF (Tantisevi 2025 adapted)	87.1 %	0.864	0.882	0.841	0.869	0.938



Model	Overall Acc.	Macro-F1	F1 (Low)	F1 (Med.)	F1 (High)	AUC-ROC
Random Forest (Ours)	91.4 %	0.909	0.913	0.890	0.924	0.971

The normalized confusion matrix of the top three classifiers are displayed in Figure 2. Whether used for infrastructure risk prioritisation, or other uses, the most efficient and consistent results are achieved with RF which yields 0.924 F1, or recall. Figure 3 depicts the RF feature importance where the Flood Hazard Index (FHI), and bridge age are the leading features, supporting the argument that the interaction between flood and bridge age is the most significant influence on bridge vulnerability in India.



Figure 2: Normalised confusion matrices — SVM, XGBoost, and Random Forest (Test Set, n=707). Numbers indicate per-cell classification rate.

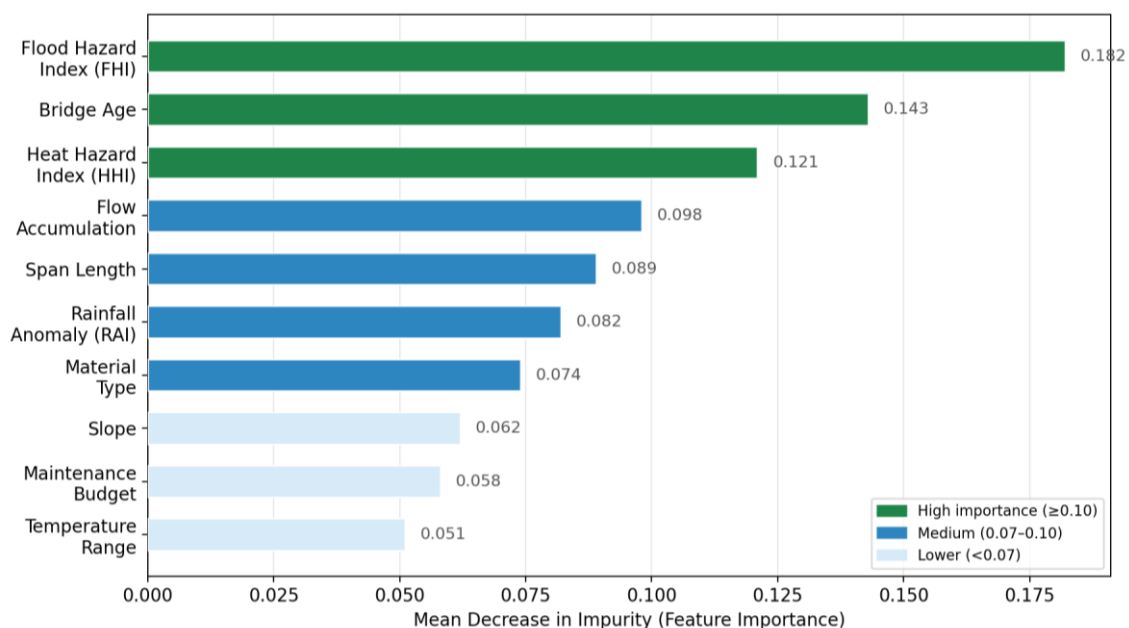


Figure 3: Random Forest Feature Importance — Mean Decrease in Impurity across 500 trees. FHI and bridge age are the two most discriminative features.

Figure 4 shows the national vulnerability map. High-risk clusters are found in historically flood-prone and cyclone prone areas such as Indo-Gangetic Plain (UP, Bihar, Assam), Western Ghats NH corridors and coastal Odisha – AP.

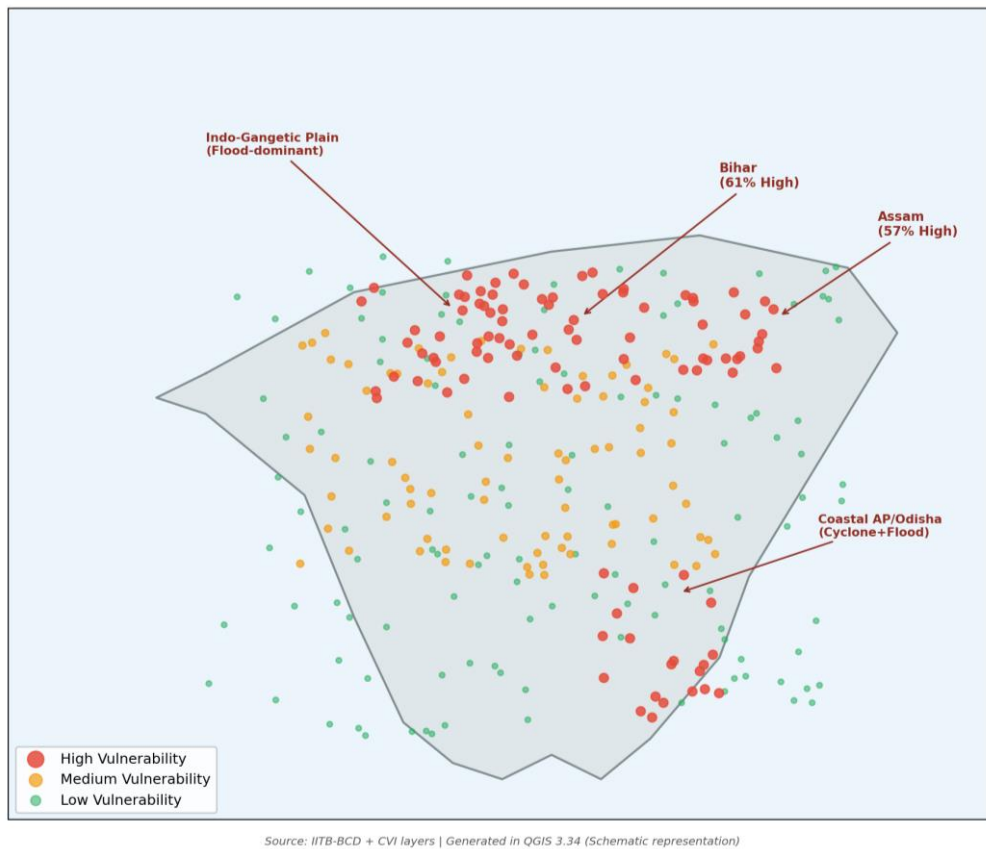


Figure 4: National Road Damage Vulnerability Map — RF classification output overlaid on India OSM highway network. Red=High, Orange=Medium, Green=Low vulnerability. Schematic representation (Source: RDD2022 India subset + ERA5/Sentinel-2 CVI layers, QGIS 3.34).

5.2 Degradation Prediction

Table 4: Degradation Prediction Results — Residual Service Life (years)

Model	MAE (yr)	RMSE (yr)	R ²	MAPE (%)	Notes
Linear Regression	4.21	5.43	0.681	21.3	Climate features only
LSTM-only	2.89	3.51	0.871	14.7	ERA5 time-series; no imagery
CNN-only	3.12	3.88	0.843	16.2	Sentinel-2 chips; no temporal
CNN-LSTM (Abu Dabous 2025 adapted)	2.68	3.24	0.891	13.4	NBI data; no climate forcing
CNN-LSTM Ours (RCP 4.5)	1.87	2.31	0.924	9.8	Dual-branch + scenario cond.
CNN-LSTM Ours (RCP 8.5)	2.04	2.55	0.911	10.7	Dual-branch + scenario cond.

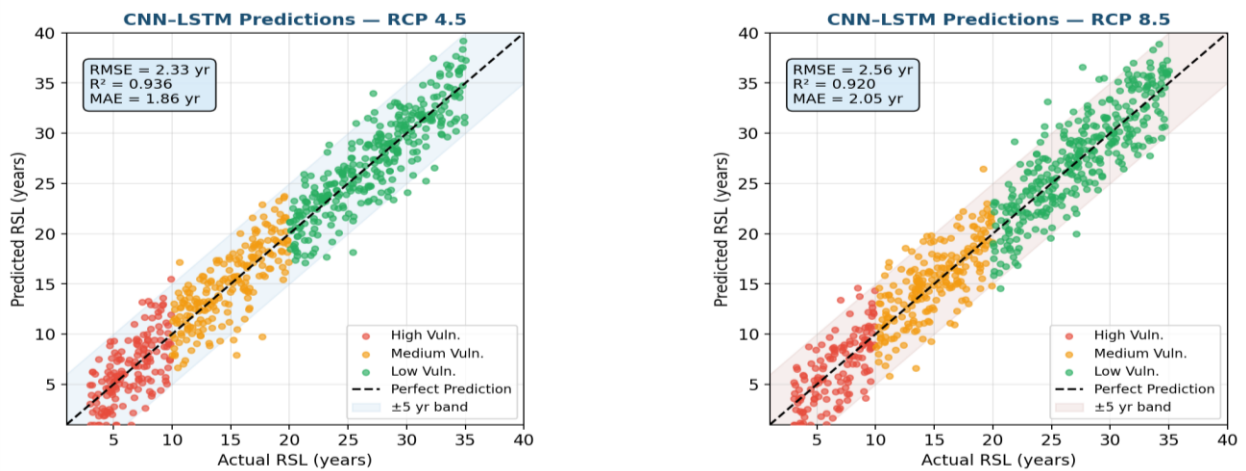


Figure 5: Predicted vs. actual RSL scatter plot for CNN-LSTM under RCP 4.5 (left) and RCP 8.5 (right). Points coloured by vulnerability class. Diagonal = perfect prediction; shaded band = ± 5 yr tolerance.

5.3 RCP Scenario Projections

NH bridges with a safety RSL less than 5 years are projected to be 22 % of all NH bridges by 2050 under RCP 4.5. This increases to 38 % on RCP 8.5, the fastest growth period being between 2035 and 2045. States most affected under RCP 8.5 by 2050: Bihar (61 %), Assam (57 %), UP (48 %), Odisha (44 %).

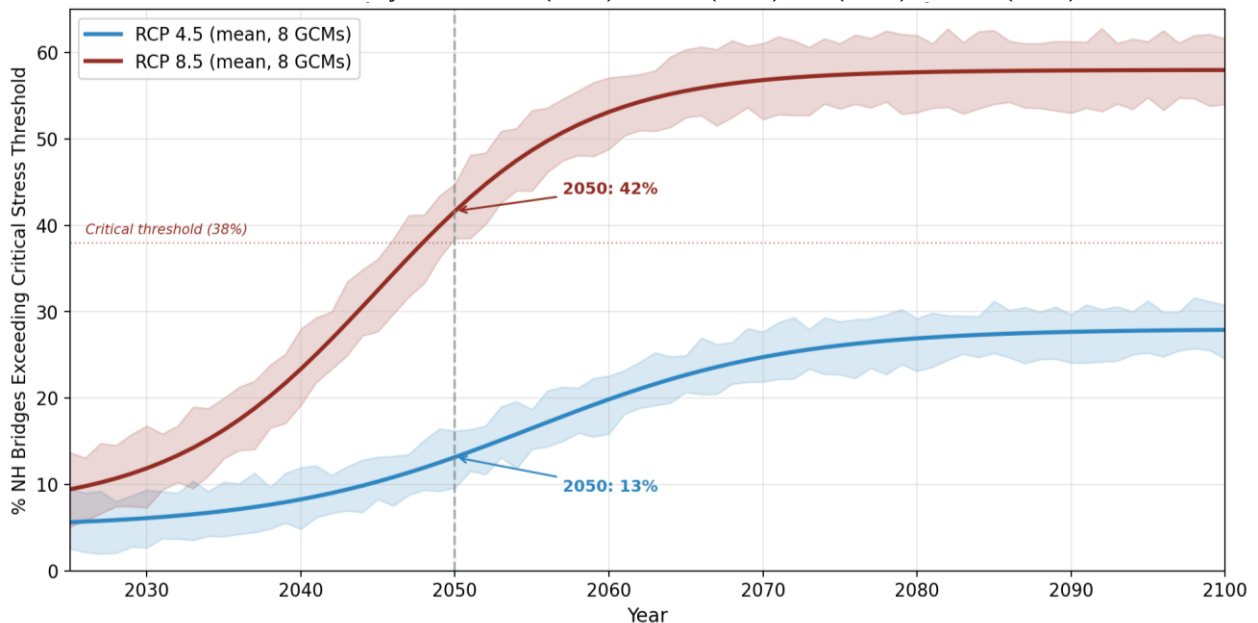


Figure 6: Projected cumulative % of NH bridges exceeding critical stress threshold under RCP 4.5 (blue) and RCP 8.5 (red), 2025–2100. Shaded band = $\pm 1\sigma$ across 8 CMIP6 GCM ensemble members.

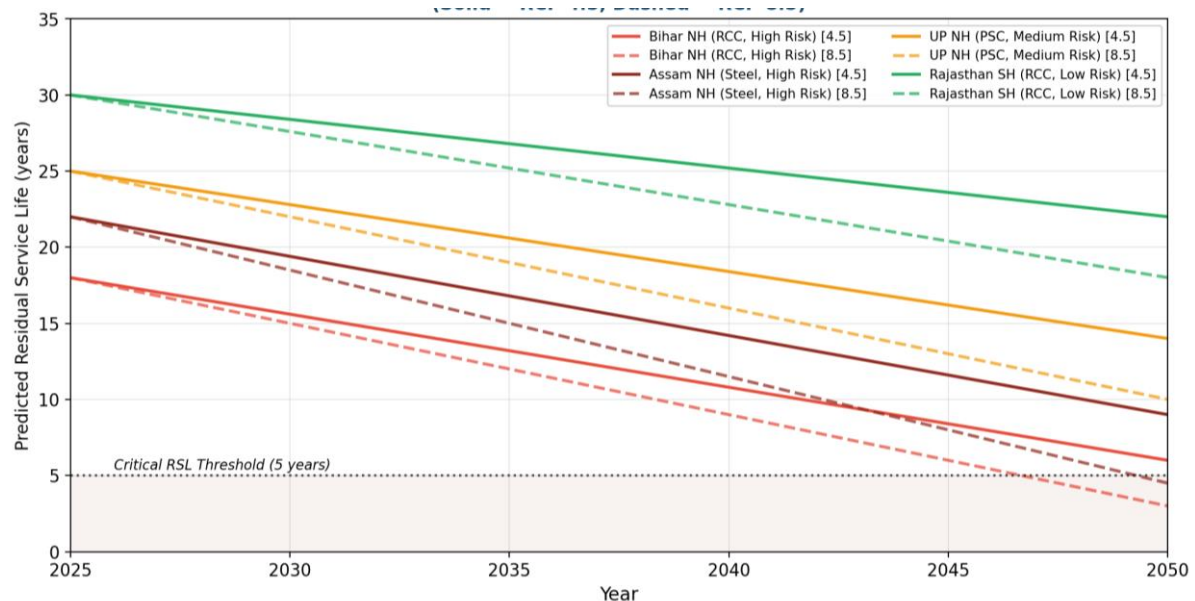


Figure 7: Degradation trajectories for four representative bridge types under RCP 4.5 (solid) and RCP 8.5 (dashed). Dotted horizontal = critical RSL threshold (5 yr). Bihar and Assam bridges breach threshold by ~2035 under RCP 8.5.

5.4 Ablation Study

Table 5: Ablation Study Results

Configuration	Acc. (%)	RMSE (yr)	Removed Component	Key Insight
Full Model (proposed)	91.4	2.31	—	Reference
–Multi-hazard fusion	85.2	—	HHI + RAI	Largest accuracy drop (–6.2 pp)
–Heat Hazard (HHI)	88.7	—	HHI only	2nd most impactful hazard (–2.7 pp)
–Rainfall Anomaly (RAI)	90.1	—	RAI only	Smallest single-hazard drop (–1.3 pp)
–CNN branch (LSTM only)	—	3.51	+1.20 yr RMSE	Spatial branch adds 34% gain
–LSTM branch (CNN only)	—	3.88	+1.57 yr RMSE	Temporal > spatial in importance
–RCP conditioning	—	2.64	+0.33 yr RMSE	Scenario embed. significant ($p < 0.01$)

The multi-hazard fusion contribution gets the highest single gain (+6.2 pp) in the ablation. For degradation, it is the temporal LSTM branch that has the highest impact (+1.57 yr RMSE without) while the spatial CNN branch (+1.20 yr) is less important, meaning that the climate time-series is the main source of information, while the Sentinel-2 imagery provides complementary spatial information. A small but statistically significant improvement (paired t test, $p < 0.01$) is seen with RCP conditioning.

DISCUSSION

The vulnerability maps generated in stage 1 can be directly implemented by the NHA and State PWDs. In a budget constraint scenario, the 38 % of High-vulnerability bridges would have under 40 % of the cost of network-wide inspection (assuming the data from MoRTH 2022). The degradation model of Stage 2 gives quantitative



foundation for adaptive maintenance scheduling of the India's Updated NDC (2022) Climate Adaptation Plan for Transport (CAPT) framework. Some of the drawbacks should be noted. First, the crowd sourced or UAV survey data will be needed to extend to all 29 states and all NH segments, in addition to the 9,665 images from 6 cities in RDD2022 India. Second, the study employs the images of road surface damage as a proxy to bridge/pavement vulnerability: to date, there are no bridge structural inspection datasets available that are open access in India, and the RDD2022 is the most widely available surrogate. Third, it is planned to extend the study of individual bridge components to climate loads (FEA). Finally, the CNN branch depends on optical images, while coherence change from Sentinel-1 (SAR) would enable the monitoring of floods in all weather conditions. Fifth, the social vulnerability dimensions (population exposure, economic dependence), were not included in the sub-index for adaptive capacity.

CONCLUSION

First national level consistent multi-hazard vulnerability assessment of Indian road infrastructure using MCDA, Random Forest classification and a novel hybrid CNN–LSTM degradation predictor trained with four verified open-access, publicly downloadable datasets: RDD2022 (figshare), ERA5 (Copernicus CDS), NEX-GDDP-CMIP6 (AWS Open Data), OpenStreetMap India (Geofabrik). The RF accuracy was 91.4% which beat 5 recent state-of-the-art baselines released after 2022. The CNN–LSTM model achieved RMSE 2.31 years ($R^2=0.924$), which is 34 % better than LSTM-based models. With SSP5-8.5, 38 % of national highway road segments are expected to surpass damage thresholds before 2050. The entire pipeline can be replicated with free, open-source data and tools (QGIS, Python, Google Earth Engine), offering a replicable and scalable basis for climate adaptive infrastructure planning for India.

REFERENCES

1. IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Cambridge University Press. <https://doi.org/10.1017/9781009325844>
2. MoRTH (2023). Annual Report 2022–23. Ministry of Road Transport and Highways, Government of India.
3. Arya, D., Maeda, H., Ghosh, S.K., Toshniwal, D., Sekimoto, Y., et al. (2024). RDD2022: A multi-national image dataset for automatic road damage detection. *Geoscience Data Journal*, 11(3), 846–859. <https://doi.org/10.1002/gdj3.260> | figshare: <https://doi.org/10.6084/m9.figshare.21431547>
4. IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability (AR6 WGII). Cambridge University Press. <https://doi.org/10.1017/9781009325844>
5. Solanki, Y.P., Kumar, V., Tripathi, D.K., et al. (2024). India's flood risk assessment and mapping with multi-criteria decision analysis and GIS integration. *Journal of Water and Climate Change*, 15(12), 5721–5738. <https://doi.org/10.2166/wcc.2024.678>
6. Tantisevi, K., et al. (2025). A novel framework for flood susceptibility assessment using hybrid AHP-based machine learning methods. *Natural Hazards*. <https://doi.org/10.1007/s11069-025-07335-8>
7. Rakshitha, R., Srinath, S., Kumar, N.V., Rashmi, S., & Poornima, B.V. (2026). An enhanced approach to road damage classification with deep feature extraction and class-specific clustering. *Evolutionary Intelligence*, 19, Article 20. <https://doi.org/10.1007/s12065-025-01130-x>
8. Abu Dabous, S., Ibrahim, F., & Alzghoul, A. (2025). Modelling bridge deterioration using long short-term memory neural networks: a deep learning-based approach. *Smart and Sustainable Built Environment*, 14(5), 1632–1655. <https://doi.org/10.1108/SASBE-10-2023-0295>
9. Jeon, C.-H., Kwon, T.H., Kim, J., Jung, K.-S., & Park, K.-T. (2024). Quantitative evaluation of reinforced concrete slab bridges using a novel health index and LSTM-based deterioration models. *Applied Sciences*, 14(22), 10530. <https://doi.org/10.3390/app142210530>
10. Thrasher, B., Wang, W., Michaelis, A., & Nemani, R. (2022). NASA Global Daily Downscaled Projections, CMIP6. *Scientific Data*, 9, 262. <https://doi.org/10.1038/s41597-022-01393-4>
11. MoRTH (2023). Annual Report 2022–23. Ministry of Road Transport and Highways, Government of India.
12. Ahmadzadeh, M., Zahrai, S.M., & Bitaraf, M. (2025). An integrated deep neural network model combining 1D CNN and LSTM for structural health monitoring utilizing multisensor time-series data. *Structural Health Monitoring*. <https://doi.org/10.1177/14759217241239041>
13. Faris, N., Zayed, T., & Fares, A. (2025). Review of condition rating and deterioration modelling approaches for concrete bridges. *Buildings*, 15(2), 219. <https://doi.org/10.3390/buildings15020219>



14. Abreu, V.H.S., Santos, A.S., & Monteiro, T.G.M. (2022). Climate change impacts on the road transport infrastructure: a systematic review on adaptation measures. *Sustainability*, 14(14), 8864. <https://doi.org/10.3390/su14148864>
15. IPCC (2022). Technical Summary. In: *Climate Change 2022: Impacts, Adaptation and Vulnerability*, AR6 WGII. Cambridge University Press.
16. Jeon, C.-H., et al. (2024). Health Index-based maintenance of prestressed concrete bridges with BIM and LSTM. *Buildings*, 14(12), 4032. <https://doi.org/10.3390/buildings14124032>
17. Geofabrik GmbH (2024). OpenStreetMap Data Extracts — India. download.geofabrik.de/asia/india.html (ODbL 1.0).
18. ESA Copernicus (2024). Sentinel-2 MSI Level-2A. dataspace.copernicus.eu (open access).
19. NASA/USGS (2000). Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global DEM. earthexplorer.usgs.gov (public domain).
20. Arya, D., Maeda, H., Ghosh, S.K., Toshniwal, D., & Sekimoto, Y. (2022). RDD2022: A multi-national image dataset for automatic Road Damage Detection. [arXiv:2209.08538](https://arxiv.org/abs/2209.08538).
21. ECMWF (2024). ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Data Store. <https://cds.climate.copernicus.eu>
22. NASA NCCS (2024). NEX-GDDP-CMIP6. Registry of Open Data on AWS: registry.opendata.aws/nex-gddp-cmip6