

Year-Wise Refitted Spatiotemporal Landslide Susceptibility Forecasting Driven by IMD Rainfall and SMAP Soil Moisture, Wayanad, India

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ABSTRACT

Landslides in hilly regions threaten life, infrastructure, and ecosystems. Landslide susceptibility is inherently transient, yet conventional analysis produces time-invariant zoning and evaluates it by random partitioning of a temporally structured inventory, which permits later events to inform predictions for earlier ones. This study develops a year-wise refitted framework for the Wayanad district of the Western Ghats, India, in which a Random Forest classifier is refitted independently for each target year from 2020 to 2024 using only events recorded earlier, with all target-year events withheld from training. Dynamic susceptibility is driven by India Meteorological Department (IMD) gridded daily rainfall and NASA Soil Moisture Active Passive (SMAP) soil moisture alongside static conditioning factors. Decomposing the evaluation set shows that the conventional random holdout returns a mean AUC-ROC of 0.913, rising monotonically, whereas withheld target-year events return 0.871 with no trend; the target-year value is lower in every year examined (sign test $p = 0.031$), and the divergence widens as the inventory grows. A Bidirectional Long Short-Term Memory (Bi-LSTM) network forecasts both triggering factors, extending susceptibility mapping to 2025 and 2026, years for which no meteorological record existed when the maps were produced. Two landslides subsequently reported in Wayanad during that period both fall within zones these maps classify as High. A cloudburst scenario is simulated to assess the response to localised extreme rainfall. The framework shifts susceptibility assessment from retrospective hindcasting to forward prediction, and makes explicit the optimism that conventional validation conceals.

Keywords: Dynamic Landslide Susceptibility, Rainfall and Soil Moisture, Forward Validation, Year-Wise Model Refitting, Random Forest, Western Ghats

1. Introduction

Landslides are among the most destructive natural hazards worldwide, posing an escalating threat to human safety, infrastructure, and natural environments (Zhang et al. 2022c; He et al. 2025). Globally, over 4,862 recorded deadly non-seismic landslide disasters were reported between 2004 and 2016 alone, claiming approximately 56,000 lives (Froude and Petley 2018). Two drivers intensify the hazard: extreme hydrological phenomena connected with climate change (Segoni et al. 2014; Vessia et al. 2016; Gariano and Guzzetti 2016), and anthropogenic factors, including unplanned urban growth, deforestation, and slope grading (Balamurugan et al. 2016). Risk reduction and infrastructure planning depend on correctly identifying where landslides are likely to occur, which has made

landslide susceptibility mapping the basis of regional geohazard analysis (Balamurugan et al. 2016; He et al. 2025).

The Static LSM, the most widely adopted methodology, describes a time-invariant map by associating the landslide inventory data with predisposing inputs. These comprise static features such as elevation, slope, aspect, and curvature, and often treat environmental triggers as static input (He et al. 2025). These frameworks have developed from bivariate statistical frameworks, such as the Frequency Ratio (Balamurugan et al. 2016; Zhang et al. 2022c), and Logistic Regression (Hong et al. 2019), to machine learning models. Random Forest has exhibited higher predictive capability, capturing the non-linear dependencies between conditioning factors (Fang et al. 2020; Zhang et al. 2022a, b; He et al. 2025; Xiao et al. 2026; Kundu et al. 2026).

Conversely, the Static LSM, irrespective of its statistical advancement, suffers from a major conceptual limitation: it is fundamentally constrained from modeling the triggering mechanism (Huang et al. 2024). Landslide onset is widely considered a two-phase process: It necessitates both the inherent risk from static causative factors and the dynamic trigger, like extreme precipitation or seismic ground movement (Gariano and Guzzetti 2016). The critical gap is the inability of validated LSMs to predict susceptibility during periods of dynamic hydrological stress.

The static framework cannot incorporate a brief, heavy rainfall event that raises pore-water pressure and leads to slope instability (Gariano and Guzzetti 2016). This observational disconnect requires an immediate framework shift from reactive time-invariant susceptibility mapping toward proactive, dynamic susceptibility forecasting (Samia et al. 2020).

Most published research, even those integrating dynamic inputs, is intrinsically retrospective. They intend to model the past landslide susceptibility using past dynamic inputs, which is hindcasting and not forecasting (Moreno et al. 2024; Zhu et al. 2026). Consequently, this implies the need for a temporally consistent framework, which is tested against unseen future inventories to ensure its predictive validity.

Landslide susceptibility models are conventionally fitted once to an integrated inventory and evaluated by random partitioning. Because such inventories are temporally structured, this permits information from later events to inform predictions for earlier ones, a practice shown in other environmental modelling contexts to yield optimistic performance estimates (Roberts et al. 2017; Ploton et al. 2020). This study instead refits the classifier independently for each target year using only events recorded prior to that year, withholding all target-year events from training and reserving them for evaluation. Scoring the two components separately quantifies how far a conventional random partition overstates the predictive skill. The magnitude of this optimism has not been quantified for landslide susceptibility models refitted on a rolling basis, and it is not addressed by reporting a

single aggregate AUC. Quantifying it is a prerequisite for treating susceptibility output as a risk estimate rather than a descriptive classification (Kim et al. 2018).

This research addresses this critical research gap with a novel year-wise refitted spatio-temporal framework. This study proposes a model that incorporates the combined strength of two advanced temporally consistent machine learning frameworks, i.e., testing the model using independent, future landslide events. The cornerstone of this methodology is the hybridization of the high-performance Random Forest model as the predictive spatial tool, and the Bi-LSTM network for time-series forecasting of the dynamic triggering inputs. This synergy aims to develop well-substantiated proactive susceptibility maps for future years. The framework is assessed on two criteria: the susceptibility maps it produces, and the extent to which its temporally stratified design alters the performance estimate relative to conventional practice. Because the triggering factors are themselves forecast, the 2025 and 2026 maps were produced for years with no meteorological record, and before the events against which they are now compared; two landslides subsequently reported in Wayanad both fall within zones these maps classify as 'High'. Retrospective assessments cannot furnish a test of this kind.

2. Study Area

To demonstrate the year-wise fitted framework for Static and Dynamic LSM, the landslide-prone area of the Wayanad district, located in the Western Ghats part of Kerala state, India, is considered as the study area, as shown in Fig. 1. The study area is located between 11°26' and 12°00' N and longitudes 75°47' and 76°27' E. With an area of 2131 km², the district contains undulating hills, forests, and valleys, with the forest cover exceeding 787 km² (Deepu et al. 2020), and altitude ranging from 700m to 2100m. The soil present in the region is mostly laterite soil, forest loam & brown hydromorphic soil (Department of Mining and Geology 2016). Between May and September, Wayanad experiences heavy rainfall, marking the annual average rainfall between 2500-3000 mm, which is the major cause for the frequent landslides and floods (Wadhawan et al. 2020). Wayanad had faced frequent fatal landslides, especially in 2024 (Kolathayar et al. 2025). Steep zones cover a small proportion of the region compared to its landslide frequency, in the area, making it ideally suited to study the combined effect of terrain and hydrometeorological factors.

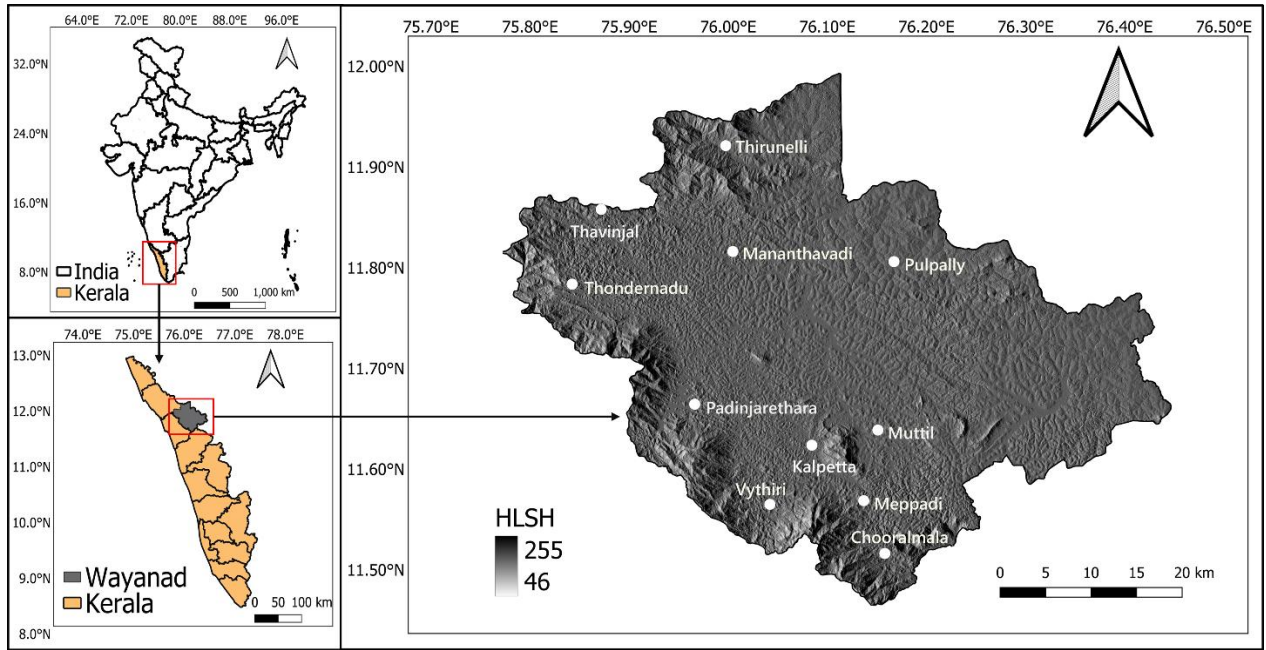


Fig. 1 Location and hill shade map of Wayanad district, Kerala, India

3. Data and Methodology

3.1. Landslide Inventory and Conditioning Factors

This research created an extensive spatial database for landslide susceptibility zoning for Wayanad. The datasets were divided into two sections: causative factors and triggering factors. The causative factors, *elevation, slope, aspect, curvature, relief, topographic position index (TPI), land use land cover (LULC), flow accumulation, horizontal & vertical distance from nearest drainage, geology, geomorphology, and lithology*, rarely change over short periods, hence categorized as static factors. The triggering factors, *rainfall* and *soil moisture*, initiate failure and change over time. Spatial maps of these factors, along with landslide inventory maps, were prepared and presented in QGIS (version 3.34.12) software. All 15 conditioning factors, along with landslide inventory data, are obtained from different sources as described in Table 1.

Table 1 Data information of conditioning factors

Dataset	Type	Source
DEM	Raster	https://www.nrsc.gov.in/
Rainfall Data	NetCDF	https://www.imdpune.gov.in/

Soil Moisture	Raster	https://smap.jpl.nasa.gov/
Landslide Points	Vector	
Geomorphology	Vector	
Lithology	Vector	https://bhukosh.gsi.gov.in/
Geology	Vector	
Land Use/Land Cover	Raster	https://dynamicworld.app/

Static factors create the baseline Static LSM, and do not change over time. The landslide susceptibility zones in that map will be susceptible due to the natural features of that area. The dynamic triggering factors, along with the static causative factors, create Dynamic LSM, which will change with a change in the triggering events. The overall workflow is shown in Fig. 2.

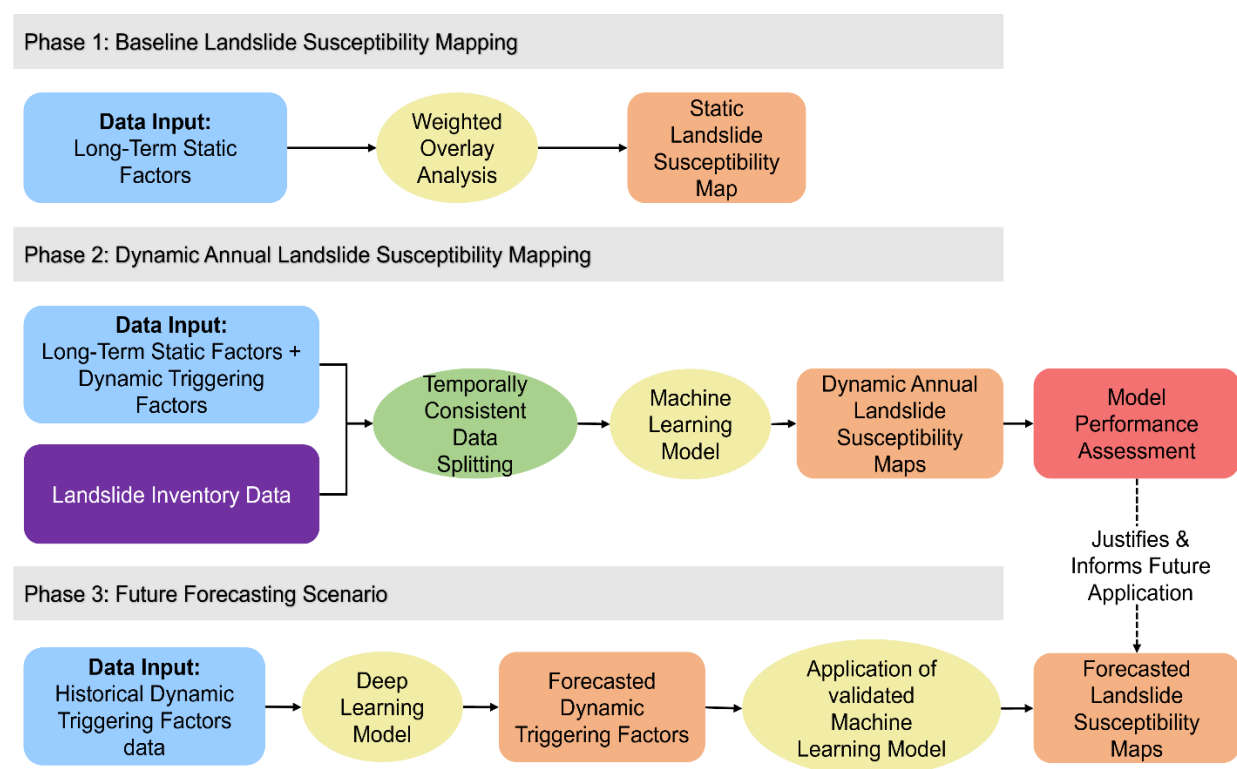


Fig. 2 Overall workflow of methodology

The landslide inventory (Fig. 3) act as a baseline for LSM (Dhakal et al. 2025), training the model to associate conditioning factors with susceptibility (Liu et al. 2024). Inventory data were collected from Bhukosh, managed

by the Geological Survey of India (GSI), whose Wayanad coverage ends in 2018. This inventory was therefore extended, compiling 76 additional events for 2019-2024 from published news reports and site-specific documentation. Each location was verified against at least one published report before inclusion. The resulting inventory consists of 299 events, of which 223 were recorded in 2018 and earlier, with individual initiation years available in the GSI attribute table, and 76 events in 2019-2024. A complete list of the compiled events with locations and supporting references is available from the corresponding author upon reasonable request.

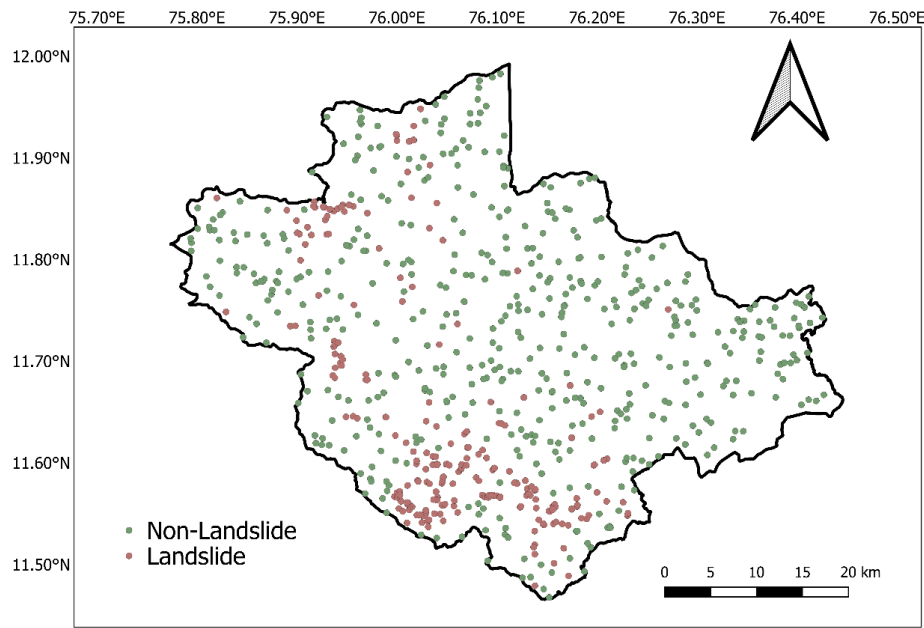


Fig. 3 Landslide inventory map of Wayanad

In this study, the elevation, slope, aspect, curvature, relief, TPI, flow accumulation, horizontal distance from nearest drainage (HDND), and height above the nearest drainage (HAND) data used were obtained from the Cartosat DEM with a resolution of 30m available on the Indian Geo-Platform of Indian Space Research Organization (ISRO), Bhuvan. Higher elevation parts are more susceptible to landslides as higher elevation areas have steeper and longer slopes and also experience higher rainfall (Liu et al. 2024). Elevation for the region ranges between 22 m to 2140 m, divided into five classes: Very Lowland (< 500m), Lowland (500-750m), Moderate (750-1000m), Highland (1000-1250m), and Very Highland (> 1250m) (Fig. 4a). Slope angle is pivotal in LSM, as the steeper slopes carry higher stress and lower stability (Hong et al. 2019; de Oliveira et al. 2019; Ali et al. 2022). The range of slope angle for Wayanad lies between 0° and 64.73°. In this research, the slope angles for the

study region were divided into five classes: Flat (0-15°), Gentle (15-25°), Medium (25-35°), Steep (35-45°), and Very Steep (> 45°) (Fig. 4b). Aspect represents slope orientation (Balamurugan et al. 2016; de Oliveira et al. 2019). Landslides on the south-facing aspect are mostly connected with reduced vegetation, sun exposure, and drought, whereas those on the north-facing aspect are associated with precipitation and humidity (Maheshwori et al. 2025). The aspect data for the region were classified into eight classes, divided from 0° to 360° clockwise (Fig. 4c). Curvature explains terrain concavity or convexity (Balamurugan et al. 2016). Curvature influences the driving and resisting stresses of the slope, which has a direct impact on landslides (Meten et al. 2015). Curvature is a continuous factor, ranging from -28.29 to 21.83 (Fig. 4d).

Relief represents the range of elevation within a neighbourhood and hence represents its ruggedness. Higher relief indicates higher landslide proneness (Ali et al. 2022; Mastrantonio et al. 2024). In this study, the range of relief was between 1 and 532 m and was divided into three classes: Low, Moderate, and High (Fig. 4e).

TPI expresses pixel height relative to its neighbours, distinguishing ridges, valleys and flat surfaces (De Reu et al. 2013; Emberson et al. 2022). TPI is a continuous factor ranging between -47.26 and 71.47 (Fig. 4f).

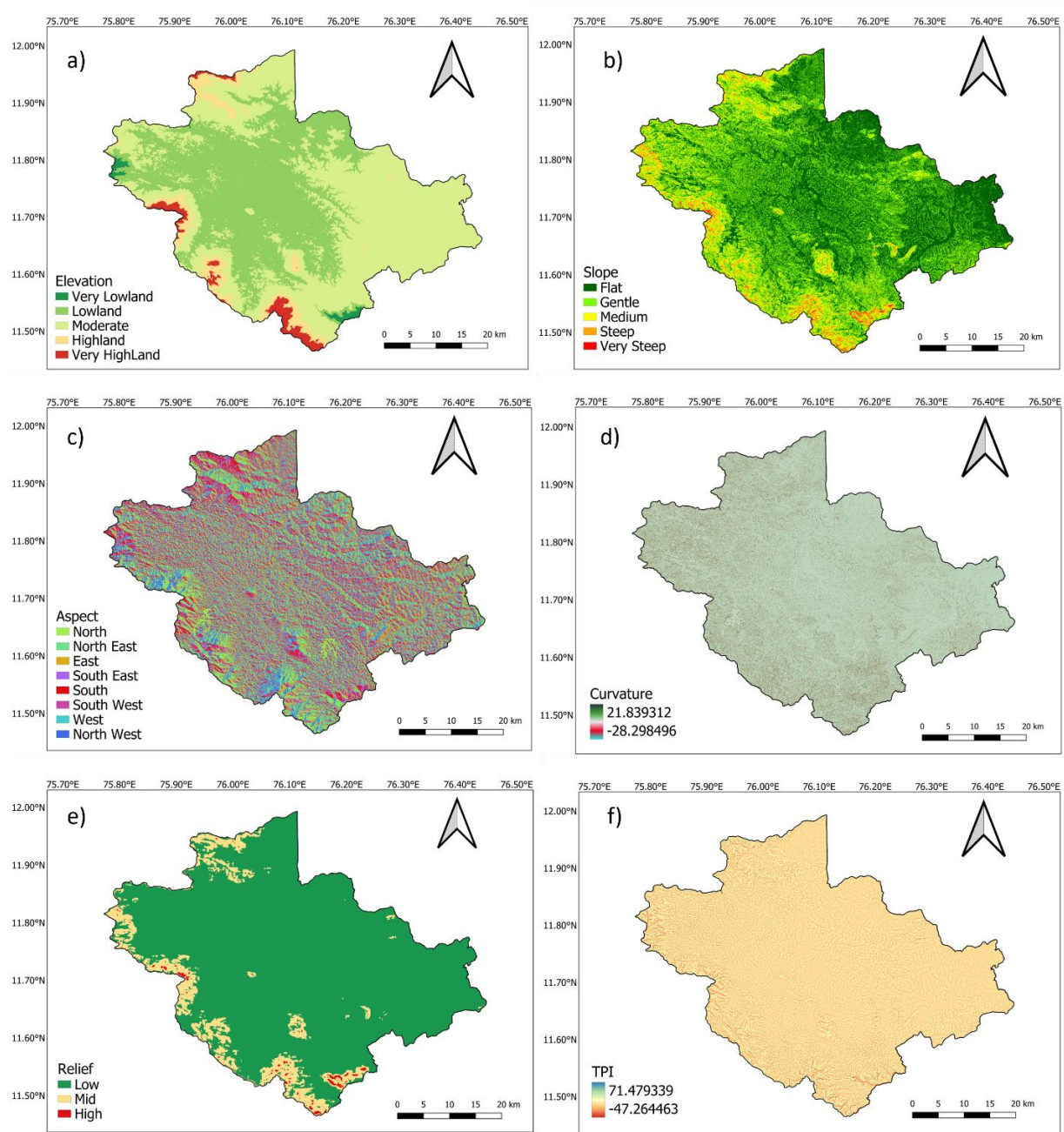
Flow accumulation derived from DEM quantifies the water accumulated in a pixel from its neighbouring cells (Xu et al. 2022). Higher flow accumulation increases surface runoff and decreases the stability of the slope. In this study, the range of flow accumulation is -4.78 to 7.29 (Fig. 4g).

HDND is the smallest planar distance of a pixel from the nearest drainage line, and vertical distance or HAND its elevation above that drainage line. Proximity to drainage is significant, as the presence of water reduces the shear strength of soil (Zhang et al. 2022c; Berhane et al. 2023). The range of HDND is 30 to 1410.32 (Fig. 4h), and the range of HAND is 0 to 150 (Fig. 4i).

LULC classifies surface land use using supervised classification. Open areas or areas with low vegetation have a high risk of landslides (Balamurugan et al. 2016; Xiao et al. 2025). In this study, the LULC used was obtained from Dynamic World and classified into nine classes as shown in Fig. 4j.

Lithology map, along with geology and geomorphology maps, was obtained from Bhukosh and prepared in QGIS. Geology represents material composition and structures, including rock and soil types, faults, and fractures. Areas with weathered rocks can create a greater risk of landslides (Ayalew et al. 2004; Balamurugan et al. 2016; He et al. 2025). It is divided into nine classes (Fig. 4k). Geomorphology represents landform types and slope morphology and their evolution over time, which contribute to landslide susceptibility (Balamurugan et al. 2016). Geomorphology is divided into fifteen classes, as shown in Fig. 4l.

187 Lithology describes rock composition, structure, size, and texture, whose categories contribute differently to
188 landslide susceptibility (LaHusen and Grant 2024; He et al. 2025) In this study, lithology is divided into 36
189 different classes, as shown in Fig. 4m.



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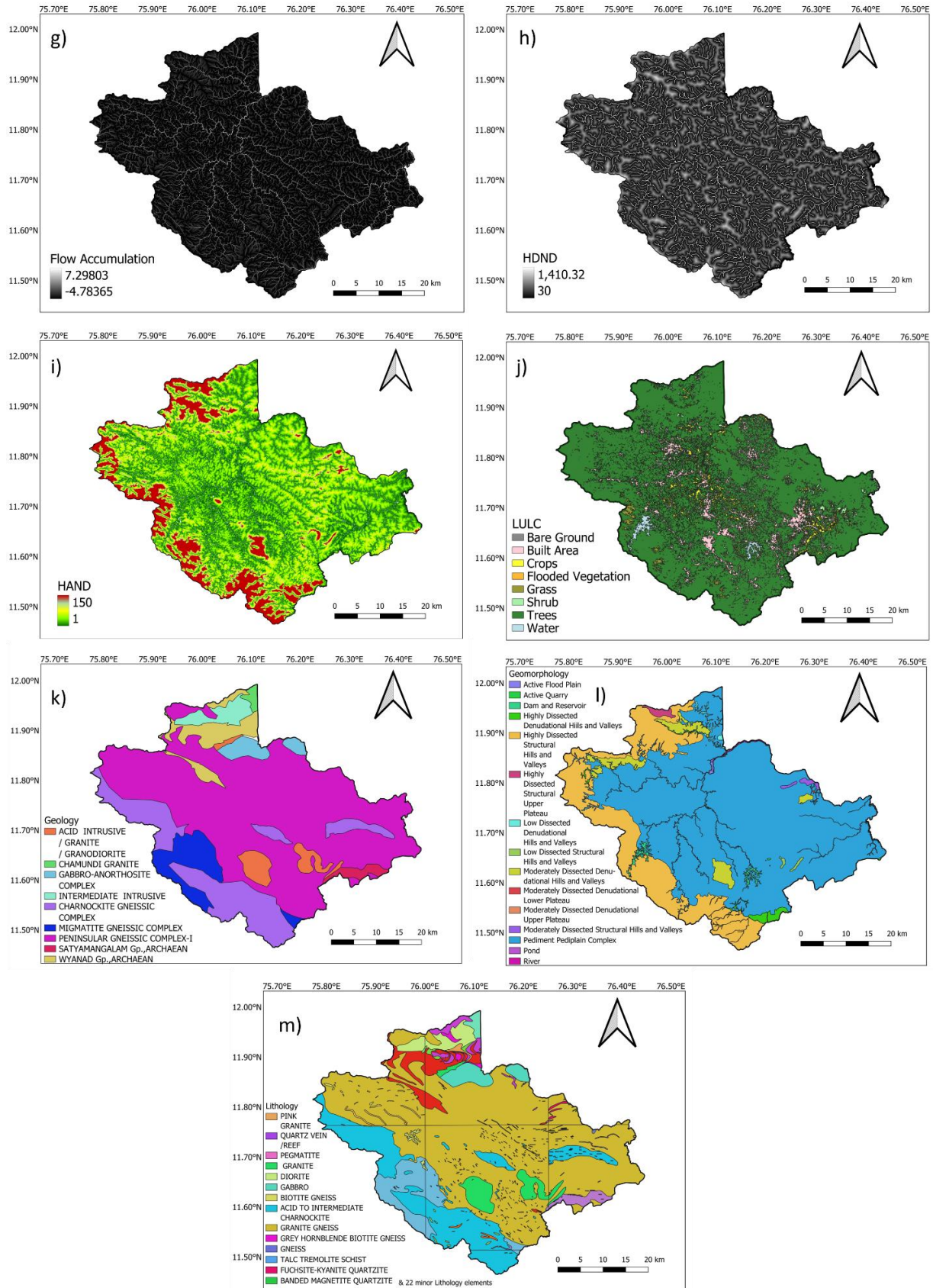


Fig. 4 Static causative factors considered for Wayanad: a) elevation, b) slope, c) aspect, d) curvature, e) relief, f) TPI, g) flow accumulation, h) HDND, i) HAND, j) LULC, k) geology, l) geomorphology, m) lithology

Rainfall directly triggers landslides (Hong et al. 2019) and is one of the two triggering parameters used here. Higher rainfall increases the pore water pressure, reducing the shear strength (Gariano and Guzzetti 2016; Manohar et al. 2026) and then induces surface runoff, and is hence taken as a dynamic factor. In this study, mean daily rainfall is considered, obtained from the IMD Pune gridded daily rainfall at $0.25^\circ \times 0.25^\circ$ resolution. Values across Wayanad range from approximately 3 to 10 mm per day. The gridded product was clipped to the district boundary, yielding 7 native grid cells across Wayanad. These were interpolated bilinearly to 100m and subsequently reprojected to the 30m analysis grid. The rainfall field, therefore, represents a regional gradient rather than variability resolved at 30 m. The rainfall data was divided into five classes: Very low, Low, Moderate, High, and Very High. The rainfall maps for each year were combined with the past three years' rainfall data to integrate the cumulative risk in the susceptibility analysis (Fig. 5).

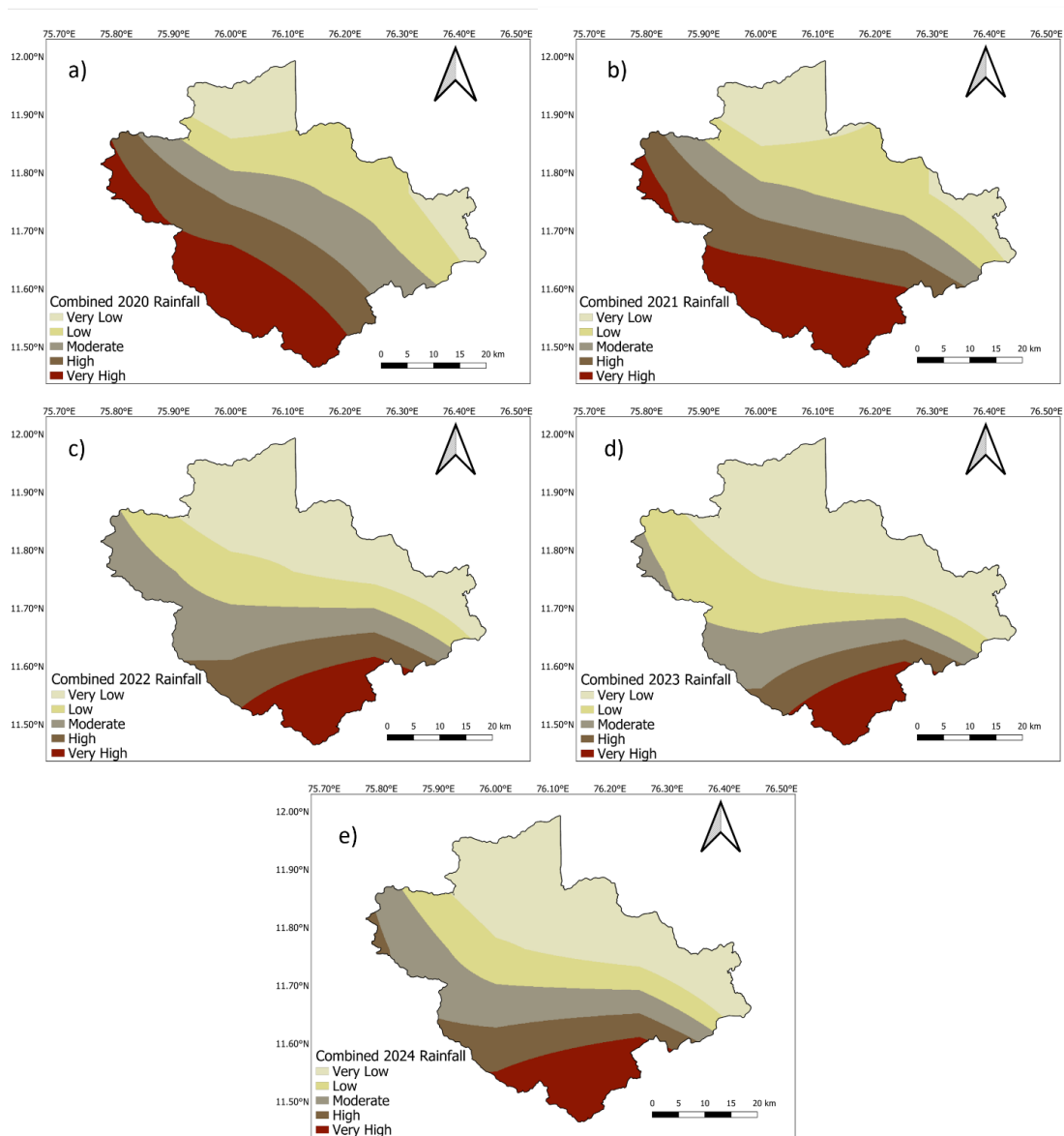


Fig. 5 Combined rainfall maps of Wayanad: a) 2020, b) 2021, c) 2022, d) 2023, e) 2024

Soil moisture is the second triggering factor. Soil moisture corresponds to the water content of the soil, which raises pore water pressure, reduces effective stress, and thereby lowers the shear strength of the slope (Gariano and Guzzetti 2016; Manohar et al. 2026). Like rainfall, soil moisture is dynamic. In this study, the soil moisture data were obtained from the NASA SMAP. The rootzone soil moisture is available up to a depth of 1 m in volumetric fraction in m^3/m^3 . The data were divided into five classes: Very Dry, Dry, Moderate, Wet, and Very Wet (Fig. 6).

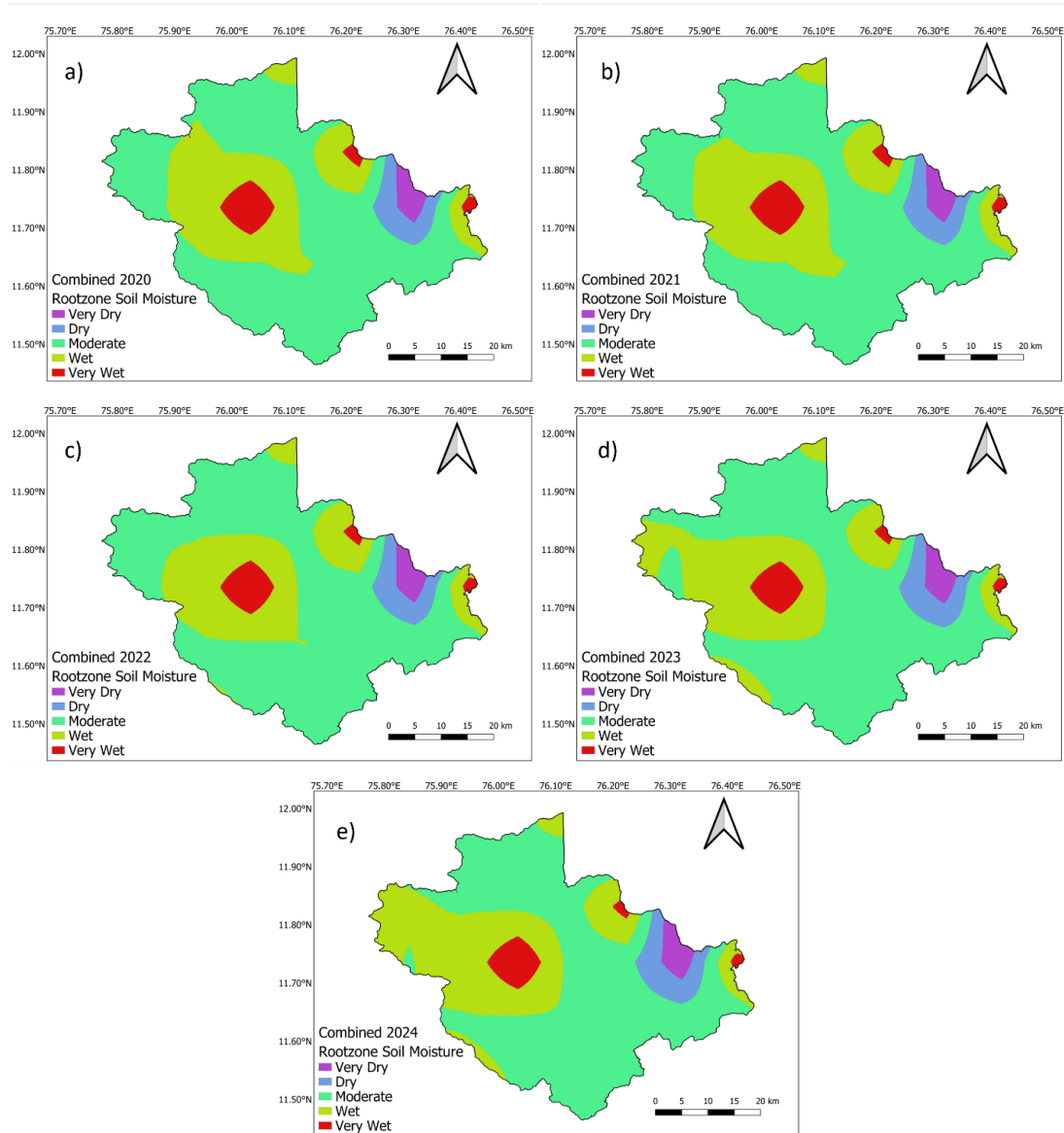


Fig. 6 Combined soil moisture maps of Wayanad: a) 2020, b) 2021, c) 2022, d) 2023, e) 2024

3.2. Methodology

3.2.1. Static LSM

The 13 static causative factors were integrated using the Weighted Overlay Method (Ayalew et al. 2004) to create the baseline Static LSM for long-term inherent landslide zones for Wayanad.

All datasets were brought to a common scale and were processed and exported at 30m resolution. Datasets for geology, geomorphology, and lithology were obtained as vector shapefiles. They were converted to raster at the same 30 m resolution. All factors were normalised to a common 0 to 1 scale. After the normalization of the dataset, the weights and ratings were assigned to it. Some of the causative factors were kept as continuous because, inherently, they were non-categorical. Ratings used in this study were back-calculated from the Random Forest feature importance to provide data-driven influence of factors, rather than depending on subjective assignments, as shown in Table 2.

Table 2 Weights and ratings for the static factors

Factor	Weight (w_i & w_j)	Classification Ratings (r_i)
Slope	0.077	[1, 3, 5, 7, 9]
Aspect	0.072	[1, 4, 7, 8, 9, 6, 3, 2]
Relief	0.009	[3, 6, 9]
Elevation	0.082	[1, 3, 5, 7, 9]
Geology	0.021	Ratings vary as per classes
Geomorphology	0.018	Ratings vary as per classes
LULC	0.009	[0, 1, 6, 6, 3, 4, 2, 9, 0]
Lithology	0.021	Ratings vary as per classes
TPI	0.076	
Curvature	0.074	
Flow Accumulation	0.072	Continuous Factor
HAND	0.066	
HDND	0.064	

After assigning the weights and ratings to all the dataset layers, they were combined in the Landslide Susceptibility Index (LSI) to create the Static LSM. The formula used for LSI in this study is shown in Eq. 1.

$$LSI = \sum_{i \in \text{classified}} w_i r_i + \sum_{j \in \text{continuous}} w_j n_j \quad (1)$$

Where w_i , r_i , w_j , and n_j are weightages of classified factors, ratings of classes, weightages of continuous factors, and normalized values of continuous factors, respectively. The Static LSM was created using the resulting LSI, dividing it into four different landslide susceptibility zones (very low, low, moderate, and high). The final Static LSM provides a baseline framework for further integrating dynamic factors to visualize the dynamic nature of LSM.

3.2.2. Dynamic LSM

The dynamic landslide susceptibility model was developed to reflect the influence of temporally changing triggering factors (Samia et al. 2020; Moreno et al. 2024) on the region's landslide risk, combining the effect of long-term static factors. This study developed annual landslide susceptibility maps from 2020 to 2024 using a structured workflow.

To align consistency, terrain-derived causative factors were resampled to a common spatial resolution of 30 m. Rainfall and root-zone soil moisture, which originate at coarser resolution, were interpolated to the same grid as described above. Dynamic factors were computed as the mean over a four-year trailing window ending at the target year, to represent cumulative hydrological memory rather than instantaneous conditions. All input factors, including triggering factors, were pre-processed the same way as in Static LSM. Rainfall and rootzone soil moisture data were used for 2020-2024.

For the Dynamic LSM, the inventory described in the Landslide Points subsection was used. For each target year t , a classifier was fitted independently using only events recorded before year t . All events occurring in year t were withheld entirely from training. The pre- t set was partitioned 70:30, the former used for training and the latter retained for evaluation; no point appears in both partitions for any target year. Non-landslide points were generated by stratified random sampling across Wayanad, excluding all locations within a 500 m buffer of a mapped landslide, with placement otherwise random outside this buffer, yielding 500 points and a landslide to non-landslide ratio of approximately 1:1.7. Class imbalance was addressed through bagging within the Random Forest, which constructs balanced training subsets.

Due to its ability to handle non-linear complex geo-spatial data and robustness against overfitting and noise, the Random Forest model was selected as the main modelling framework (de Oliveira et al. 2019). Random Forest develops an ensemble of various decision trees by continually training on bagged subsets of the data. Meanwhile, it arbitrarily selects a subset of predictors at each split. Using majority votes from the outputs of all decision trees

and accumulating them, the final prediction is attained, providing a stable classification result for landslide susceptibility.

The evaluation set for each target year comprised the held-out 30% of pre-t events together with all events from year t, and the primary performance metrics were computed across this combined set. To distinguish the contribution of each component, the identical trained classifier was additionally scored on the two subsets separately, first on the held-out pre-t events alone, corresponding to the random splitting conventional in susceptibility studies; and second on the target-year events alone, paired with the same held-out non-landslide points, providing a forward assessment. 95% confidence intervals for the decomposed evaluations were obtained by bootstrap resampling of the relevant evaluation set with 1000 iterations, reported as the 2.5th and 97.5th percentiles, following the bootstrap ensemble approach applied to susceptibility models by (Taherdangkoo et al. 2026).

Random Forest model efficiency strongly relies on parameters such as the number of decision trees and the bag fraction considered at each node. These hyperparameters were tuned to get the optimized model performance. The selected hyperparameters for the model are summarized in the Table 3.

Table 3 Hyperparameters of the Random Forest model

Year	Number of Trees	Bag Fraction
2020	456	0.7
2021	133	0.7
2022	30	0.5
2023	824	0.7
2024	62	0.7

Multiple evaluation metrics were used to evaluate the model's performance. To assess classification credibility, metrics like overall accuracy, precision, recall, F1 score, and AUC-ROC as the primary metrics, as they are reliable and robust in distinguishing between positive and negative classes.

For each year (2020-2024), the optimized Random Forest model was implemented independently to develop annual Dynamic LSMs. The LSMs were reclassified into four susceptibility zones (very low, low, moderate, and high). These annual maps captured the year-to-year variability of landslide-prone zones under varying rainfall and soil moisture conditions, thereby providing a dynamic representation of susceptibility evolution.

3.2.3. Forecasted LSM

The future forecasted LSMs were created in two-stage models: a) Forecasting of future year dynamic triggering factors, i.e., rainfall and soil moisture data using past ten years data and a time-series prediction model, and b) Incorporating long-term static causative factors with future forecasted triggering factors to develop forecasted LSMs using the validated Dynamic LSM.

a) Forecasting Triggering Factors

For time-series forecasting of rainfall and soil moisture for the goal years 2025 and 2026, the past ten years of gridded data from 2015 to 2024 were collected from IMD and NASA SMAP, respectively. For the forecasting component only, data were interpolated to a 5 km grid across Wayanad, yielding 89 grids. This grid is used exclusively for time-series forecasting and is not used in susceptibility mapping, which is performed at 30 m. The Bi-LSTM model is suitable for complex sequential data as it learns from both past and future subsequent, i.e., forward and backward directions, and both long-term and short-term memory, making learning of long-standing dependencies in climatic parameters efficient (Anshuka et al. 2022; Yang et al. 2025). The hyperparameters of the model are summarized in the Table 4. The model's performance was tested and validated using 2024 rainfall and soil moisture data. The performance was evaluated using metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R^2 , and correlation using 2024 test data. After validation, the model was used to forecast the rainfall and soil moisture data of 89 grids for the years 2025 and 2026.

b) Development of Forecasted LSMs

The forecasted LSMs were developed using the optimized Random Forest model, which was used and validated in the Dynamic LSMs part. The same long-term static causative factors were used in the model along with the forecasted triggering factors as input. The maps were then classified similarly to those Dynamic LSMs for 2025 and 2026. These maps are generated to help provide the susceptibility information before the event to improve the pre-disaster preparedness.

Table 4 Hyperparameters for the Bi-LSTM model

Section	Hyperparameter	Value
Input Data	Lookback Window	13 months
Input Data	Input Features	2 (Rainfall, Month)
Model Architecture	Type	Bidirectional LSTM

Model Architecture	Bi-LSTM Units (Layer 1)	64
Model Architecture	LSTM Units (Layer 2)	32
Model Architecture	Dropout Rate	0.2
Training	Optimizer	Adam
Training	Learning Rate	0.005
Training	Loss Function	Mean Squared Error (MSE)
Training	Early Stopping Patience	15 epochs

4. Results and Discussion

4.1. Static LSM

The baseline Static LSM provides the necessary foundational map, representing the long-term, non-transient, inherent likelihood of the topography to failure. This map is mainly composed of long-term consistent terrain and geological variables. ‘Moderate’ and ‘High’ susceptible zones show the long-term vulnerability. The ‘High’ susceptibility zones mainly coincide with the steep western boundary, the shift in the Western Ghat section to the coastal plains area. These zones consist of very high elevations and steep slope changes. The Area coverage of different susceptibility classes is summarized in Table 5.

The Static LSM of Wayanad (Fig. 7) bolsters the conception of inherent vulnerability, which is the core structural instability that makes the topography very likely to fail at any moment. The susceptibility level in these areas is unchangeable for a long time, irrespective of climatic patterns.

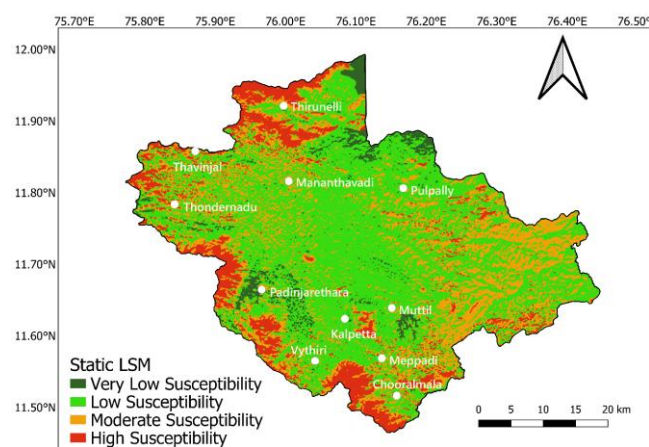


Fig. 7 Static LSM of Wayanad

4.2. Feature Importance, SHAP Analysis, and Correlation Analysis

The contribution of each factor was computed through Feature Importance using Gini impurity. While static causative factors like slope, elevation, and curvature are among the top five most important factors in the LSM, dynamic triggering factors, i.e., rainfall and soil moisture, are the most influential inputs for the Dynamic LSM, confirming their high predictive ability, as shown in the Fig. 8a.

These outcomes validate the foundational theory that the susceptibility in the region is not only a function of inherent terrain features, but also intrinsically triggered by the dynamic environmental or hydrological factors.

The responsiveness of the model to these triggering factors is very dominant for spatiotemporal mapping.

While the Feature Importance analysis aims to recognize and rank globally, on average, across the region, SHapley Additive exPlanations (SHAP) describes locally the prediction of the model for every single grid cell by explaining its explicit contribution (positive or negative) to the susceptibility. The SHAP summary (Fig. 8b) shows that the high feature values for slope and rainfall frequently generated substantial positive SHAP values, as they strongly drove the model's prediction in favor of "landslide". The low feature values of these features developed negative values, minimizing the predicted susceptibility. The Features like lithology and LULC have shown minimal contribution to predicting both landslide and non-landslide.

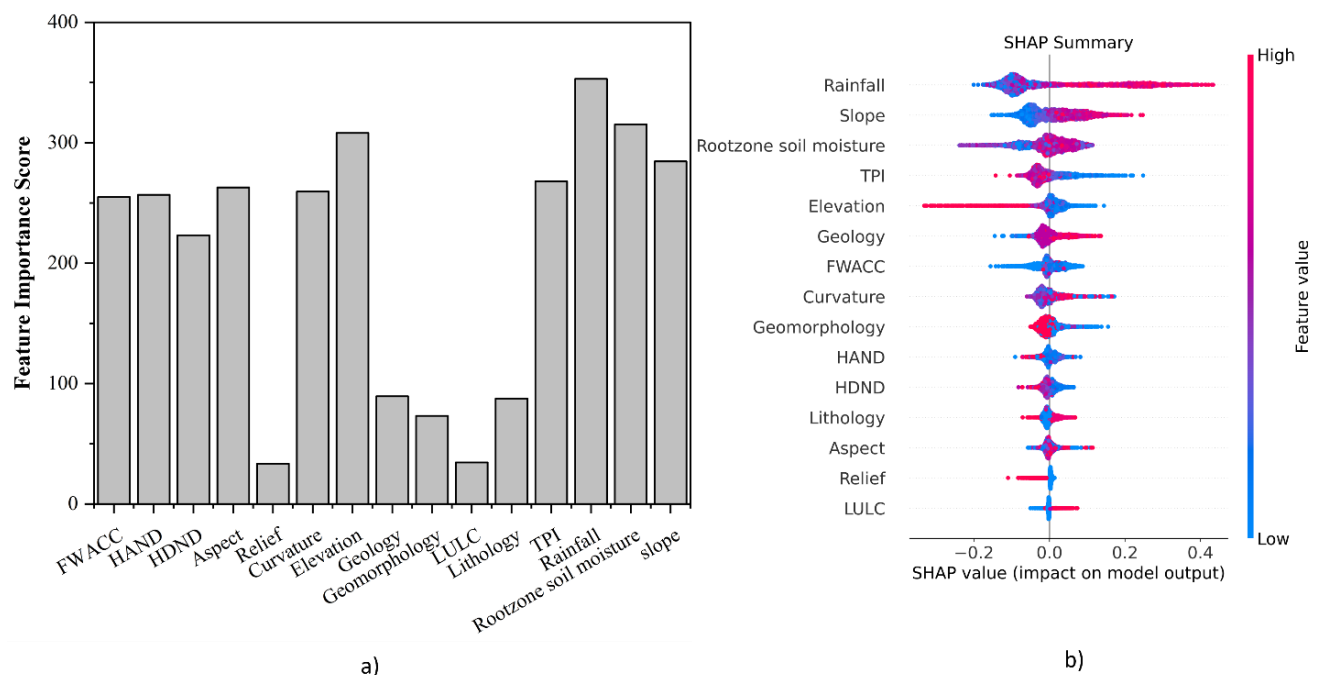


Fig. 8 a) Feature importance score and b) SHAP summary plots of the Dynamic LSM model

Moreover, the correlation analysis was done to ensure the independence and to test the multicollinearity of the features. A correlation matrix (Fig. 9) was developed for all the features. The high correlation of the features can distort the model's interpretation of which feature is actually responsible for a prediction. The matrix validated that all the key features showed low correlation coefficients, i.e., Pearson coefficient < 0.7 . This result confirms the robustness of the feature selection and that each feature gives unique and independent predictive information to the model, ensuring the decisive assessment of the contribution to landslide susceptibility.

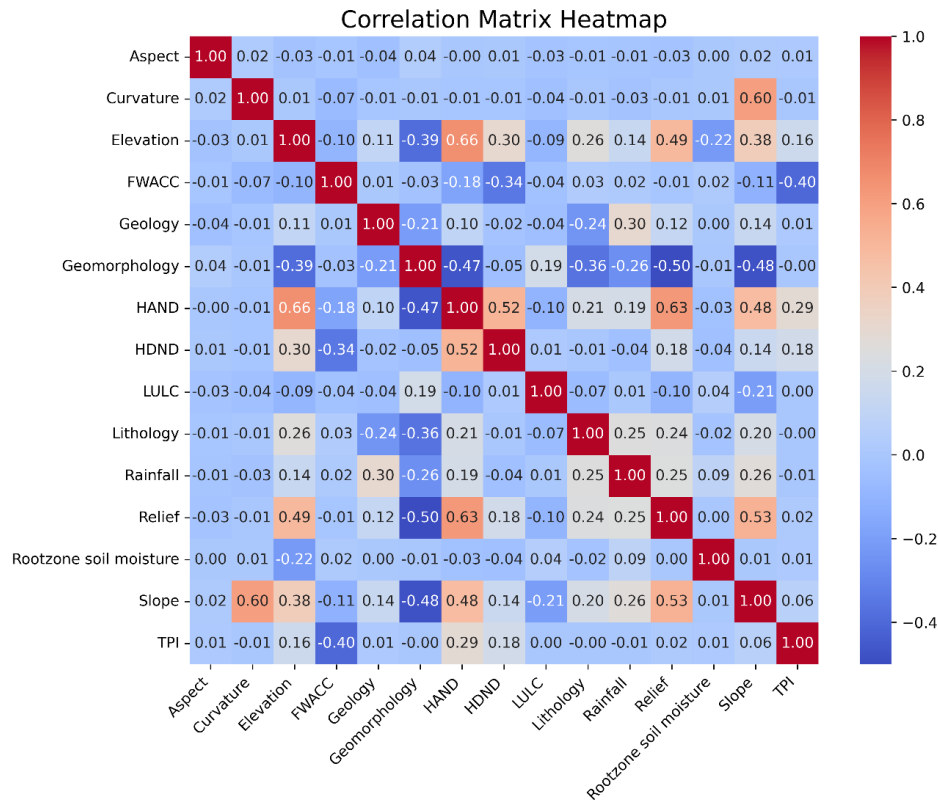


Fig. 9 Correlation matrix of features used in the Dynamic LSM model

4.3. Model Validation

The optimized Random Forest model was tested against the landslide inventory for each target year from 2020 to 2024, assessing robustness across differing annual climatic patterns.

The AUC-ROC curve (Fig. 10a) served as the key metric for the model's discriminatory ability to distinguish between landslides and non-landslides accurately. The AUC values were consistently high throughout all five validation years, exceeding 0.85. These consistently high results are a significant finding and confirm that the model is reliable across dynamic annual environments.

Across the combined evaluation set, the mean AUC was 0.907, ranging from 0.859 in 2020 to 0.941 in 2024. This set comprises a random partition of events of the pre-target year and the target-year events, withheld entirely from training. To distinguish their respective contributions, each model was additionally scored on the two components separately (Table 6). On the random holdout partition alone, which corresponds to the conventional evaluation reported in most susceptibility studies, AUC rose steadily from 0.862 in 2020 to 0.957 in 2024 (Spearman $\rho = 1.00$). On target-year events alone, AUC showed no comparable trend ($\rho = 0.20$, $p = 0.75$), ranging between 0.832 and 0.904. The forward estimate was lower in every year, with a mean difference of 0.042 (sign test $p = 0.031$), and the divergence widened from 0.002 in 2022 to 0.084 in 2023 and 0.081 in 2024. This indicates that the apparent year-on-year improvement under conventional evaluation reflects growth of the pooled inventory rather than improvement in predictive capability.

Confidence intervals for the forward evaluation are wide, reflecting the 11 to 18 events available in each target year; no individual year is conclusive in isolation, and the inference rests on the consistency of the direction of the effect across all five years.

A set of standard classification metrics was also computed, as shown in the Radar Plot (Fig. 10b). All the metrics remain highly stable throughout all years, confirming the model's reliability. The model consistently attained high Precision (> 0.88), signifying that the model was accurate the majority of the time when predicting a landslide, avoiding overly false alarms.

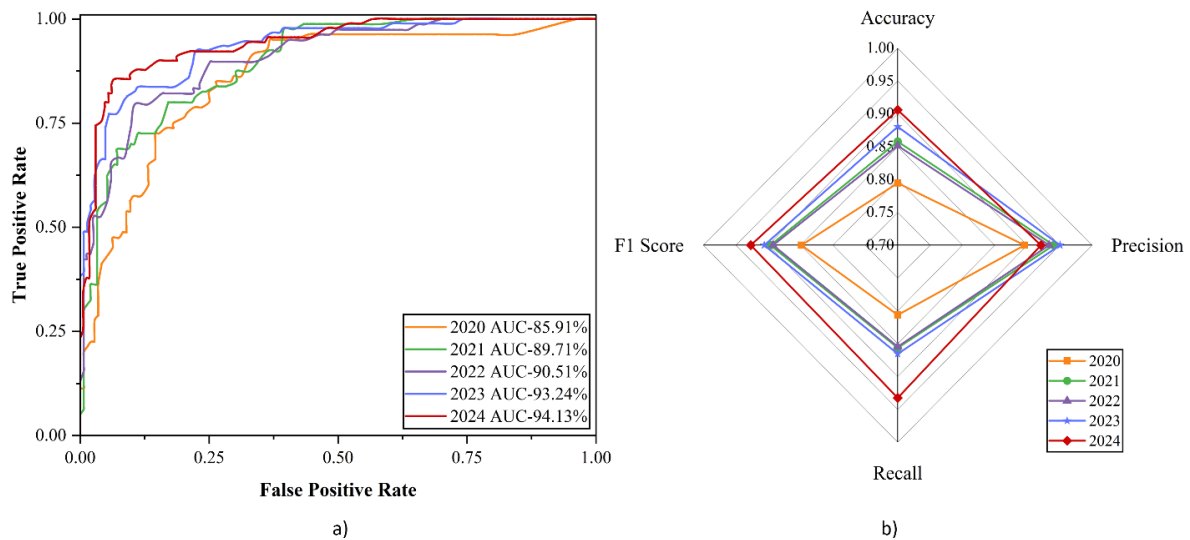


Fig. 10 a) AUC-ROC curve and b) accuracy metrics graph for the Dynamic LSM model for 2020-2024, correspond to the combined evaluation set

The confusion matrices (Fig. 11) for all five years give the precise, fundamental raw data behind the metrics. These matrices visually validate the results from the Radar Plot. In all five matrix sets, the quadrants for True Positives (TP) and True Negatives (TN) are overpowering. On the contrary, the quadrants for False Positives (FP) and False Negatives (FN), which are the wrong predictions, are fewer. The persistently low value of FPs and FNs validates the model's robustness and its applicability for real-world implementation.

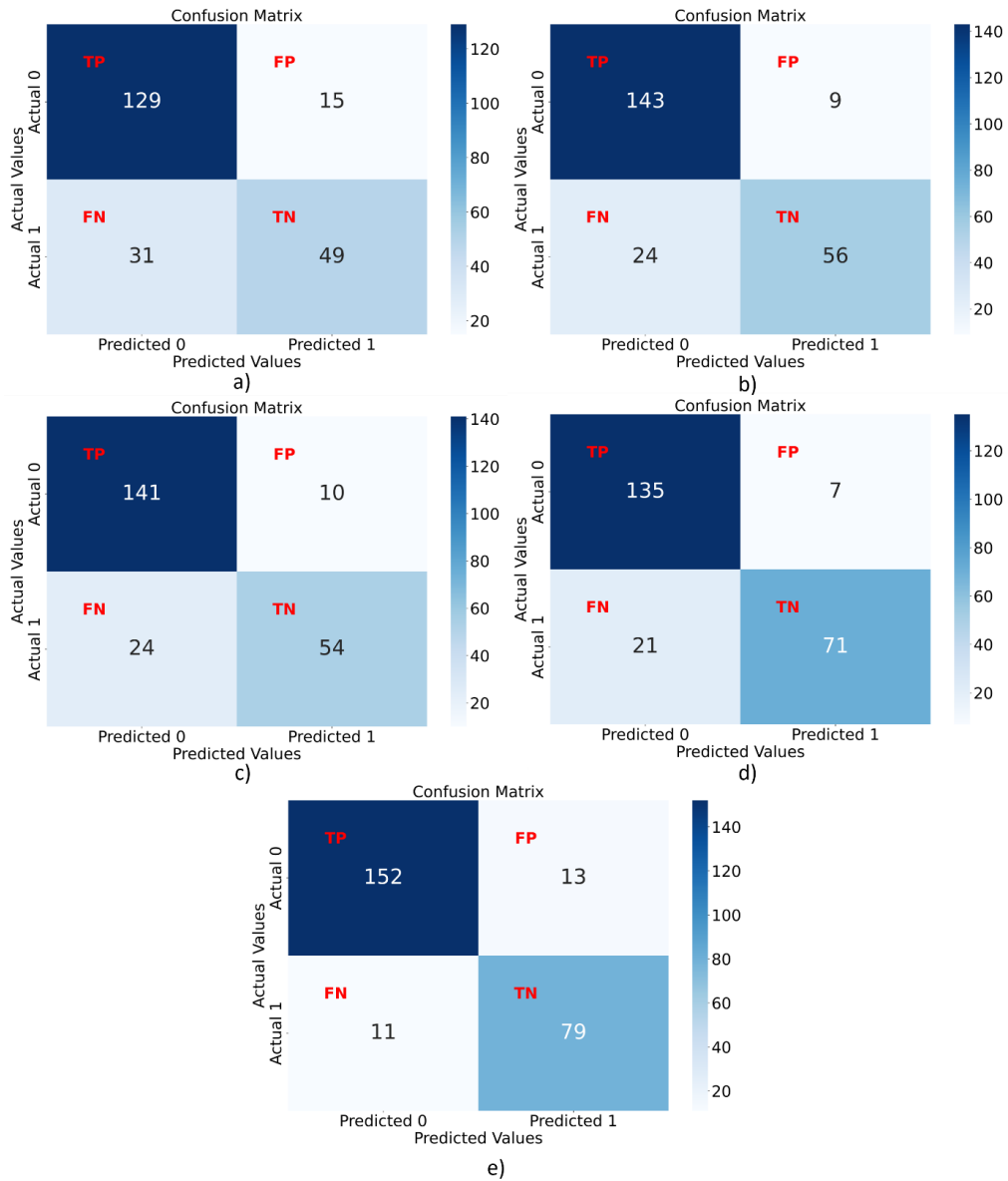


Fig. 11 Confusion matrices of the Dynamic LSM model for the years a) 2020, b) 2021, c) 2022, d) 2023, e)

2024

In conclusion, this validation confirms that the Dynamic LSMs framework performs consistently across the study period, while the decomposition above indicates that conventional evaluation alone would overstate its forward predictive skill.

4.4. Dynamic LSMs for Wayanad (2020-2024)

Following the evaluation of the model's robustness and predictive accuracy, the analysis now moves towards the spatial explanation of the model's output. The actual usefulness of the dynamic model is its capability to overcome the limitations of a single Static LSM and generate a time series of yearly susceptibility maps that demonstrate real-world environmental fluctuations.

The series of Dynamic LSMs (Fig. 12) shows how landslide susceptibility evolves. Contrary to the past single static analysis of LSM by (Arumugam et al. 2023) and (P et al. 2025), which mapped fixed high-susceptible zones in the western Wayanad, the spatio-temporal assessment in this research highlights that these susceptibility zones are highly dynamic in nature. Specifically, the 2020 LSM, characterized by significantly higher rainfall in a wider area, shows a significant increase in the 'High' susceptibility class compared to other years (Table 5). This expansion is most noticeable in the upland transition zone and along the slope base, categorized as 'Moderate' in Static LSM, especially around Meppadi. The variability of susceptibility zones in regions like Padinjarethara, from 'High' in 2020 to 'Moderate' in 2021, validates the dynamic nature of LSMs.

This spatio-temporal response validates the key finding that landslide susceptibility is not a fixed risk but is dynamic in nature. These maps demonstrate the model's ability to capture the localised, short-term response to hydrological variation, and highlight the need for susceptibility re-evaluation as the regions are uniquely susceptible under specific climatic patterns.

Table 5 Area coverage (km²) of landslide susceptibility classes in Static and Dynamic LSMs.

Susceptibility class	Static LSM	Dynamic 2020	Dynamic 2021	Dynamic 2022	Dynamic 2023	Dynamic 2024
Very Low	83.03	1538.92	1476.27	1326.72	1384.51	1244.70
Low	1221.55	229.81	287.46	417.75	394.48	511.65
Moderate	569.88	36.51	60.64	112.15	70.77	71.12
High	256.25	313.09	296.19	256.41	271.18	289.74

Note: The total area of Wayanad is 2131 km².

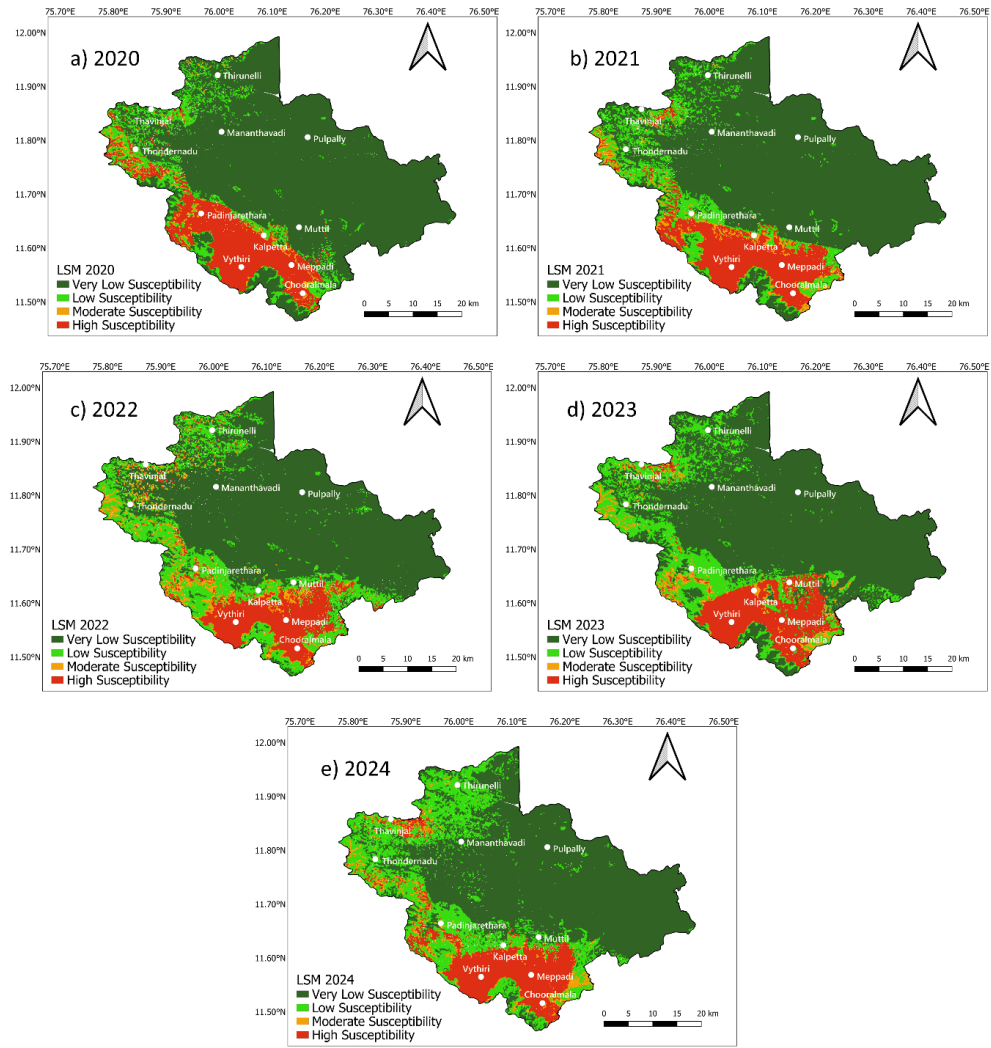


Fig. 12 Dynamic LSMs of Wayanad for the years a) 2020, b) 2021, c) 2022, d) 2023, e) 2024

Table 6 Model performance across the combined evaluation set, and scored separately on its two components: Random holdout partition and Target-year, along with confidence intervals.

Year	Combined evaluation AUC	Random holdout AUC [95% CI]	Target-year AUC [95% CI]
2020	0.859	0.862 [0.805, 0.910]	0.832 [0.652, 0.941]
2021	0.897	0.899 [0.855, 0.938]	0.884 [0.775, 0.969]
2022	0.905	0.906 [0.862, 0.947]	0.904 [0.759, 0.990]
2023	0.932	0.943 [0.916, 0.969]	0.859 [0.724, 0.977]
2024	0.941	0.957 [0.930, 0.979]	0.876 [0.774, 0.962]
Mean	0.907	0.913	0.871

4.5. Forecasted LSMs (2025-2026)

After the validation of the model's reliability against past years' data, its main goal was to predict future vulnerability. The Bi-LSTM network first predicts rainfall and soil moisture, and the Random Forest model then uses these forecasts to produce the forecasted LSMs.

The model was trained on 2015-2024 rainfall and soil moisture, across 89 5x5 km grids covering the entire Wayanad. This 5 km resolution was opted for as an optimal trade-off between computational efficiency and required spatial resolution. The key performance metrics were analyzed on the already available 2024 rainfall and soil moisture data to confirm the reliability of the Bi-LSTM model for future forecasting. The overall statistics findings are summarized in Table 7.

The framework showed a good predictive capability, with a very high R^2 (> 0.85) and correlation (> 0.95) for both variables, and low RMSE and MAE. This indicates that the model is suitable for creating plausible future inputs for the susceptibility model. To visualize the model's predicted output, Fig. 13 shows the time-series forecasted data for the years 2025 and 2026 for four representative grid samples.

Table 7 The performance metrics of the Bi-LSTM model for rainfall and soil moisture

Metrics	RMSE	MAE	R^2	Correlation
Rainfall	2.28 mm	1.67 mm	0.87	0.95
Soil Moisture	0.03 m ³ /m ³	0.02 m ³ /m ³	0.87	0.98

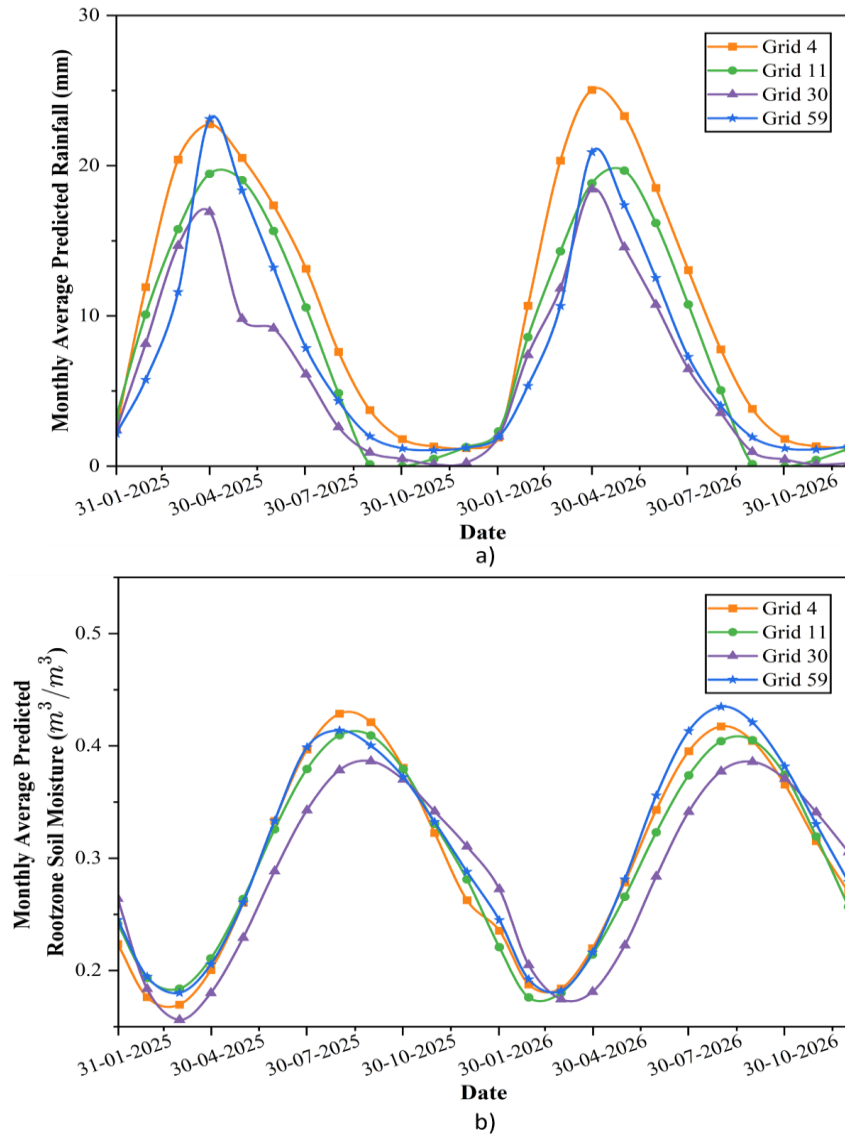


Fig. 13 Typical time-series forecasted a) rainfall data and b) soil moisture data of the four representative samples of the grids 4, 11, 30, and 59 out of 89 grids

Using all spatially reconstructed and interpolated 89 forecasted grids of rainfall and soil moisture data, the final maps of forecasted triggering inputs for the Random Forest model were generated. Fig. 14a-d visualizes the complete forecasted maps for the entire region for 2025 and 2026.

The final, concluding phase of the model was to incorporate these forecasted triggering factor maps with the long-term static causative factors. It is crucial to highlight that the same validated Random Forest model was used to forecast the target year LSMs. This ensures the model's high reliability in the output.

The resulting forecasted 2025 and 2026 LSMs (Fig. 14e-f) demonstrate the main predictive outcome of the entire region. Two landslide events have been reported in Wayanad during the forecast period, both falling within zones

classified 'High' in the corresponding forecast maps. The first was a heavy rainfall-generated mudflow near Chooralmala in 2025, which aligned with the 'High' susceptibility zone in the 2025 forecasted map (The Hindu Bureau 2025). The second occurred on 7 July 2026 near Kalladi, triggered by monsoon rainfall at an active road tunnel construction site (Petley 2026). This event has been attributed in part to the deposition of excavated material; since the present framework represents natural causative and triggering factors only, the correspondence should be read as indicating pre-existing terrain susceptibility rather than as prediction of a construction-induced failure. With only two events these observations are indicative rather than statistically conclusive, and systematic validation of the forecast maps awaits a longer observational record.

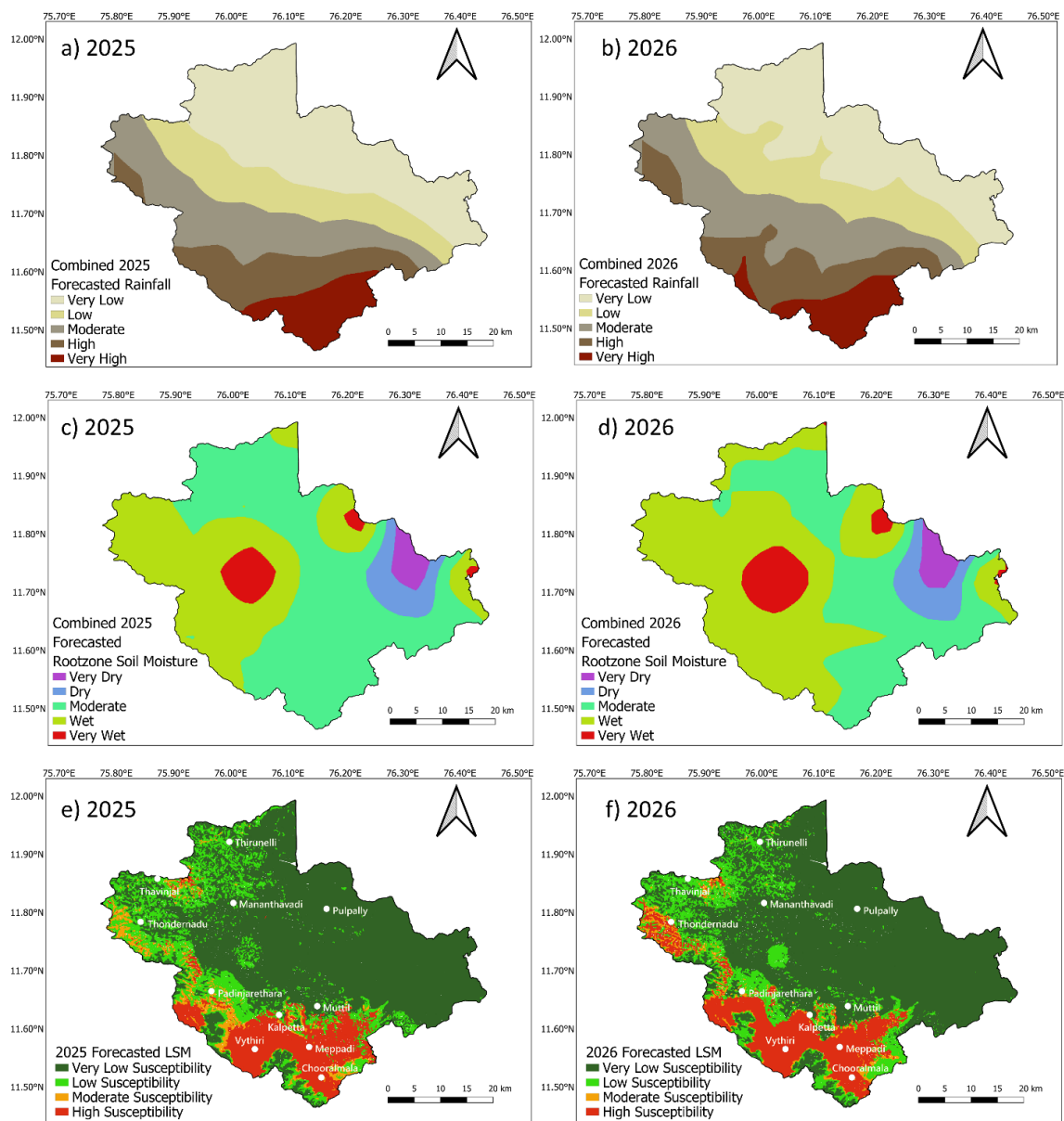


Fig. 14 Forecasted maps of a) combined rainfall of 2025, b) combined rainfall of 2026, c) combined soil moisture of 2025, d) combined soil moisture of 2026, e) LSM for 2025, and f) LSM for 2026

4.5.1. Hypothetical Cloudburst Hotspots Modeling

An assumptive cloudburst situation was developed over the forecasted 2025 and 2026 LSMs to evaluate its reliability under a sudden, localized maximum rainfall event. IMD identifies the Western Ghats among the regions at elevated risk alongside the Himalayan states. Within the study area, the July 2024 Mundakkai-Chooralmala failures followed intense localised rainfall, providing a direct local precedent for the scenario considered here. The IMD defines a cloudburst as precipitation exceeding 100 mm/h over a small, localised area (Singh and Thapliyal 2022). To assess the susceptibility response, four hotspots were laid throughout the highly susceptible areas in Wayanad. The hotspots were created using three variables: i) the center of the event, ii) the maximum additional rainfall depth at the center ($I_{\max}$), i.e., 150 mm, and iii) the radius up to which the event spreads ($D_{\max}$), i.e., 7 km. Rainfall decayed linearly from the center to the maximum radius, a conservative simplification of the radial decay in the convective cells. Under the decay function, the area receiving an increment exceeding the 100 mm cloudburst threshold is approximately 17 km² per hotspot, consistent with the localised extent of such events, while the mean increment across the full 154 km² disc is 50 mm. The hotspots' rainfall was added to the original forecasted rainfall maps, and at any grid cell, this additional intensity was added using the following function, Eq. 2:

$$I_{\text{added}} = I_{\max} \times \left(1 - \frac{d}{D_{\max}}\right) \quad (2)$$

Where d is the distance from the center of the hotspot.

The I_{added} layer was then incorporated with the forecasted 2025 and 2026 rainfall map ($I_{\text{forecasted}}$) (Fig. 15(a) and Fig. 15(b)) by adding it to the original layer using the following Eq. 3:

$$I_{\text{Final}} = I_{\text{forecasted}} + \max(I_{\text{added},1}, I_{\text{added},2}, \dots, I_{\text{added},N}) \quad (3)$$

Using the same optimized Random Forest model, the forecasted LSMs incorporating hypothetical cloudburst conditions were developed (Fig. 15c-d). The addition of the cloudburst condition showed a significant transition of 'Moderate' susceptibility zones to the 'High' susceptibility zones for the year 2025, which resulted in the increase of area coverage of 'High' susceptibility zone from 12.8 % to 15.4 %. It also demonstrated the elevation of 'Very Low' susceptibility zones to the 'High' one in 2025 and 'Low' to 'Moderate' in 2026. Because the imposed increment lies above the range of rainfall values on which the classifier was trained, and Random Forest

predictions are bounded by the training domain, the response at the hotspot centers represents the model's maximum rainfall sensitivity. The analysis, therefore, identifies zones assigned moderate susceptibility at baseline that sit close to a classification threshold under extreme rainfall.

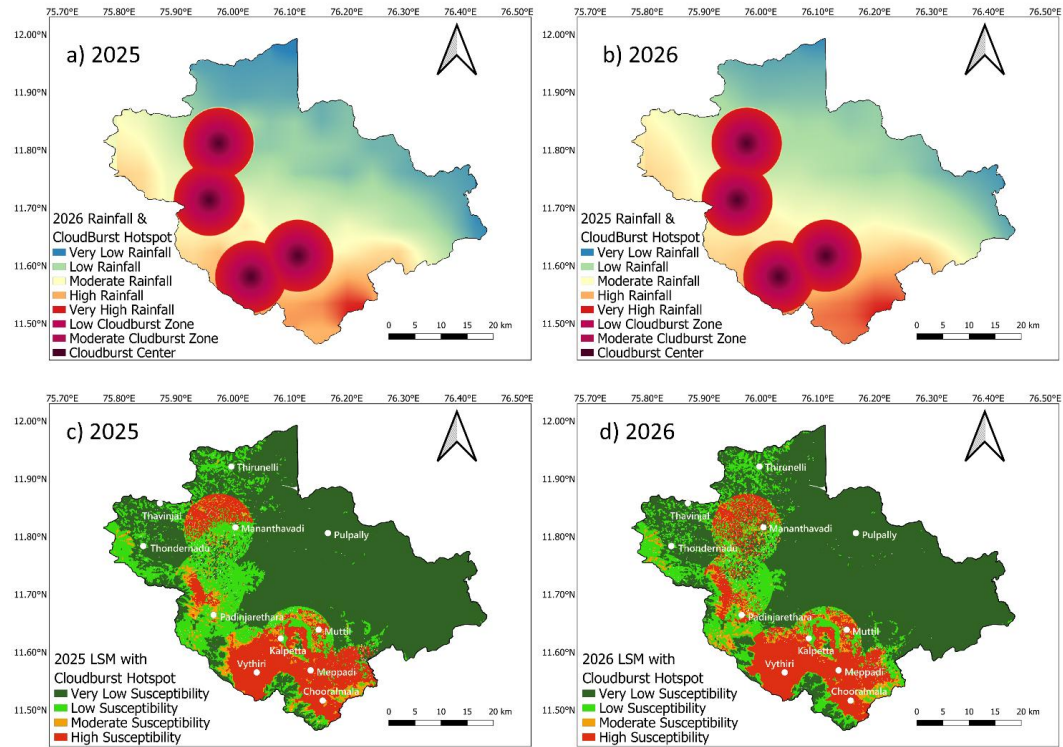


Fig. 15 Hypothetical cloudburst hotspots map of a) 2025, b) 2026, and the LSMs incorporating cloudburst hotspots for c) 2025, d) 2026

Conclusions

This study generated and validated a combined spatio-temporal model for landslide susceptibility, shifting from the conventional way of single static assessment. By integrating the temporally consistent Random Forest model (Machine Learning) for reliable spatial analysis and the Bi-LSTM model (Deep Learning) for time-series analysis, this study not only validated past dynamic vulnerability but also showed the ability to create proactive, prospective risk analysis and evaluate extreme-event conditions. In doing so, it also establishes how much of the apparent performance of a conventionally validated susceptibility model is attributable to the partitioning scheme rather than to predictive skill.

The following primary conclusions can be drawn from the findings:

- The Random Forest model, when incorporated with dynamic input, is a precise and intuitive framework for Landslide Susceptibility Assessment. This model demonstrated a highly robust performance

throughout all validation years (2020-2024), with AUC scores consistently exceeding 0.85. In particular, SHAP analysis validated that dynamic triggering inputs (rainfall and soil moisture) are key predictive variables, confirming the model's governing logic and the requirement of moving beyond static analysis alone.

- Decomposing the evaluation set demonstrated that the conventional random holdout and the withheld target-year events do not measure the same quantity. The holdout component returned a mean AUC of 0.913 and rose monotonically across the study period, while the target-year component returned 0.871 and showed no trend. The target-year value was lower in every year (sign test $p = 0.031$), and the separation widened from 0.002 in 2022 to 0.084 in 2023 and 0.081 in 2024. Reporting a single pooled metric for a temporally structured inventory therefore conceals a systematic and growing optimism, and bootstrap intervals are required alongside point estimates if susceptibility output is to be used for risk-informed decisions.
- This research successfully implemented a predictive model by incorporating a Bi-LSTM network. Two landslide events reported in Wayanad during the forecast period, in 2025 and 2026, both fell within zones classified 'High' in the corresponding forecast maps. With only two events, this is indicative rather than conclusive, but it represents a direct test of forecast maps against failures that post-date their production, which retrospective susceptibility assessments cannot provide. This framework robustly forecasted future dynamic inputs at a 5 km resolution (e.g., rainfall MAE of 1.67 mm), facilitating the development of the proactive Forecasted LSMs for 2025 and 2026.
- The assumed cloudburst scenario (150 mm extreme rainfall hotspots) showed that localized, extreme rainfall events can generate intensified, concentrated 'High' susceptibility zones. This identifies zones close to a classification threshold, informing intensity-dependent criteria for Early Warning Systems.

Finally, this study provides a crucial advancement for risk management, offering a practical two-stage framework for policymakers: The static susceptibility assessment of landslides for long-term land-use planning and the Forecasted LSM for pre-disaster annual resource allocation.

5. Limitations and Recommendations

The inventory comprises 299 events over 2,131 km², of which 76 were compiled from reported sources with settlement-level positional accuracy; terrain attributes extracted at these locations are correspondingly less precise. Between 11 and 18 events were available for each target year, which limits the precision of the forward evaluation

and accounts for the width of the associated confidence intervals. The inventory is point-based rather than polygon-based and derives from reported events, so smaller failures are likely under-represented. Rainfall was interpolated from a 0.25° gridded product, clipped to the district boundary before interpolation for computational reasons; minor edge effects may therefore be present at the district margin. The extreme-rainfall scenario lies above the range of rainfall values on which the classifier was trained and therefore indicates an upper-bound response rather than a calibrated one. The error statistics reported for the forecast triggering factors are not propagated into the forecast susceptibility maps, so the uncertainty attaching to those maps is not quantified; this remains a priority for further work. A further limitation concerns data availability. The framework depends on consolidated annual meteorological datasets, which are released only after the year ends. This suits the objective of a proactive planning tool but not an operational warning system, which requires real-time feeds. Calibrating the framework against daily data would extend it toward automated real-time susceptibility analysis.

Statements and Declarations

Author contributions

Swati Swati: Methodology, Data curation, Conceptualisation, Visualization, Validation, Writing – original draft.

Sireesh Saride: Supervision, Conceptualisation, Methodology, Visualization, Writing – review & editing.

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Data and Code Availability

The code and data supporting this study are available from the corresponding author upon reasonable request.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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