

Article

Landslide Susceptibility Assessment in a Complex Mountain Basin Transition Zone by Integrating Mamba and SBAS-InSAR Deformation Evidence: A Case Study of the Xining Basin, China

Heming Yang, Wenhui Liu *  and Yabin Liu

School of Geological Engineering, Qinghai University, Xining 810016, China; ys240859010316@qhu.edu.cn (H.Y.); 2019990011@qhu.edu.cn (Y.L.)

* Correspondence: 2019990102@qhu.edu.cn

Highlights

What are the main findings?

- A Mamba-based landslide susceptibility mapping framework was developed for the Xining Basin and achieved the highest AUC under region-based spatial hold-out validation, with an AUC of 0.9011 and an F1-score of 0.7431.
- SBAS-InSAR deformation evidence was incorporated as an independent post-model bidirectional reclassification layer, and the refined high- and very-high-susceptibility classes occupied 25.31% of the study area while containing 69.84% of mapped landslides.

What are the implications of the main findings?

- Integrating deformation information after model prediction improves the physical interpretability of susceptibility zonation without introducing InSAR data into model training.
- The refined susceptibility map can support priority monitoring and risk mitigation in valley–mountain transition belts, river-incised slopes, and engineering-disturbed sectors.

Abstract

Landslide susceptibility mapping (LSM) in mountain–basin transition zones remains challenging because conventional approaches rely mainly on historical inventories and static conditioning factors, whereas independent deformation evidence is seldom incorporated to refine susceptibility zonation. This study proposes an integrated LSM framework for the Xining Basin by coupling a Mamba-based model (Mamba-LSM) with SBAS-InSAR-based deformation-informed bidirectional reclassification, with the key innovation lying in the use of independent deformation evidence to refine susceptibility zonation after model prediction. Specifically, Mamba-LSM integrates six-channel neighborhood patches, CNN-based local spatial encoding, and Mamba-based latent feature transformation to improve the representation of local terrain context for landslide susceptibility assessment. Results show that Mamba-LSM achieved the highest AUC among the evaluated models, reaching 0.9011 with an F1-score of 0.7431. After deformation-informed bidirectional reclassification, the high- and very-high-susceptibility classes occupied only 25.31% of the study area but contained 69.84% of the mapped landslides, and were concentrated mainly in valley–mountain transition belts, river-incised slopes, and engineering-disturbed sectors where SBAS-InSAR deformation hotspots were also preferentially distributed. These findings demonstrate that integrating independent SBAS-InSAR deformation evidence can



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improve both the spatial concentration of landslides in high-susceptibility zones and the physical interpretability of susceptibility zonation.

Keywords: landslide susceptibility mapping; Xining Basin; Mamba-LSM; SBAS-InSAR; deformation-informed bidirectional reclassification

1. Introduction

Landslides are among the most destructive geological hazards in tectonically active mountainous regions, causing severe infrastructure damage, casualties, and environmental degradation. Their broad societal impacts highlight the need for effective regional hazard assessment and prevention [1–4]. At broader scales, global landslide inventories have also revealed pronounced spatial and temporal heterogeneity in landslide occurrence, further underscoring the importance of inventory-based hazard analysis for regional risk reduction [5]. On the northeastern margin of the Qinghai–Tibet Plateau, slope instability is particularly pronounced because of steep terrain, fragile lithologies, seasonal precipitation, and intensive human disturbance. The Xining Basin, a typical mountain–basin transition zone, is widely mantled by loose and porous loess deposits that are highly sensitive to moisture changes. Under rainfall infiltration, freeze–thaw cycles, and engineering disturbance, these materials are prone to strength reduction and slope failure, making the region especially susceptible to landslides [6–8]. In this context, landslide susceptibility mapping (LSM) provides an important basis for hazard mitigation, infrastructure planning, and land-use management.

Existing LSM methods can generally be classified into heuristic, physical, and data-driven approaches. Heuristic methods rely heavily on expert knowledge and often suffer from limited reproducibility, whereas physical models usually require detailed geotechnical and hydrological parameters that are difficult to obtain at regional scale [9,10]. With the rapid development of GIS, landslide databases, and remote sensing technologies, data-driven methods, especially machine learning and deep learning approaches, have been increasingly applied because of their ability to capture nonlinear relationships between landslide occurrence and environmental controls [11–14]. Recent studies have further demonstrated the value of optimized negative-sample design, ensemble modeling, and meta-learning for improving LSM performance and interpretability [15–20]. However, most current LSM studies still depend primarily on historical landslide inventories and relatively static conditioning factors. As a result, the resulting susceptibility maps are generally more effective in describing long-term spatial predisposition than in representing current slope activity.

This limitation is particularly important in the Xining Basin and similar loess-covered mountain–basin transition environments, where slope instability is controlled not only by static environmental conditions but also by ongoing deformation processes and human-induced disturbances. Conventional machine learning models usually rely on tabular factor representations and therefore have limited capacity to preserve neighborhood-scale spatial context. More importantly, susceptibility zonation derived solely from static predictors and historical inventories may fail to identify slopes that are currently active or kinematically evolving. Interferometric Synthetic Aperture Radar (InSAR) provides spatially continuous deformation information and has increasingly been incorporated into landslide susceptibility studies to identify active deformation and improve the temporal relevance of susceptibility assessment [21–26]. In addition, recent studies have shown that factor assignment strategies and evaluation units can substantially influence the readability and interpretability of susceptibility maps [27]. Nevertheless, in many previous studies,

InSAR has mainly been used as auxiliary evidence or for simple spatial comparison, rather than being incorporated to refine initial susceptibility results and independently examine their physical plausibility from a kinematic perspective. Therefore, integrating deformation evidence into LSM is important for improving the credibility and physical interpretability of susceptibility zonation in dynamically active slope environments.

To address these issues, this study develops an integrated landslide susceptibility mapping framework for the Xining Basin by coupling a Mamba-based model (Mamba-LSM) with SBAS-InSAR-based deformation-informed bidirectional reclassification. Mamba-LSM is first used to generate the initial susceptibility map, after which SBAS-InSAR deformation evidence is introduced to refine susceptibility levels and to provide independent kinematic support for evaluating the physical plausibility of the final zonation. The rationale for introducing SBAS-InSAR after model prediction is that Mamba-LSM is designed to characterize the long-term spatial predisposition of landslides from static conditioning factors, whereas SBAS-InSAR provides independent kinematic evidence during the observation period. Introducing deformation information at the post-model stage avoids mixing short-term deformation signals into the model training process and allows the final zonation to be independently constrained by current slope activity, thereby improving its physical interpretability. The framework is further compared with several commonly used baseline models under a region-based spatial hold-out protocol. Accordingly, this study aims to: (1) develop a regional Mamba-based LSM framework for the Xining Basin; (2) incorporate SBAS-InSAR deformation evidence to refine and independently examine the initial susceptibility result; and (3) reveal the spatial correspondence between susceptibility patterns and active ground deformation, thereby providing a more reliable basis for regional landslide hazard identification.

2. Materials and Methods

2.1. Study Area

As shown in Figure 1a–c, the Xining Basin is located on the northeastern margin of the Qinghai–Tibet Plateau, in the northeastern part of Qinghai Province, China, and lies within the geomorphic transitional zone toward the Chinese Loess Plateau. The study area covers approximately 490 km² and extends from 101°33′45″ to 101°56′15″E and 36°25′05″ to 36°47′30″N. As illustrated in Figure 1b, the terrain is characterized by a typical river–mountain transition pattern, with relatively low-elevation valley floors in the central basin and higher relief along the surrounding margins. Elevation ranges from approximately 2116 to 2778 m, with a mean elevation of about 2261 m, and generally decreases from southwest to northeast, consistent with the regional structural framework. The principal river systems include the Beichuan River, Huangshui River, and Nanchuan River (Figure 1b), which together define the main valley network and exert strong control on slope incision and geomorphic differentiation. In addition, a major railway corridor crosses the basin (Figure 1b), forming an important engineering-disturbance belt within the study area.

The climate of the basin is a high-altitude continental type, characterized by large diurnal temperature variations, long sunshine duration, and strongly seasonal precipitation. The mean annual temperature is approximately 5.8 °C, ranging from about −7.5 °C in the coldest month to 17.6 °C in the warmest month. The mean annual precipitation is approximately 770 mm, of which more than 80% occurs between June and September. This pronounced concentration of rainfall, together with high potential evaporation and a long freezing period, exerts strong control on regional hydrothermal conditions and slope processes. Recent climatic warming and increasing precipitation may further reduce slope stability and increase the probability of loess landslides [28,29].

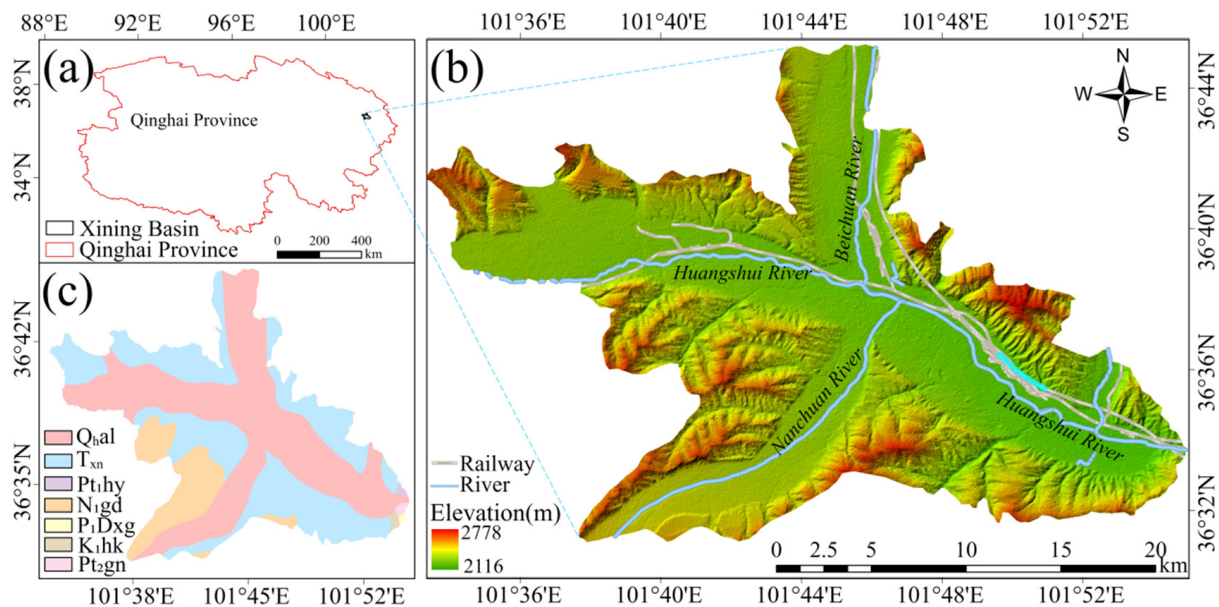


Figure 1. Study area. (a) Geographic location of Xining Basin in Qinghai Province, China. (b) DEM of the Xining Basin highlighting the basin-scale relief. (c) Lithological units in the study area.

Geologically, the Xining Basin exhibits a heterogeneous lithological framework (Figure 1c) and lies within an active tectonic zone dissected by multiple fault systems, resulting in frequent seismic activity. The basin includes Holocene alluvium in valley and basin-floor areas and a series of older bedrock units, including the Triassic Txn unit, Paleoproterozoic Huangyuan Group, Lower Neogene Guidé Group, Lower Permian Daxigou Formation, Lower Cretaceous Hekou Group, and Mesoproterozoic gneiss. Together with the widespread distribution of thick loess deposits, this lithological complexity provides favorable geological conditions for landslide development. The loess is typically loose, porous, and moisture-sensitive, with well-developed vertical joints, and is therefore prone to structural collapse under seasonal wetting–drying cycles and intense summer rainfall [8,30]. Consequently, rainfall- or earthquake-induced landslides are common in the surrounding high-relief terrain, threatening villages, infrastructure, and transportation corridors [8]. Details of landslide inventory construction and sampling are provided in Section 2.3.

2.2. Overall Workflow

To conduct landslide susceptibility assessment in the Xining Basin, a multi-source conditioning-factor database was constructed under a unified spatial reference. Terrain attributes were derived from a digital elevation model, while proximity-related predictors were generated as Euclidean distance rasters from the river network and fault polylines. Lithological information was compiled from the regional geological map and gridded to the 30 m working resolution. Vegetation conditions were characterized by the normalized difference vegetation index, which was resampled to the same working grid to ensure consistency with the remaining predictors. All conditioning layers were co-registered to a common projection and grid system so that pixel-level consistency was maintained during sampling and model input preparation. Following factor screening and importance ranking, six predictors were retained for subsequent modeling: slope, NDVI, lithology, distance to river, aspect, and distance to fault. Figure 2 shows the overall technical workflow of this study, which is organized into three phases: data preparation and factor selection (Phase I), model construction and training (Phase II), and validation and susceptibility mapping (Phase III).

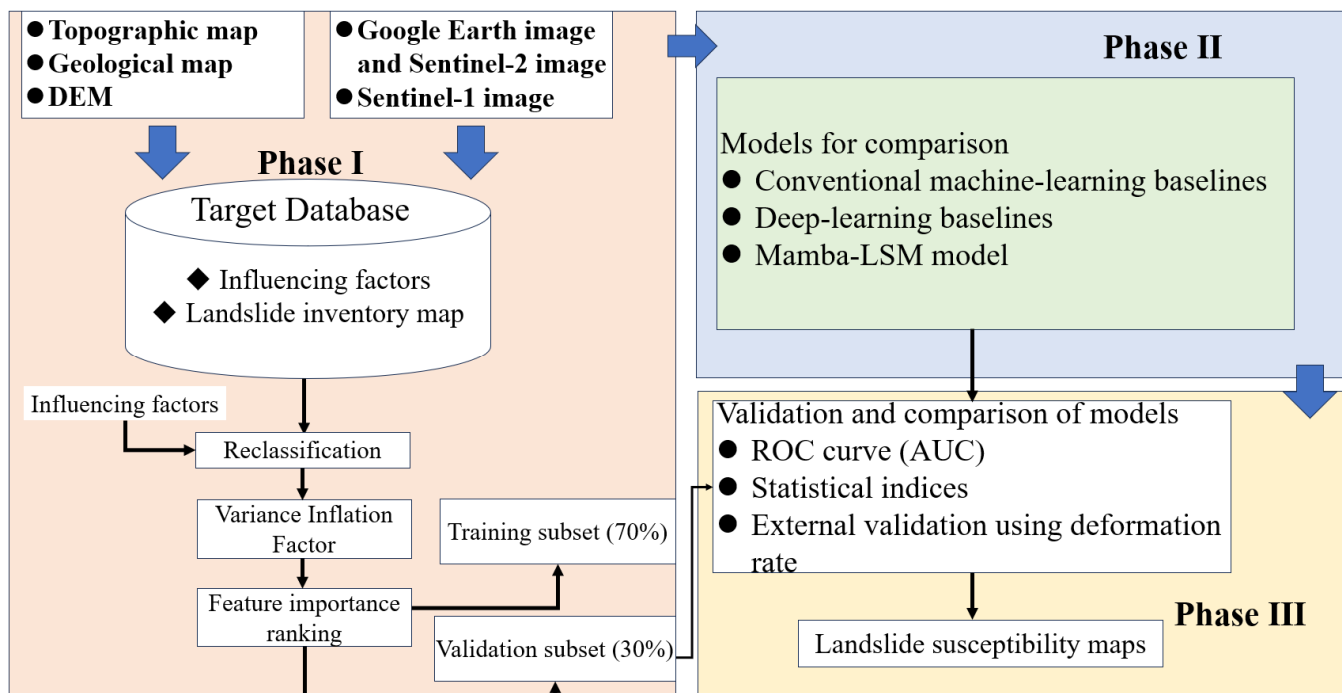


Figure 2. Technical roadmap.

2.3. Landslide Inventory and Sampling

A landslide inventory for the Xining Basin was compiled through expert visual interpretation of a cloud-free Sentinel-2 image acquired on 5 June 2024 [31], in combination with historical Google Earth imagery. Landslide boundaries were delineated according to diagnostic geomorphic features, including arcuate head scarps, displaced or disturbed surface materials, tongue-shaped accumulation zones, and local slope breaks. The interpretation results were cross-checked using Google Earth imagery, and representative landslides were further examined through field investigation and unmanned aerial vehicle (UAV) surveys to provide supplementary validation. To improve inventory reliability, each mapped object was checked against multi-temporal Google Earth imagery and available field/UAV observations to distinguish persistent landslide-related geomorphic features from temporary bare soil, road cuts, construction surfaces, and erosion gullies. Ambiguous objects that lacked consistent diagnostic evidence were revised or removed from the final inventory. Following this procedure, 315 landslide polygons were identified and subsequently converted into centroid points as positive samples to reduce areal bias. Non-landslide samples were generated from relatively stable areas, and an 800 m exclusion buffer was imposed around mapped landslides to reduce boundary-related label noise and spatial contamination. The 800 m buffer was selected by considering the mapped landslide scale, terrain fragmentation, the possibility of adjacent unstable slopes, and the need to retain sufficient candidate stable areas for balanced sampling. A balanced 1:1 ratio between positive and negative samples was adopted. To avoid overly optimistic evaluation caused by spatial autocorrelation, a region-based spatial hold-out strategy was adopted instead of a purely random split. Samples were partitioned into geographically separated regional subsets, with approximately 70% assigned to training and 30% assigned to validation. Under this protocol, patch-derived summary feature matrices were extracted for the conventional machine learning baselines. For the neural-network models, including Mamba-LSM, CNN, LeNet-style CNN, and Tiny Transformer, 8×8 neighborhood windows centered on each sample were used as six-channel patch inputs to preserve local spatial context.

2.4. Conditioning Factor Selection

A multi-source conditioning-factor database was constructed for landslide susceptibility modeling in the Xining Basin. The candidate factors included topographic, geological, hydrological, environmental, and engineering-disturbance variables. Their data sources and preprocessing procedures are summarized in Table 1. Among them, topographic derivatives such as slope, aspect, and profile curvature were generated from the DEM; NDVI was calculated from the Sentinel-2 image acquired on 5 June 2024 [31]; hydrological and engineering-disturbance factors, including distance to river and distance to railway, were derived from OpenStreetMap (OSM) data [32]; lithology was obtained from the National Geological Archives of China; and distance to fault was derived from fault data interpreted with reference to a previous study [30]. Distance to railway was included only as an initial candidate engineering-disturbance proxy because railway construction may locally modify slope conditions through excavation, embankment construction, drainage alteration, and slope-foot disturbance. This consideration is supported by a documented destructive landslide affecting a high-speed railway corridor in Xining [8]. Nevertheless, railway-related disturbance is spatially localized rather than pervasive across the basin. As shown by the subsequent gain-based ranking, distance to railway made only a marginal contribution and was not retained in the final six-factor set; therefore, the final susceptibility prediction was not dominated by railway proximity.

Table 1. Candidate conditioning factors, data provenance, temporal information, source resolution or map scale, and final working resolution.

Factor	Category	Data Source	Time	Original Resolution	Final Resolution
Slope	Topographic	SRTM DEM	-	30 m	30 m
Aspect	Topographic	SRTM DEM	-	30 m	30 m
Profile curvature	Topographic	SRTM DEM	-	30 m	30 m
NDVI	Environmental	Sentinel-2 image	5 June 2024	10 m	30 m
Distance to river	Hydrological	OpenStreetMap (OSM) [32]	2021	Vector	30 m
Distance to railway	Engineering-disturbance	OpenStreetMap (OSM) [32]	2021	Vector	30 m
Distance to fault	Geological	Previous study [30]	Sun (2013) [30]	Vector fault data interpreted with reference to [30]	30 m
Lithology	Geological	National Geological Archives of China	-	1:500,000	30 m

All factor layers were resampled and unified to a common 30 m grid for subsequent analysis.

Elevation and relative relief or other slope-height-related variables were considered during the initial factor-design stage. However, these variables showed redundancy with the retained topographic predictors or provided limited additional contribution after multicollinearity and importance screening. To maintain model parsimony and reduce redundant spatial information, they were not included in the final modeling set.

After the candidate conditioning factors had been compiled, a two-stage screening strategy was adopted to improve parsimony and interpretability while reducing multicollinearity. Specifically, variance inflation factor (VIF) diagnostics and a data-driven importance ranking were sequentially performed on the training subset defined by the

region-based spatial hold-out split, thereby avoiding information leakage into the validation subset [33,34].

2.4.1. Multicollinearity Diagnosis

VIF was computed for all continuous predictors on the training subset. For a given factor,

$$VIF_j = \frac{1}{1 - R_j^2} \quad (1)$$

where VIF_j denotes the variance inflation factor of the j -th conditioning factor, and R_j^2 is the coefficient of determination obtained by regressing this factor against the remaining predictors [33,34]. A VIF value of 1 indicates the absence of collinearity, whereas progressively larger values indicate stronger linear dependence among predictors. Although no absolute cutoff exists, VIF values greater than 10 are commonly considered indicative of problematic multicollinearity that should be addressed [33,34], whereas some studies have suggested a more conservative threshold of 5 [34]. In this study, the conventional threshold of 10 was adopted for screening.

2.4.2. Importance Ranking

After multicollinearity had been examined through VIF screening, the remaining factors were further ranked according to their predictive contribution. For this purpose, an initial XGBoost classifier was trained on the training subset, and feature importance was quantified using the gain metric, which reflects the relative contribution of each factor to the predictive performance of the model [35]. Although permutation importance has been recommended as a model-agnostic alternative and potential bias in tree-based importance measures has also been noted [36,37], gain-based ranking was adopted here to provide a data-driven basis for selecting the final conditioning factors.

2.5. Mamba-LSM Model and Training Protocol

2.5.1. Model Architecture

To characterize landslide susceptibility while incorporating local neighborhood information, a Mamba-based landslide susceptibility model [38], termed Mamba-LSM, was constructed using the patch-derived factor representation described in Section 2.3. For each sample, $K = 6$ conditioning factors were retained. The corresponding 8×8 neighborhood patches centered on the sample location were stacked as six input channels. At the 30 m working resolution, the 8×8 window represents an approximate spatial extent of $240 \text{ m} \times 240 \text{ m}$, which is suitable for capturing hillslope-scale terrain and environmental context while avoiding excessive background information from a much larger neighborhood.

Accordingly, the input of the i -th sample is expressed as

$$X_i = [P_i^{(1)}, P_i^{(2)}, \dots, P_i^{(K)}] \in \mathbb{R}^{K \times 8 \times 8} \quad (2)$$

where i denotes the sample index, K is the number of selected conditioning factors, and $P_i^{(k)} \in \mathbb{R}^{8 \times 8}$ represents the neighborhood patch of the k -th conditioning factor. In this study, $K = 6$.

As illustrated in Figure 3, the proposed Mamba-LSM consists of a multi-factor patch input, a shallow CNN encoder, a Mamba block, and a final classification head. The six-channel

input patch was first processed by two convolution–ReLU–max-pooling blocks. The first block transformed the input into 64 feature maps and reduced the spatial size from 8×8 to 4×4 :

$$F_i^{(1)} = \text{MaxPool}[\text{ReLU}(\text{Conv}_{3 \times 3}^{K \rightarrow 64}(X_i))] \in \mathbb{R}^{64 \times 4 \times 4} \quad (3)$$

The second convolutional block further extracted local spatial features and generated a 128-channel feature map with a spatial size of 2×2 :

$$F_i^{(2)} = \text{MaxPool}[\text{ReLU}(\text{Conv}_{3 \times 3}^{64 \rightarrow 128}(F_i^{(1)}))] \in \mathbb{R}^{128 \times 2 \times 2} \quad (4)$$

The resulting feature map was flattened into a 512-dimensional vector and linearly projected into a 128-dimensional latent representation:

$$z_i = W_p \text{vec}(F_i^{(2)}) + b_p \in \mathbb{R}^{128} \quad (5)$$

where $\text{vec}(\cdot)$ denotes vectorization, and W_p and b_p are learnable projection parameters.

The projected latent representation was subsequently processed by a Mamba block:

$$h_i = \text{Mamba}(z_i) \in \mathbb{R}^{128} \quad (6)$$

where h_i denotes the transformed latent feature representation. The Mamba block was configured with a model dimension of 128, a state dimension of 16, a convolution width of 4, and an expansion factor of 2.

Finally, the transformed representation was passed through a classification head composed of a fully connected layer, ReLU activation, dropout, and a two-unit output layer:

$$o_i = f(h_i) \in \mathbb{R}^2 \quad (7)$$

$$p_i = \text{Softmax}(o_i) \quad (8)$$

where $f(\cdot)$ denotes the classification head, o_i denotes the output logits, and p_i is the predicted class-probability vector for the i -th sample.

Overall, Mamba-LSM first uses a shallow CNN encoder to extract joint local spatial features from six-channel 8×8 conditioning-factor patches. The CNN-derived feature map is then compressed into a 128-dimensional latent representation and processed by a Mamba block before final binary classification.

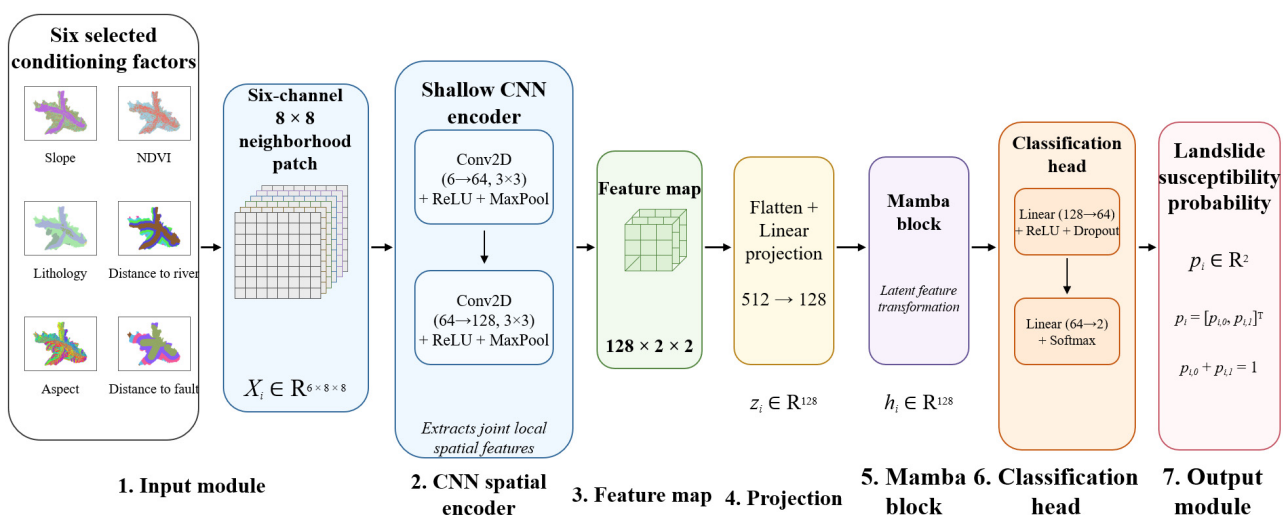


Figure 3. Mamba-LSM model architecture.

2.5.2. Training Strategy and Evaluation

A region-based spatial hold-out strategy was adopted for model evaluation. Samples were divided into geographically separated training and validation subsets at an approximately 7:3 ratio, rather than using a purely random split. Normalization statistics were estimated from the training subset only and were applied unchanged to the validation subset to prevent information leakage. Model checkpoints were evaluated after each epoch on the validation subset, and the checkpoint achieving the highest validation AUC was retained for subsequent susceptibility mapping and reporting. For comparative evaluation, LR [39], RF [40], XGBoost, ANN [41], CNN, LeNet-style CNN, and Tiny Transformer were used as baseline models. All models were evaluated using the same six selected conditioning factors, the same region-based spatial hold-out partition, and the same evaluation metrics. The conventional machine learning baselines used patch-derived summary feature matrices, whereas Mamba-LSM, CNN, LeNet-style CNN, and Tiny Transformer used six-channel 8×8 neighborhood patch inputs. CNN served as a convolutional baseline that retained the Mamba-LSM CNN encoder and classification head while removing the Mamba block. LeNet-style CNN represented a shallow convolutional baseline, whereas Tiny Transformer represented a lightweight spatial Transformer baseline.

2.6. Evaluation Metrics

In this study, model performance for landslide susceptibility classification is evaluated using Accuracy (Acc), Precision (Pre), Recall (Rec), and F1-score (F1). Threshold-free discriminative ability is further assessed using the receiver operating characteristic (ROC) curve and its area (AUC). Accuracy measures the overall proportion of correctly classified samples; Precision reflects the reliability of positive predictions; Recall quantifies the proportion of true landslide samples correctly identified; and F1, the harmonic mean of Precision and Recall, balances omission and commission errors. The ROC curve is obtained by sweeping the decision threshold, and AUC summarizes the model's overall separability between landslide and non-landslide classes [42,43].

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (9)$$

$$\text{F1} = 2 \times \frac{\text{Pre} \times \text{Rec}}{\text{Pre} + \text{Rec}} \quad (10)$$

$$\text{Pre} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (11)$$

$$\text{Rec} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (12)$$

where true positive (TP) denotes the number of landslide samples correctly predicted as landslides, true negative (TN) denotes the number of non-landslide samples correctly predicted as non-landslides, false positive (FP) denotes the number of non-landslide samples incorrectly predicted as landslides, and false negative (FN) denotes the number of landslide samples incorrectly predicted as non-landslides.

2.7. SBAS-InSAR-Based External Examination and Deformation-Informed Bidirectional Reclassification

To incorporate dynamic deformation evidence without interfering with model training, SBAS-InSAR observations were introduced at the post-model stage for two purposes: to provide independent kinematic evidence for examining the physical plausibility of the susceptibility results, and to support deformation-informed bidirectional reclassification after prediction. A total of 41 C-band Sentinel-1A descending images acquired between

5 January 2023 and 11 May 2024 [44] were processed to generate a mean line-of-sight (LOS) deformation velocity map. The main SBAS-InSAR processing workflow used in this study is illustrated in Figure 4 [45]. The deformation map was geocoded and resampled to the same 30 m grid as the conditioning-factor layers for spatial overlay. Following Yi et al. [46], $V_{\text{LOS}} \geq 10 \text{ mm} \cdot \text{yr}^{-1}$ was used to indicate significant activity, whereas $V_{\text{LOS}} < 2 \text{ mm} \cdot \text{yr}^{-1}$ was treated as a stable reference. These thresholds were used only for external examination and post-model reclassification, rather than for model training. Consistency was evaluated by examining whether deformation hotspots were preferentially distributed within the predicted high- and very-high-susceptibility zones. Because the SBAS-InSAR results represent deformation only along the LOS direction, the detected anomalies were interpreted mainly in terms of kinematic activity rather than by sign alone. After the initial susceptibility map had been generated, a deformation-informed post-model correction was applied as a rule-based bidirectional reclassification step without re-training or re-parameterizing the original model. The LOS deformation velocity map was first co-registered with the initial susceptibility map, and the deformation values were stratified into five predefined levels. The initial Mamba-LSM susceptibility map was also represented as five ordinal classes, ranging from 1 (very low) to 5 (very high). A deformation–susceptibility coupling matrix was then used to adjust the initial susceptibility classes according to the classified LOS deformation levels (Table 2), where D denotes the classified LOS deformation level. Deformation classes 1, 4, and 5 were regarded as relatively active deformation zones and were used to upgrade the initial susceptibility class by one level, whereas deformation classes 2 and 3 were treated as relatively low-activity deformation zones and were used to downgrade the initial susceptibility class by one level. The corrected class was constrained within the range from 1 to 5. This correction was applied only after model prediction and did not alter the training samples, selected conditioning factors, model parameters, or initial probability outputs.

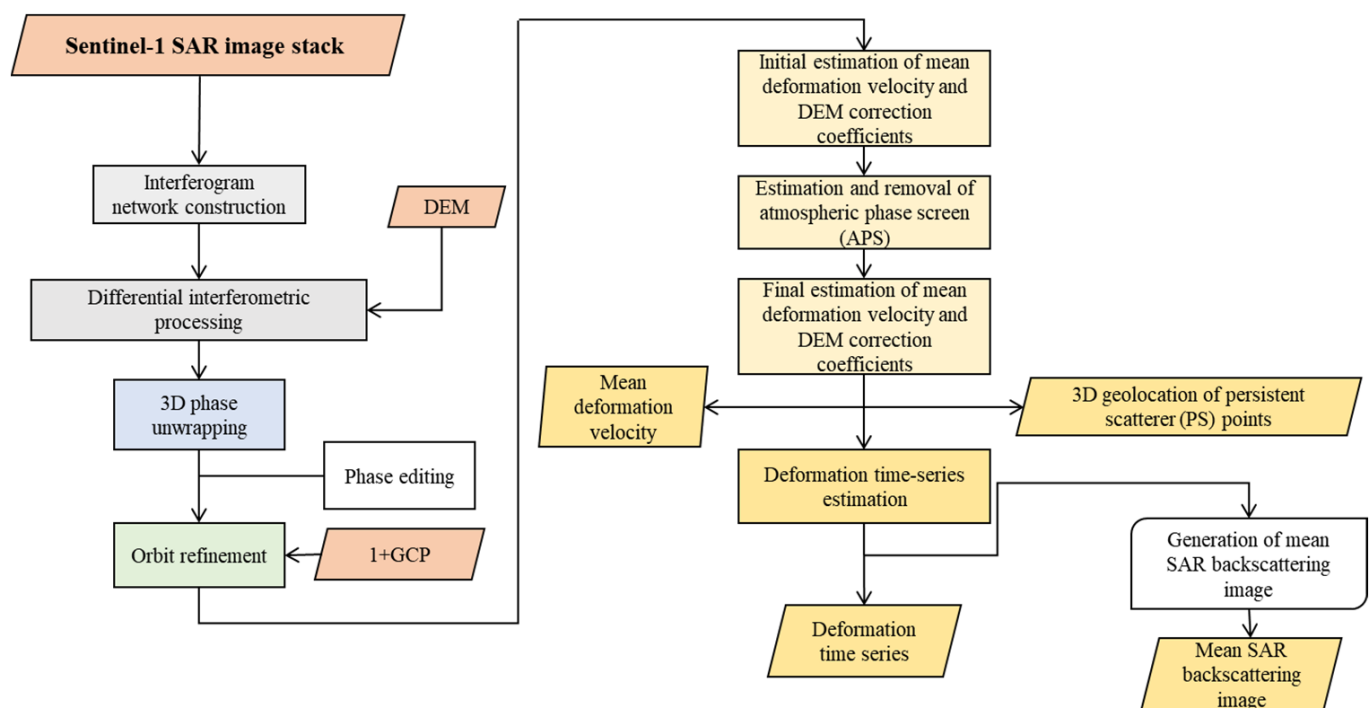


Figure 4. SBAS-InSAR workflow.

Table 2. Rule-based deformation-informed bidirectional reclassification scheme based on classified LOS deformation levels.

Initial Susceptibility Class	Initial Value	Active Deformation Classes (D = 1, 4, 5)	Low-Activity Deformation Classes (D = 2, 3)
Very low	1	Low	Very low
Low	2	Medium	Very low
Medium	3	High	Low
High	4	Very high	Medium
Very high	5	Very high	High

3. Results

3.1. Factor Screening by VIF

To suppress multicollinearity and improve interpretability, variance inflation factor diagnostics were performed for the candidate predictors. VIF values ranged from 4.96 to 10.88, and most variables satisfied the conventional criterion of VIF below 10. Although the VIF value of NDVI slightly exceeded the conventional threshold of 10 (VIF = 10.88), NDVI was retained because of its clear geomorphic and environmental relevance in the loess-covered Xining Basin. Vegetation condition is associated with surface cover, soil-moisture response, erosion intensity, and human disturbance, all of which may influence slope stability. Moreover, NDVI ranked second in the XGBoost gain-based importance analysis, indicating a non-negligible predictive contribution. Retaining NDVI therefore represents a balance between statistical screening and process-based interpretability. After screening, the candidate set comprised slope, aspect, NDVI, distance to river, distance to fault, lithology, profile curvature, and distance to railway (Table 3), which were carried forward to feature-importance ranking and subsequent susceptibility modeling. As visualized in Figure 5, pairwise correlations among the candidate factors are generally moderate, supporting the multicollinearity diagnostics.

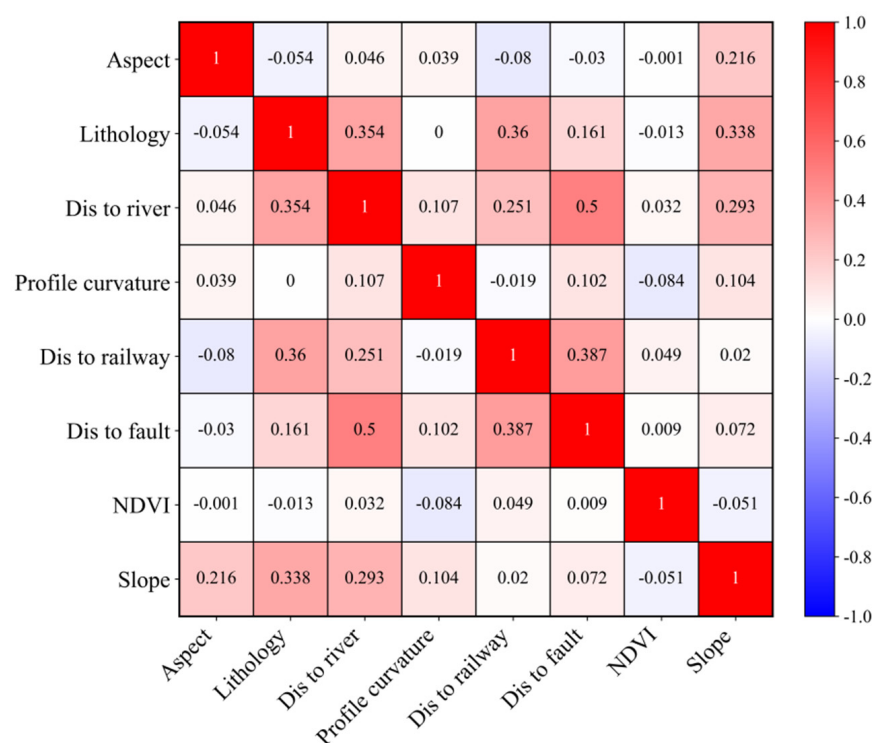
**Figure 5.** Correlation heatmap of the candidate conditioning factors.

Table 3. Final VIF statistics after iterative multicollinearity screening.

Factor	VIF	Decision
Slope	5.49	Remain
Distance to river	7.53	Remain
Distance to railway	6.03	Remain
Distance to fault	7.14	Remain
Lithology	4.96	Remain
Profile curvature	8.14	Remain
NDVI	10.88	Remain
Aspect	7.92	Remain

3.2. Feature Importance

Using the VIF-screened candidate set, an XGBoost classifier was fitted on the training subset, and predictors were ranked by gain. Figure 6a visualizes the gain-based ranking, whereas Table 4 reports the exact gain values, corresponding proportions, and final selection results. Figure 6b shows the SHAP-based feature contributions. Slope and NDVI were identified as the most influential variables, followed by lithology, distance to river, aspect, and distance to fault. Profile curvature and distance to railway contributed additional information but produced only marginal gains. Therefore, the top six variables by gain were selected as the final modeling set, namely slope, NDVI, lithology, distance to river, aspect, and distance to fault (Table 4). This set preserves physical interpretability while maintaining parsimony and reduced redundancy among predictors. Profile curvature and distance to railway showed only marginal gain contributions and were excluded from the final modeling set. The multicollinearity screening results are reported in Table 3 and Figure 5, whereas the gain-based importance ranking and final selection decisions are presented in Table 4 and Figure 6. Figure 7a–f present the spatial distributions of the six final conditioning factors retained for Mamba-LSM modeling after multicollinearity screening and gain-based importance ranking.

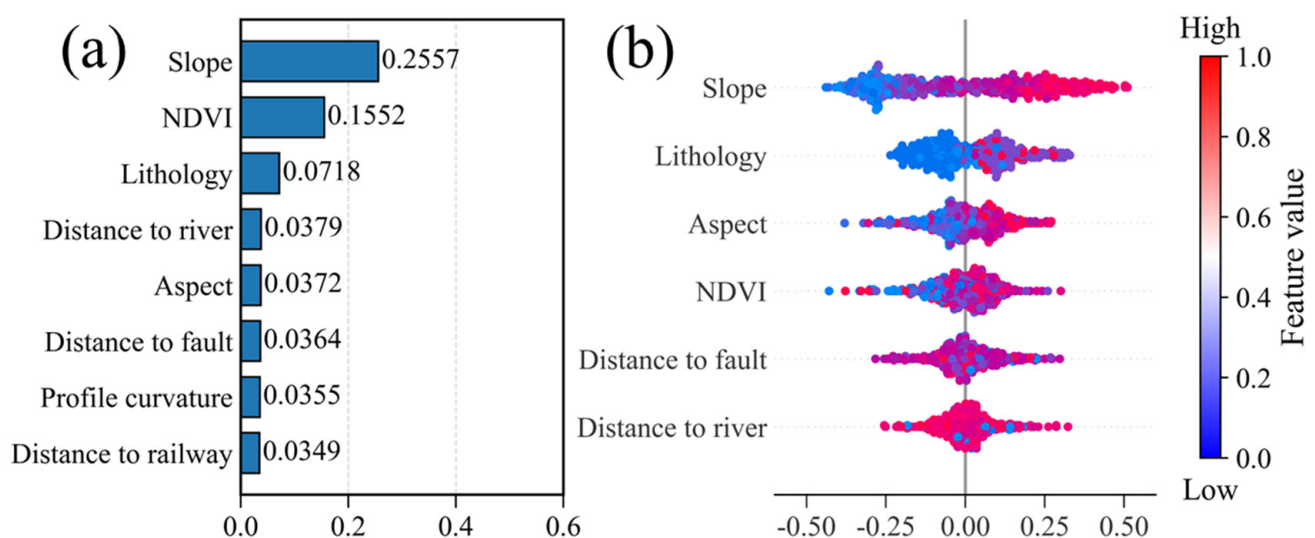


Figure 6. XGBoost-based feature importance analysis. (a) Gain-based ranking of the eight candidate factors; exact values and selection results are listed in Table 4. (b) SHAP summary plot of feature contributions.

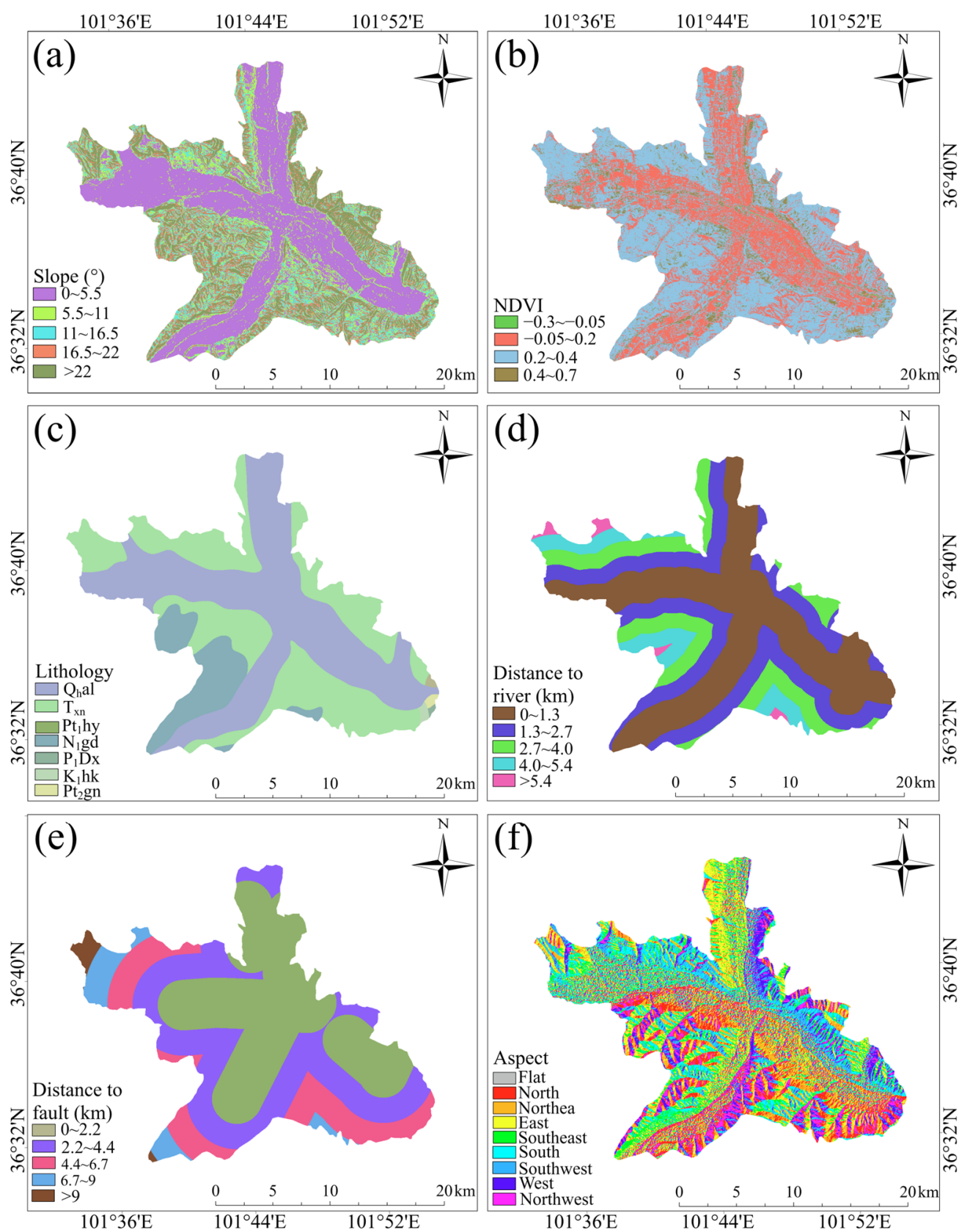


Figure 7. Spatial distributions of the six final conditioning factors retained for Mamba-LSM modeling after multicollinearity screening and gain-based importance ranking: (a) slope; (b) NDVI; (c) lithology; (d) distance to river; (e) distance to fault; and (f) aspect.

Table 4. XGBoost gain-based feature importance and final factor selection.

Ranking	Factor	Gain	Proportion (%)	Selected
1	Slope	0.2557	38.48	Yes
2	NDVI	0.1552	23.35	Yes
3	Lithology	0.0718	10.80	Yes
4	Distance to river	0.0379	5.70	Yes
5	Aspect	0.0372	5.59	Yes
6	Distance to fault	0.0364	5.48	Yes
7	Profile curvature	0.0355	5.34	No
8	Distance to railway	0.0349	5.25	No

3.3. Overall Model Performance

On the region-based spatial hold-out validation subset, the evaluated models showed measurable but different predictive behavior (Table 5 and Figure 8). Mamba-LSM achieved the highest AUC (90.11%), indicating the strongest threshold-independent discriminative ability among the evaluated models. Among the added deep learning baselines, CNN was the closest to Mamba-LSM in terms of AUC (89.03%). At the default threshold of 0.5, CNN also produced slightly higher threshold-dependent metrics, including F1 (75.77%), ACC (77.17%), Recall (65.68%), and MCC (57.50%), compared with Mamba-LSM. LeNet-style CNN achieved an AUC of 84.47% and F1 of 74.50%, whereas Tiny Transformer achieved an AUC of 84.10% and F1 of 69.26%. Among the traditional models, LR remained a strong baseline (AUC = 83.77%; F1 = 70.95%), followed by RF (AUC = 82.75%; F1 = 67.84%), XGBoost (AUC = 81.08%; F1 = 70.00%), and ANN (AUC = 74.75%; F1 = 62.86%). Overall, AUC and AP describe threshold-independent ranking and discrimination, whereas F1, ACC, Recall, and MCC reflect threshold-dependent behavior at the fixed decision threshold of 0.5.

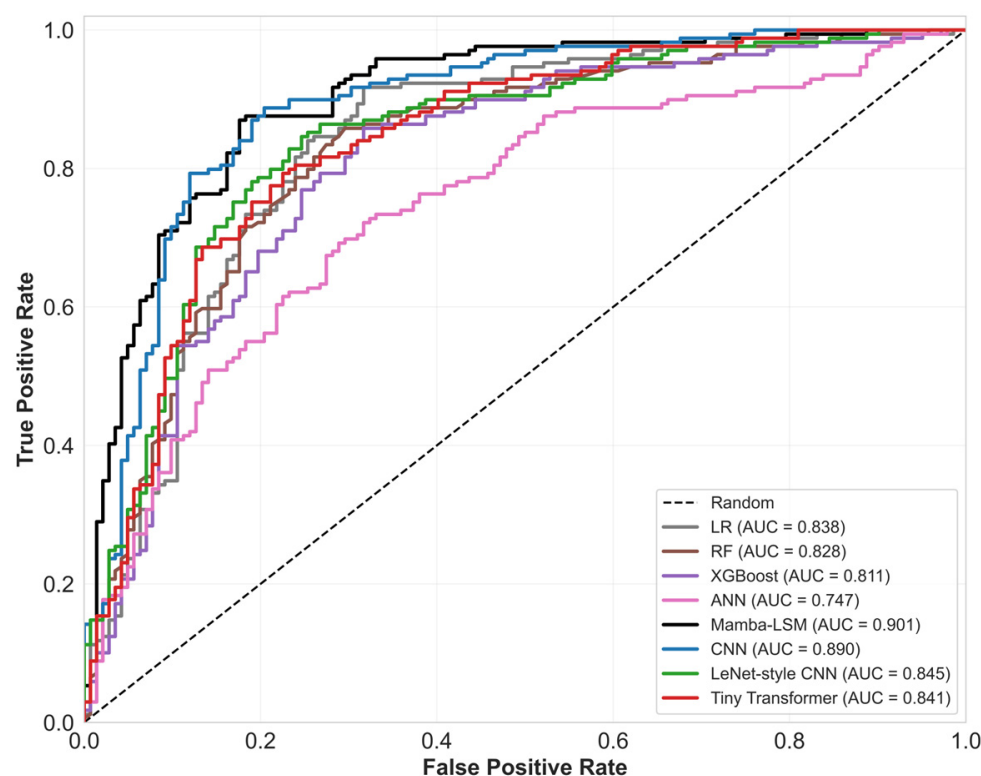
**Figure 8.** ROC curves of the evaluated models, including the added deep learning baselines.

Table 5. Comparison of model evaluation metrics.

Model	AUC (%)	F1 (%)	Pre (%)	ACC (%)	Recall (%)	MCC (%)
LR	83.77	70.95	82.68	72.35	62.13	47.26
RF	82.75	67.84	84.21	70.74	56.80	45.62
XGBoost	81.08	70.00	80.15	71.06	62.13	44.21
Mamba-LSM	90.11	74.31	89.92	76.21	63.31	56.23
ANN	74.75	62.86	79.28	66.56	52.07	37.30
CNN	89.03	75.77	89.52	77.17	65.68	57.50
LeNet-style CNN	84.47	74.50	86.05	75.56	65.68	53.59
Tiny Transformer	84.10	69.26	85.96	72.03	57.99	48.30

3.4. Spatial Pattern of Susceptibility

To improve interpretability and facilitate inter-model comparison, continuous susceptibility outputs were reclassified into five ordered categories: very low, low, medium, high, and very high. This five-class scheme enables standardized reporting of areal allocation by susceptibility level and the concentration of mapped landslide points within the upper classes. Overall, coherent regional patterns were produced, in which high and very high classes delineate the principal potentially unstable zones, whereas low-susceptibility classes represent comparatively stable terrain. As summarized in Table 6, landslide points are preferentially enriched in the upper susceptibility classes, while the degree of concentration differs across models. For Mamba-LSM, the very high class occupied 73.9638 km² (18.57%) but contained 188 points (59.68%), and the combined medium to very high classes captured 80.32% of landslide points within 33.52% of the area. As illustrated in Figure 9a–h, the five-class susceptibility maps generated by the eight evaluated models show broadly consistent high-susceptibility belts, with local differences in the spatial extent and boundary delineation of the upper susceptibility classes. Figure 9a–d present the XGBoost, LR, RF, and ANN results, whereas Figure 9e–h present the CNN, LeNet-style CNN, Tiny Transformer, and Mamba-LSM results, respectively.

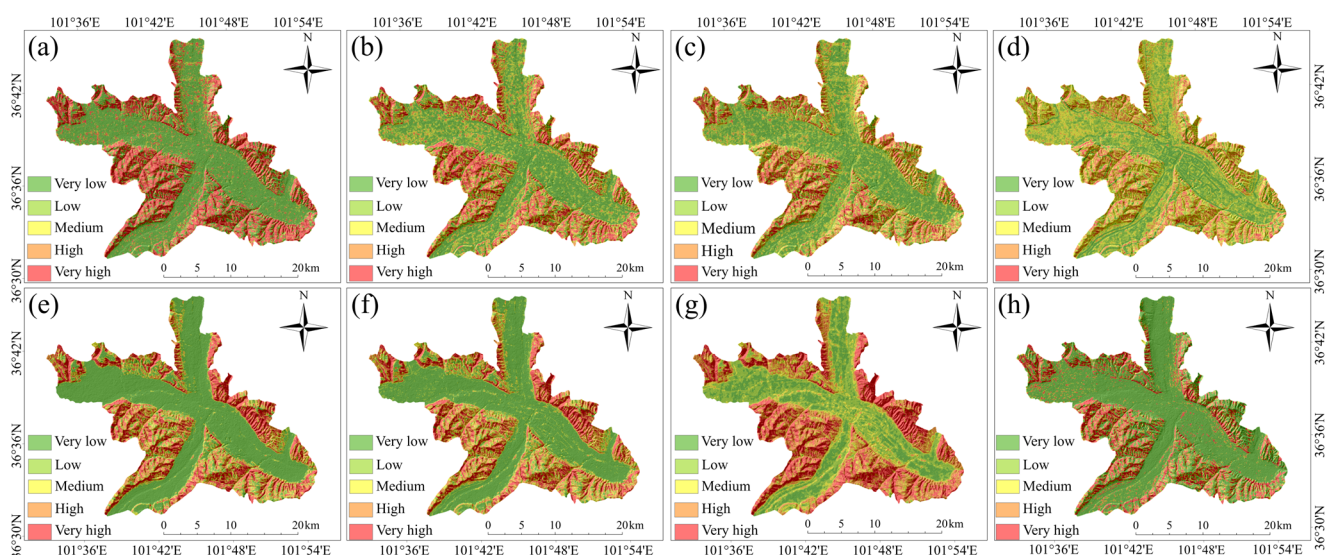


Figure 9. Spatial distributions of five-class landslide susceptibility maps generated by the evaluated models: (a) XGBoost; (b) LR; (c) RF; (d) ANN; (e) CNN; (f) LeNet-style CNN; (g) Tiny Transformer; and (h) Mamba-LSM.

Table 6. Zonation statistics of five-class susceptibility maps for different models.

Model	Class	Area (km ²)	Areal Percentage (%)	Points	Share of Points (%)	Points/100 km ²
LR	Very low	115.0254	28.88	12	3.81	10.43
	Low	77.6538	19.5	40	12.7	51.51
	Medium	63.7434	16.01	56	17.78	87.85
	High	68.3937	17.17	93	29.52	135.98
	Very high	73.4463	18.44	114	36.19	155.22
XGBoost	Very low	190.9782	47.95	44	13.97	23.04
	Low	28.9638	7.27	14	4.44	48.34
	Medium	24.2433	6.09	14	4.44	57.75
	High	28.8909	7.25	26	8.25	89.99
	Very high	125.1864	31.43	217	68.89	173.34
RF	Very low	101.8026	25.56	13	4.13	12.77
	Low	102.6342	25.77	35	11.11	34.1
	Medium	72.5868	18.23	61	19.37	84.04
	High	82.8432	20.8	77	24.44	92.95
	Very high	38.3958	9.64	129	40.95	335.97
ANN	Very low	53.0667	13.32	18	5.71	33.92
	Low	104.6646	26.28	33	10.48	31.53
	Medium	137.0016	34.4	105	33.33	76.64
	High	90.63	22.76	142	45.08	156.68
	Very high	12.8997	3.24	17	5.4	131.79
Mamba-LSM	Very low	235.0062	59.01	40	12.7	17.02
	Low	29.754	7.47	22	6.98	73.94
	Medium	25.2135	6.33	24	7.62	95.19
	High	34.3251	8.62	41	13.02	119.45
	Very high	73.9638	18.57	188	59.68	254.18
CNN	Very low	242.8920	60.99	19	6.03	7.82
	Low	27.0819	6.80	29	9.21	107.08
	Medium	23.0337	5.78	20	6.35	86.83
	High	27.1143	6.81	38	12.06	140.15
	Very high	78.1407	19.62	209	66.35	267.47
LeNet-styleCNN	Very low	249.2586	62.59	27	8.57	10.83
	Low	30.7017	7.71	27	8.57	87.94
	Medium	21.1518	5.31	34	10.79	160.74
	High	27.3762	6.87	39	12.38	142.46
	Very high	69.7743	17.52	188	59.68	269.44
Tiny Transformer	Very low	178.1586	44.73	1	0.32	0.56
	Low	38.6172	9.70	6	1.90	15.54
	Medium	38.7540	9.73	32	10.16	82.57
	High	51.5421	12.94	85	26.98	164.91
	Very high	91.1907	22.90	191	60.63	209.45

Zonation statistics are summarized in Table 6 in terms of areal percentage, landslide-point share, and landslide density. In all models, landslide points were preferentially enriched in the upper classes, indicating general consistency between zonation and the inventory, while the degree of concentration differed across methods. For Mamba-LSM, the very high class occupied 73.9638 km² (18.57%) but contained 188 points (59.68%), corresponding to a density of 254.18 points per 100 km². The high and medium classes covered 34.3251 km² (8.62%) and 25.2135 km² (6.33%), containing 41 points (13.02%) and 24 points (7.62%), respectively. Collectively, the medium to very high classes captured

80.32% of landslide points within 33.52% of the area. Meanwhile, the very low to low classes accounted for 66.48% of the area but contained 19.68% of the points, with markedly lower densities. These statistics indicate that Mamba-LSM retained a high proportion of observed landslides while limiting the medium-to-very-high-susceptibility classes to about one-third of the mapped area.

As shown in Figure 9e–g and summarized in Table 6, the added deep learning baselines also produced generally interpretable susceptibility patterns. CNN captured 84.76% of landslide points within the medium-to-very-high classes, which occupied 32.21% of the area, whereas LeNet-style CNN captured 82.86% within 29.70% of the area. Tiny Transformer captured 97.78% of landslide points, but its medium-to-very-high classes occupied 45.57% of the area, indicating that its higher coverage partly resulted from a broader priority zone. These zonation statistics describe the trade-off between priority-zone area and landslide-point coverage and therefore complement, rather than replace, Table 5, ROC, and PR evaluations. Considering the highest AUC and AP, stronger threshold-independent discrimination, and the spatial consistency of high-susceptibility zones with historical landslides and regional terrain-geological conditions, Mamba-LSM remains the preferred model for final susceptibility mapping and interpretation.

3.5. SBAS-InSAR LOS Deformation and Consistency with Susceptibility Zonation

The mean V_{LOS} derived from SBAS-InSAR ranged from -24.63 to 41.58 $\text{mm}\cdot\text{yr}^{-1}$ across the study area (Figure 10). Negative deformation anomalies ($-24.63\sim-11.39$ $\text{mm}\cdot\text{yr}^{-1}$) were mainly distributed in the southwestern sector, whereas positive anomalies, especially those of $15.09\sim28.34$ $\text{mm}\cdot\text{yr}^{-1}$ and $28.34\sim41.58$ $\text{mm}\cdot\text{yr}^{-1}$, were concentrated mainly in the northern part of the basin and along the east-central valley–mountain transition belt. Mapped landslides were densely distributed within these deformation-active zones, particularly along the Huangshui River valley-side slopes and adjacent engineering-disturbed sectors.

A spatial overlay analysis further showed that deformation hotspots were preferentially located within the predicted high- and very-high-susceptibility belts of the initial susceptibility map. This pattern was especially evident along the northern margin, the central eastern valley-side slopes, and several river-incised hillslope sectors, where elevated V_{LOS} values and dense landslide occurrences were observed simultaneously (Figure 10). These results indicate that the initial Mamba-LSM susceptibility map captured the principal belts of active slope instability at the regional scale.

After deformation-informed bidirectional reclassification, the areal proportions of the susceptibility classes were 42.82% (very low), 23.25% (low), 8.62% (medium), 14.07% (high), and 11.24% (very high) (Table 7; Figure 11). The high and very high classes together occupied 25.31% of the study area but contained 69.84% of the mapped landslides. Specifically, 99 landslide points were located in the high-susceptibility class and 121 in the very-high-susceptibility class. Landslide point density increased systematically from 12.91 points/100 km^2 in the very low class to 41.07, 102.03, 176.75, and 270.34 points/100 km^2 in the low, medium, high, and very high classes, respectively. This result indicates that the deformation-constrained reclassification improved the spatial concentration of mapped landslides within the upper susceptibility classes while avoiding excessive expansion of the very-high-susceptibility zone.

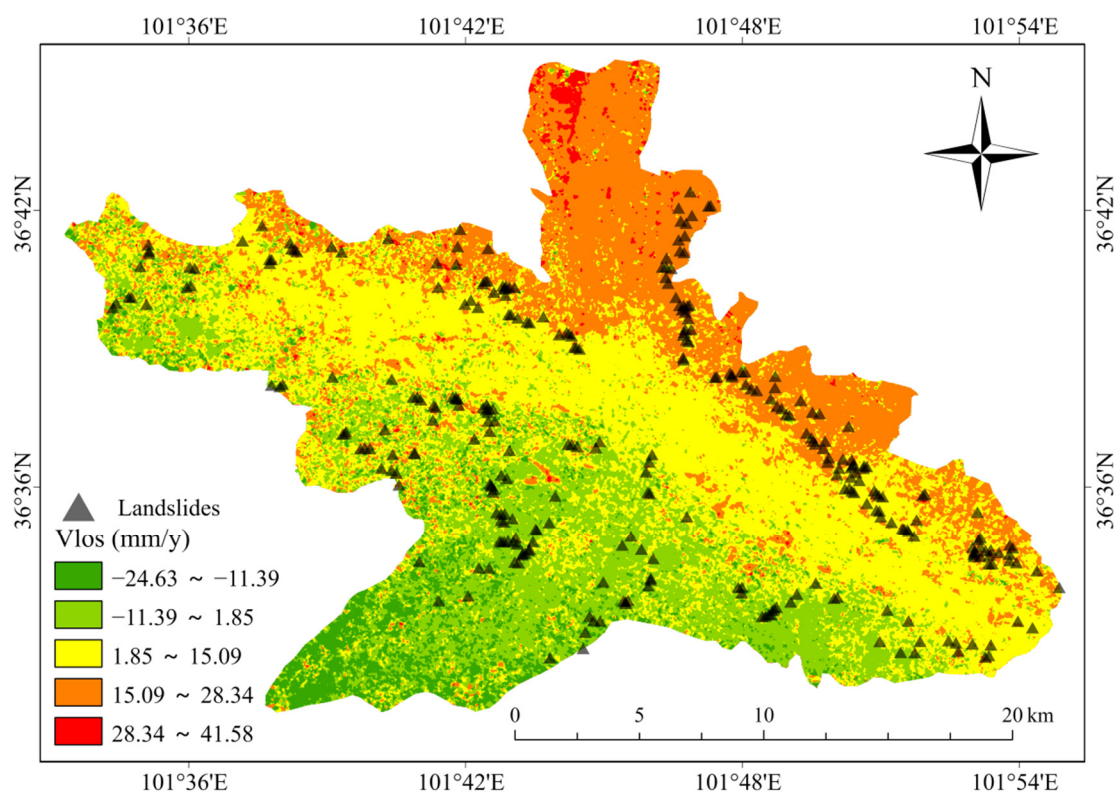


Figure 10. Mean SBAS-InSAR line-of-sight deformation velocity and mapped landslide points in the Xining Basin.

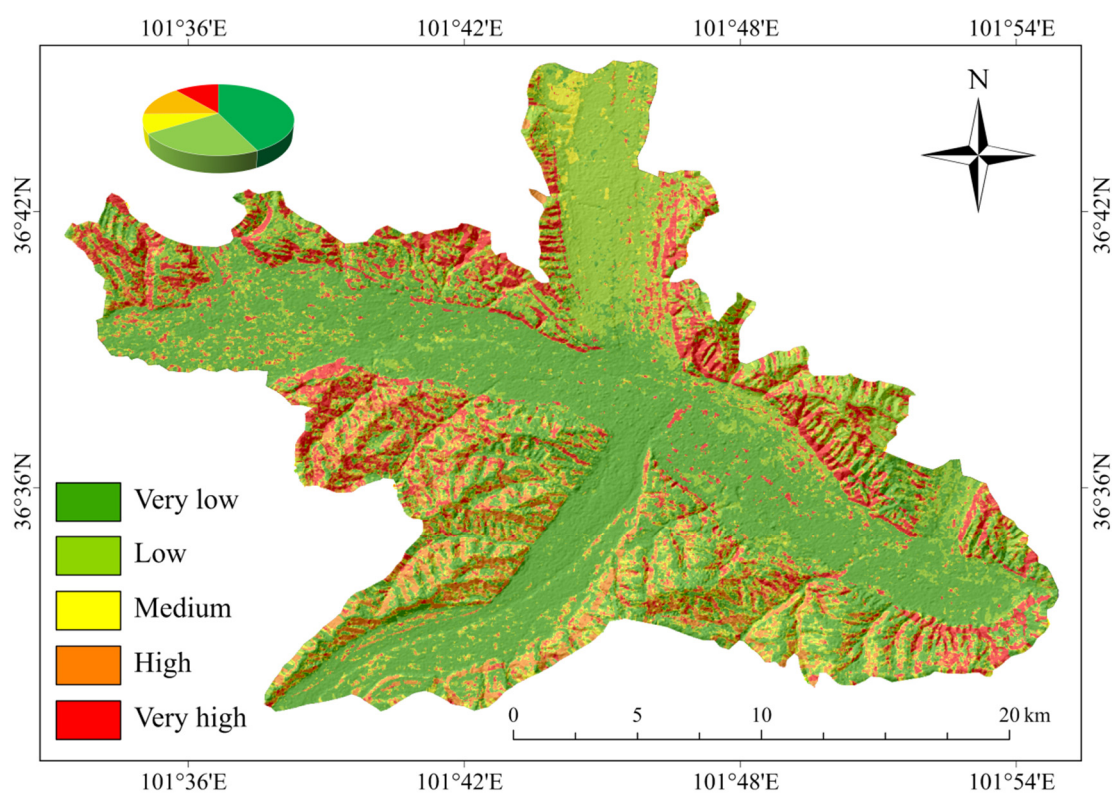


Figure 11. Landslide susceptibility map after deformation-informed bidirectional reclassification. The correction was based on the classified SBAS-InSAR LOS deformation levels and the initial Mamba-LSM susceptibility classes.

Table 7. Spatial distribution of landslide points across susceptibility classes after deformation-informed bidirectional reclassification.

Model	Class	Area (km ²)	Areal Percentage (%)	Points	Share of Points (%)	Points/100 km ²
Deformation-corrected Mamba-LSM	Very low	170.451	42.82	22	6.98	12.91
	Low	92.533	23.25	38	12.06	41.07
	Medium	34.303	8.62	35	11.11	102.03
	High	68.3937	14.07	99	31.43	176.75
	Very high	56.012	11.24	121	38.41	270.34

4. Discussion

4.1. Dominant Controls on Landslide Susceptibility in the Xining Basin

The final factor set indicates that landslide susceptibility in the Xining Basin is governed by a combination of terrain steepness, vegetation and surface conditions, lithological contrasts, river-related incision, slope orientation, and structural proximity. Slope and NDVI ranked highest in the gain analysis, while lithology, distance to river, aspect, and distance to fault retained complementary geomorphic, environmental, hydrological, and geological meaning. This combination is consistent with the mountain–basin transition setting, where steep loess-mantled slopes interact with valley incision, heterogeneous materials, seasonal moisture conditions, and tectonic structure.

A two-stage screening workflow was adopted to balance parsimony and process interpretability while limiting redundancy among predictors. Multicollinearity was first checked to reduce confounding effects and to improve the stability of factor-response interpretation, particularly for coefficient-based models. The remaining predictors were then ranked by gain-based importance so that a compact set could be retained without removing variables that are physically meaningful for slope instability. As a result, model comparison was conducted on a reduced and more coherent predictor set, and spurious contributions from strongly correlated factors were less likely to be amplified during fitting. This screening step was therefore treated as a prerequisite for fair benchmarking across models rather than as a model-specific optimization.

Although local details vary among models, the regional susceptibility pattern is broadly consistent. High- and very-high-susceptibility zones are preferentially aligned with steep relief, valley–mountain transition belts, and structurally controlled slopes, whereas low to very low classes are dominated by gentler terrain and more competent lithologies. This organization is supported by inventory-based checks, as landslide points are clearly concentrated in the medium to very high classes and the highest point densities are observed in the high and very high classes, indicating that the zonation captures the observed spatial tendency of slope failures.

4.2. Contribution of Mamba-LSM and Neighborhood-Based Representation

As shown in Figure 12a–c, model behavior is further evaluated from three complementary perspectives, including the precision–recall curve, probability calibration, and predicted-probability distributions. Overall, the complementary diagnostics show that Mamba-LSM maintains strong threshold-independent discrimination, while the added deep learning baselines provide additional context for interpreting threshold-dependent performance.

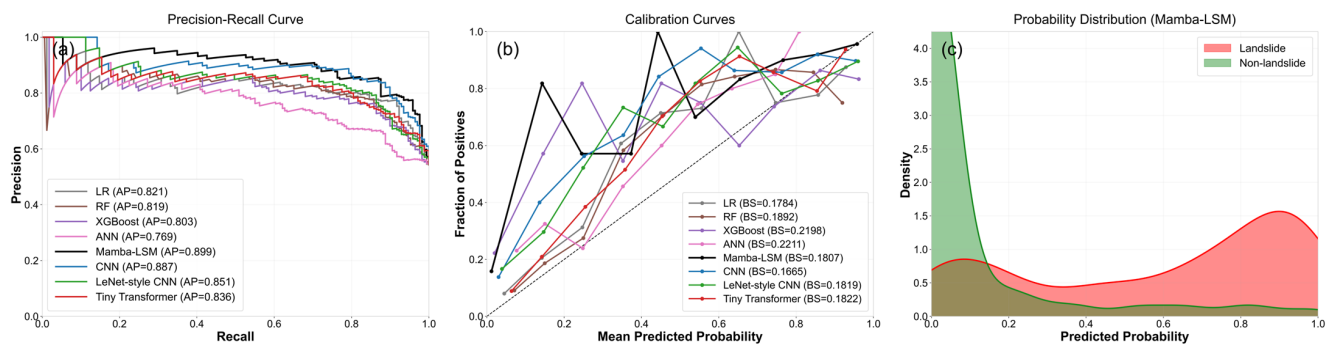


Figure 12. Complementary performance diagnostics for the evaluated models. (a) Precision–recall curves with average precision (AP). (b) Calibration curves with Brier scores (BS). (c) Predicted-probability distributions for Mamba-LSM.

In the PR space (Figure 12a), Mamba-LSM achieved the highest average precision (AP = 0.899), followed by CNN (AP = 0.887), LeNet-style CNN (AP = 0.851), Tiny Transformer (AP = 0.836), LR (AP = 0.821), RF (AP = 0.819), XGBoost (AP = 0.803), and ANN (AP = 0.769). This result indicates that the advantage of Mamba-LSM is most evident in threshold-independent ranking and positive-class retrieval across varying decision thresholds. The calibration comparison, including the added deep learning baselines, is shown in Figure 12b. CNN achieved the lowest Brier score (BS = 0.1665), while Mamba-LSM (BS = 0.1807), LeNet-style CNN (BS = 0.1819), and Tiny Transformer (BS = 0.1822) showed comparable probability-calibration errors and outperformed XGBoost (BS = 0.2198) and ANN (BS = 0.2211).

The predicted-probability distribution for Mamba-LSM (Figure 12c) provides an intuitive view of class separability. Non-landslide samples concentrate at low predicted probabilities, whereas landslide samples shift toward higher probabilities, indicating clear distributional separation. Residual overlap remains in the low-probability range, implying that some landslide cases share factor patterns similar to stable terrain or that the available predictors do not fully capture local triggering conditions.

The comparative results indicate that clear performance differences exist across algorithms under an identical factor set and evaluation protocol. Tree-based ensembles remain strong references for susceptibility mapping because nonlinear thresholds and factor interactions can be captured with limited assumptions about functional form, and model fitting is generally less sensitive to feature scaling. LR provides an interpretable baseline with directionally meaningful effects, but the decision boundary is constrained to be globally linear and can be affected by redundancy among predictors. Under the present factor dimensionality and sample size, the ANN yields only modest gains, which is consistent with the expectation that stronger advantages typically require richer inputs or substantially larger training sets.

Taken together, the expanded comparison shows that Mamba-LSM achieved the highest AUC and AP, whereas CNN was competitive at the default threshold. The performance of Mamba-LSM should therefore not be attributed to the Mamba component alone, but rather interpreted as the combined effect of multi-factor neighborhood representation, CNN-based local spatial encoding, and Mamba-based latent feature transformation before classification. The inclusion of lightweight CNN and Transformer baselines strengthens this interpretation by showing how the complete Mamba-LSM framework compares with related patch-based deep learning alternatives under the same evaluation setting. Nevertheless, these comparisons should not be interpreted as a comprehensive benchmark of all possible deep learning architectures.

4.3. Role of SBAS-InSAR Deformation Evidence in Post-Model Correction

Independent kinematic evidence for interpreting and refining susceptibility patterns at the map scale was provided by SBAS-InSAR line-of-sight (LOS) deformation velocity. Broad correspondence between deformation corridors and high-susceptibility belts was observed, particularly along incised valleys and near railway cut slopes. Importantly, InSAR-derived information was not used for model training, feature screening, or probability calibration. Instead, classified LOS deformation levels were incorporated only after the initial susceptibility prediction through rule-based bidirectional reclassification, providing an external kinematic constraint on the static Mamba-LSM zonation (Figure 11 and Table 7; see Section 3.5).

The downgraded areas should be interpreted cautiously. A relatively low LOS deformation class does not necessarily indicate complete slope stability, because SBAS-InSAR measures only the displacement component along the satellite line-of-sight direction and may be affected by viewing geometry, slope aspect, surface coherence, lay-over, and shadow. The downgrade therefore represents a deformation-constrained adjustment under the available observation period rather than a definitive exclusion of landslide susceptibility.

To further examine the physical meaning of the deformation-informed susceptibility zonation, zonal statistics were calculated using the refined susceptibility classes as zones and the reclassified SBAS-InSAR deformation-level raster as the value layer. The resulting class-wise mean deformation levels are shown in Figure 13. The mean values are 3.01, 2.83, 2.79, 2.74, and 2.76 for the very-low-, low-, medium-, high-, and very-high-susceptibility classes, respectively. Overall, the differences among classes are limited, and no clear monotonic trend is observed from lower- to higher-susceptibility classes. In particular, the very-low-susceptibility class exhibits the highest mean deformation level, indicating that zonal mean statistics are affected by the large spatial extent of this class and by spatially distributed background deformation. Therefore, the mean deformation level alone cannot be regarded as a robust standalone indicator for distinguishing susceptibility classes. However, when Figure 13 is interpreted together with the deformation-hotspot pattern in Figure 10 and the landslide density statistics in Table 7, the physical significance of the refined susceptibility map becomes clearer. Although the class-wise mean deformation levels differ only slightly, landslide point density increases systematically from 12.91 points/100 km² in the very low class to 41.07, 102.03, 176.75, and 270.34 points/100 km² in the low, medium, high, and very high classes, respectively. In addition, the high- and very-high-susceptibility classes together contain 69.84% of the mapped landslides while occupying only 25.31% of the study area. These results indicate that the contribution of SBAS-InSAR deformation to susceptibility refinement is expressed more clearly by the spatial concentration of kinematic anomalies and landslide occurrences than by zonal mean deformation level alone. Overall, these results suggest that SBAS-InSAR contributes to susceptibility refinement primarily through the localization of deformation hotspots and their spatial correspondence with landslide clustering, rather than through a monotonic increase in zonal mean deformation level across susceptibility classes.

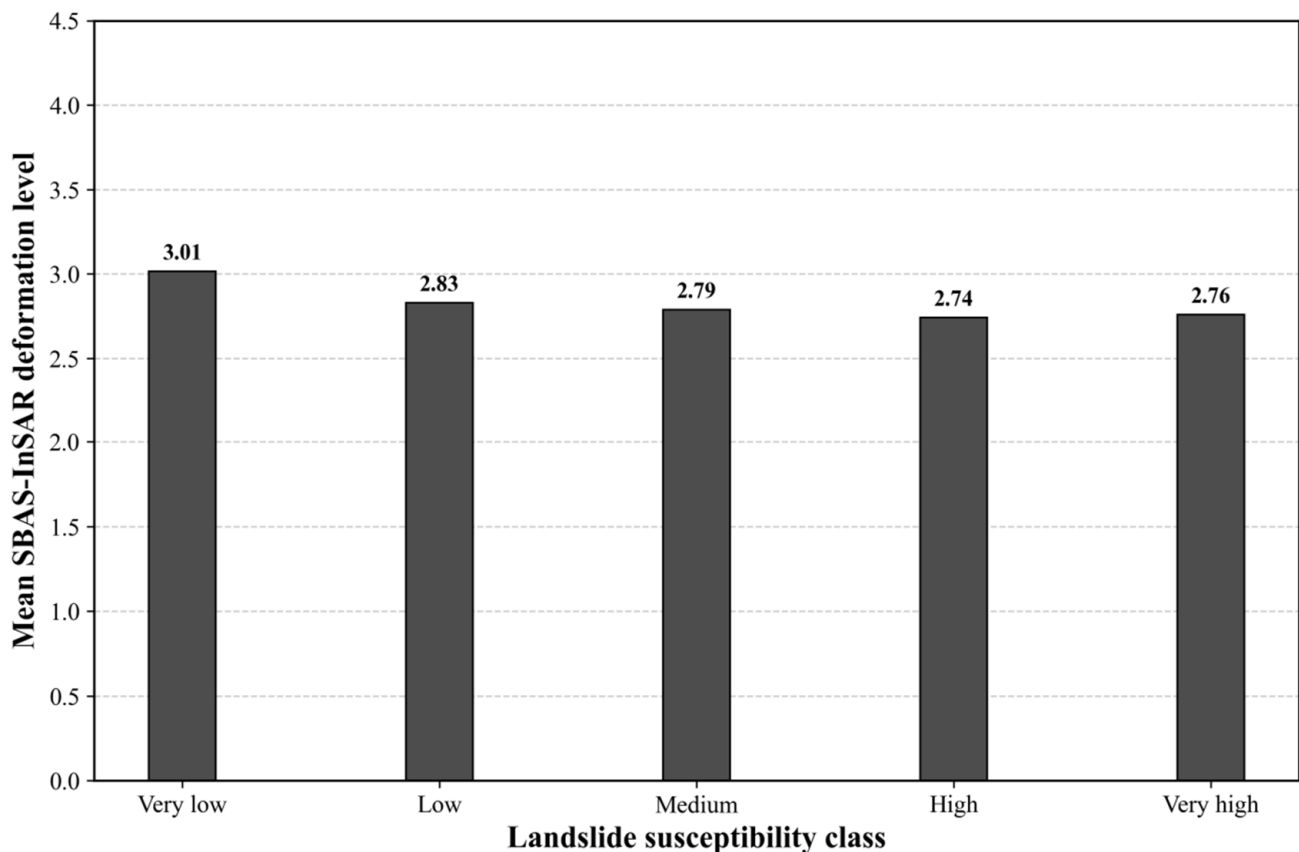


Figure 13. Mean SBAS-InSAR deformation level across landslide susceptibility classes.

4.4. Limitations and Future Work

In landslide susceptibility mapping, the evaluation unit serves as the carrier of conditioning information and the basic support for model prediction and map presentation; therefore, its choice directly influences computational efficiency, spatial interpretability, and the comparability of susceptibility patterns. Previous studies have used a variety of units, including regular grids, administrative partitions, geomorphic/terrain units, slope units, and watershed units. Among them, slope units are often considered geomorphologically meaningful because they tend to be internally more homogeneous in terms of topography and, to some extent, lithology, consistent with the “one-slope-one-process” perspective. However, slope-unit delineation usually relies on user-defined parameters (e.g., flow-routing thresholds or segmentation rules), and the resulting boundaries can be sensitive to these settings. Such sensitivity may limit reproducibility and complicate cross-region comparisons when different delineation schemes are adopted.

Given our objective of integrating multi-source raster conditioning factors (e.g., slope, aspect, distance to river and fault, NDVI, and lithology) under a unified spatial framework, we adopted 30 m grid cells as evaluation units. Grid-based units align naturally with raster predictors, simplify data harmonization and batch processing, and preserve a one-to-one correspondence with input pixels, thereby enabling straightforward pixel-level statistics and susceptibility mapping. In addition, the grid unit facilitates consistent sampling and model training because both landslide and non-landslide samples can be linked unambiguously to co-registered predictor values. To mitigate potential label leakage and data-imbalance effects, landslide polygons were quality-controlled and represented on the 30 m lattice, while non-landslide samples were generated outside mapped landslides with an exclusion buffer to reduce boundary uncertainty. We acknowledge that regular grids may locally mix micro-landform elements near slope breaks or complex terrain

boundaries; nevertheless, at the scale of the study area and the adopted resolution, the stability, efficiency, and reproducibility of grid-based units outweigh these limitations.

Several limitations remain. Regular grid units may locally mix micro-landform elements near slope breaks, and the present inventory, static conditioning factors, and single-geometry LOS observations cannot fully represent time-dependent triggering processes or three-dimensional slope motion. Although ANN, CNN, LeNet-style CNN, and Tiny Transformer were included as neural or deep learning baselines, broader benchmarking using additional patch-based deep learning architectures, repeated spatial validation, and more extensive hyperparameter evaluation would further strengthen the generalizability assessment of Mamba-LSM. Many image-based deep learning models, including U-Net-style semantic-segmentation networks, are designed for raw remote-sensing imagery and cannot be compared directly with the structured factor-based neighborhood patches used here without changing the task formulation. Future work should therefore incorporate rainfall time series, multi-geometry deformation observations, and potentially slope-unit representations to improve temporal relevance and physical interpretability.

5. Conclusions

This study developed a Mamba-based landslide susceptibility mapping framework (Mamba-LSM) for the Xining Basin and further incorporated SBAS-InSAR deformation evidence through a deformation-informed bidirectional reclassification. Three main conclusions can be drawn. First, among the evaluated models, Mamba-LSM achieved the highest AUC (0.9011), indicating the strongest threshold-independent discriminative ability, with an F1-score of 0.7431, Precision of 0.8992, and MCC of 0.5623 on the region-based spatial hold-out validation subset. These results indicate that the neighborhood-informed Mamba-LSM framework is effective in representing landslide-related spatial context for susceptibility assessment in the mountain–basin transition environment of the Xining Basin. Second, SBAS-InSAR deformation observations provided independent kinematic evidence for examining the physical plausibility of the susceptibility results and supported a deformation-informed bidirectional reclassification. Rather than being used for model training, the InSAR-derived deformation field was incorporated only after the initial susceptibility prediction to refine susceptibility levels in deformation-active areas. The refined susceptibility zonation showed improved spatial correspondence with mapped landslides and deformation hotspots, demonstrating the value of integrating dynamic deformation information into regional landslide susceptibility assessment. Third, the final deformation-informed susceptibility map exhibited a clear spatial concentration of landslides within the upper susceptibility classes. The high- and very-high-susceptibility classes together occupied only 25.31% of the study area but contained 69.84% of the mapped landslides. Landslide point density increased systematically from 12.91 points/100 km² in the very low class to 270.34 points/100 km² in the very high class. Spatially, high-susceptibility and deformation-active zones were concentrated mainly along the valley–mountain transition belts, river-incised slopes, and engineering-disturbed sectors, indicating that these areas represent the principal belts of active slope instability in the study area. Future work should incorporate dynamic triggering factors, such as rainfall time series, and multi-geometry or time-dependent deformation observations to further improve the temporal relevance and physical interpretability of landslide hazard assessment.

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Data Availability Statement: The Sentinel-1 and Sentinel-2 data used in this study are publicly available from the Copernicus data access services. OpenStreetMap data are publicly available from <https://www.openstreetmap.org>. The processed conditioning-factor layers, interpreted landslide inventory, SBAS-InSAR deformation products, and derived landslide susceptibility maps are available from the corresponding author upon reasonable request, subject to data-use restrictions.

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Abbreviations

The following abbreviations are used in this manuscript:

LSM	Landslide susceptibility mapping
Mamba-LSM	Mamba-based landslide susceptibility mapping model
SBAS	Small baseline subset
InSAR	Interferometric Synthetic Aperture Radar
SBAS-InSAR	Small baseline subset interferometric synthetic aperture radar
LOS	Line of sight
V _{LOS}	Line-of-sight velocity
SAR	Synthetic aperture radar
DEM	Digital elevation model
NDVI	Normalized difference vegetation index
OSM	OpenStreetMap
VIF	Variance inflation factor
LR	Logistic regression
RF	Random forest
ANN	Artificial neural network
ROC	Receiver operating characteristic
AUC	Area under the receiver operating characteristic curve
MCC	Matthews correlation coefficient
AP	Average precision
BS	Brier score
UAV	Unmanned aerial vehicle

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