

Article

Land Subsidence Susceptibility Mapping Using SBAS-InSAR and Machine Learning: A Case Study of Ghaenat County, Iran

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Abstract

Land subsidence is a geohazard in groundwater-dependent regions, requiring assessment to support hazard mitigation and regional planning. This study presents an integrated framework combining Sentinel-1 deformation monitoring and machine learning-based susceptibility mapping in Ghaenat County, Iran. Ground deformation was reconstructed from Sentinel-1 time series interferometry using the Small Baseline Subset (SBAS) InSAR approach, generating deformation time series and deformation-rate products. The InSAR-derived deformation was compared with piezometric well records to assess hydrogeological consistency. Higher subsidence rates coincided with the period of minimum groundwater levels in late 2021, followed by reduced rates and slight fluctuations in early 2022 as groundwater levels partially recovered, supporting the plausibility of the observed deformation patterns. For susceptibility mapping, a binary response variable was derived from the InSAR-based mean deformation velocity using a threshold of -10 mm/yr, with velocities equal to or lower than this value classified as significant subsidence. The threshold was supported by the background variability of the InSAR velocity field and evaluated through sensitivity analysis using alternative velocity thresholds. Thirteen conditioning factors were harmonized to a common spatial extent, grid resolution, and valid-data mask and subsequently used for model development. Random Forest and LightGBM demonstrated comparable predictive performance, achieving mean AUC values of 0.912 and 0.909, respectively, within the validation variability. All models identified consistent susceptibility patterns in the main alluvial plain, while differences were observed in the spatial extent of very-high-susceptibility areas among the modelling approaches. The framework can support regional assessment of land subsidence susceptibility, groundwater management, and land use planning.



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1. Introduction

Land subsidence is a widespread form of ground deformation that may develop gradually but can accumulate to levels capable of damaging buildings, roads, railways, buried pipelines, and other critical infrastructure [1,2] In many sedimentary basins, subsidence is

closely associated with aquifer-system compaction, whereby groundwater-level decline reduces pore pressure and increases effective stress in compressible deposits [3–5]. Such deformation is commonly heterogeneous in space and non-stationary in time because of variations in lithology, aquifer–aquitard architecture, groundwater conditions, and other environmental controls (Hasan et al. 2023) [6]. These characteristics make the monitoring and assessment of land subsidence dependent on observations that are both spatially distributed and temporally consistent.

Satellite Interferometric Synthetic Aperture Radar (InSAR) has become an important tool for regional subsidence monitoring because it provides spatially distributed deformation measurements with repeated observations in time [7–9]. Time series approaches are particularly useful because they reconstruct deformation evolution from multiple acquisitions and can reduce the influence of common interferometric artefacts through network design and temporal inversion. Accordingly, small-baseline subset (SBAS) and persistent scatterer interferometry (PSI) have been widely applied to balance measurement density, coherence constraints, and robustness to nonlinear or high-gradient deformation [10–12].

In Iran, multi-temporal InSAR has been widely used to characterize land subsidence in groundwater-dependent regions. Dehghani et al. [13] demonstrated the applicability of interferometric observations for investigating ground-surface subsidence associated with groundwater overexploitation. More recently, Ghorbani et al. [14] used Sentinel-1 InSAR and LiCSBAS to investigate long-term subsidence in the Ardabil Plain and linked the observed deformation to groundwater pumping and reduced rainfall. Azarakhsh et al. [15] combined Sentinel-1 PS-InSAR with machine-learning approaches to model land subsidence in the Tehran–Shahriar Plain, incorporating groundwater-table and precipitation information among the conditioning variables. Moradi et al. [16] further applied Sentinel-1A InSAR to assess land subsidence and its controlling surface and subsurface factors in the Tehran metropolitan area. These studies demonstrate the value of multi-temporal InSAR for characterizing subsidence in Iranian groundwater-dependent regions and provide a basis for extending such monitoring and susceptibility assessment to other vulnerable areas.

The effectiveness of time-series InSAR can nevertheless be affected by land-cover conditions and deformation characteristics. Radar coherence and stable-target density may decrease in agricultural and mixed land-cover environments, while high deformation rates can challenge conventional processing strategies. Methodological developments have therefore sought to improve deformation retrieval under demanding conditions. Sadeghi et al. [17] demonstrated the need for improved persistent-scatterer processing for monitoring high-rate subsidence, while Chen et al. [18] developed a persistent-scatterer interpolation approach to retrieve deformation over agricultural areas affected by severe vegetation-related decorrelation. Jiang and Lohman [19] further showed that agricultural activities and associated changes in vegetation and soil moisture can degrade InSAR time-series quality and introduce confounding signals. More recently, Ma et al. [20] evaluated multi-temporal SBAS-InSAR approaches in low-coherence agricultural areas and demonstrated their applicability for monitoring groundwater-related deformation. These studies highlight the importance of obtaining spatially meaningful deformation observations in areas where conventional stable-target approaches may provide sparse or spatially heterogeneous coverage.

Beyond deformation mapping itself, recent studies have emphasized the importance of interpreting deformation time series together with external environmental and hydrogeological variability. For example, PS-InSAR time series have been used to characterize deformation in province of Frosinone [21]. Related work has examined the relationship between InSAR-derived ground deformation and environmental drivers, including climate variability and groundwater conditions [2]. Such approaches highlight the value of com-

binning deformation observations with independent environmental information to improve the interpretation of temporal deformation patterns. This evolution from deformation mapping toward time-series interpretation is particularly relevant in groundwater-dependent regions, where understanding the spatial distribution of deformation together with its hydrogeological and environmental context is important for subsequent assessment.

A further development has been the integration of deformation observations with machine-learning approaches to produce spatial susceptibility information, with some studies further extending the analysis to risk assessment. Chen et al. [22], for example, combined InSAR with hybrid machine-learning models to map land-subsidence susceptibility and risk in Xi'an, China, using multi-source predictor variables. Qin et al. [23] similarly integrated multisource geoscience data, InSAR, and machine learning for subsidence susceptibility assessment. These studies demonstrate the potential of InSAR-derived deformation as an observation-based input for spatial susceptibility modelling. However, the integration of these approaches should be adapted to the hydrogeological, geological, climatic, and land-surface characteristics of the target region rather than being considered a universally transferable modelling configuration.

Despite the progress in InSAR-based monitoring and InSAR-machine-learning integration, land-subsidence susceptibility in Ghaenat County, a groundwater-dependent arid region in eastern Iran, has received limited systematic investigation within a unified framework linking observed deformation with multiple hydrogeological, geological, and climatic conditioning factors. In particular, there is a need to characterize the spatial and temporal deformation patterns of the county and to examine how different supervised learning approaches represent the resulting susceptibility patterns when the same set of conditioning information is used. Addressing this regional gap is important because subsidence in groundwater-dependent environments can be spatially heterogeneous, and areas identified from deformation observations alone do not necessarily provide sufficient information for spatial susceptibility assessment.

Accordingly, this study focuses on Ghaenat County, South Khorasan Province, eastern Iran, and develops an integrated two-stage assessment framework. First, Sentinel-1 time series observations are processed using SBAS through LiCSBAS to characterize the spatial and temporal patterns of ground deformation using ascending and descending observations after atmospheric correction. Second, the deformation-derived information is integrated with 13 hydrogeological, geological, and climatic conditioning factors to generate probability-based land-subsidence susceptibility maps using Logistic Regression (LR), Random Forest (RF), and LightGBM. The three models are evaluated within a common modelling framework to compare their predictive performance and the spatial patterns of predicted susceptibility.

The main contributions of this study are threefold: (i) characterization of spatiotemporal ground deformation in Ghaenat County using multi-temporal SBAS-InSAR observations; (ii) development of a regional susceptibility framework integrating deformation observations with multiple conditioning factors; and (iii) comparative evaluation of LR, RF, and LightGBM in terms of predictive performance and spatial susceptibility patterns. The resulting maps are intended to support regional screening, prioritization of areas for further investigation and monitoring, and groundwater-management and land-use planning.

2. Materials and Methods

2.1. Study Area

Ghaenat County is located in South Khorasan Province, eastern Iran, at approximately 33° N latitude and 59° E longitude (Figure 1). Its administrative center, Qaen, is situated at

an elevation of approximately 1400 m above sea level and is one of the major urban centers of the province.

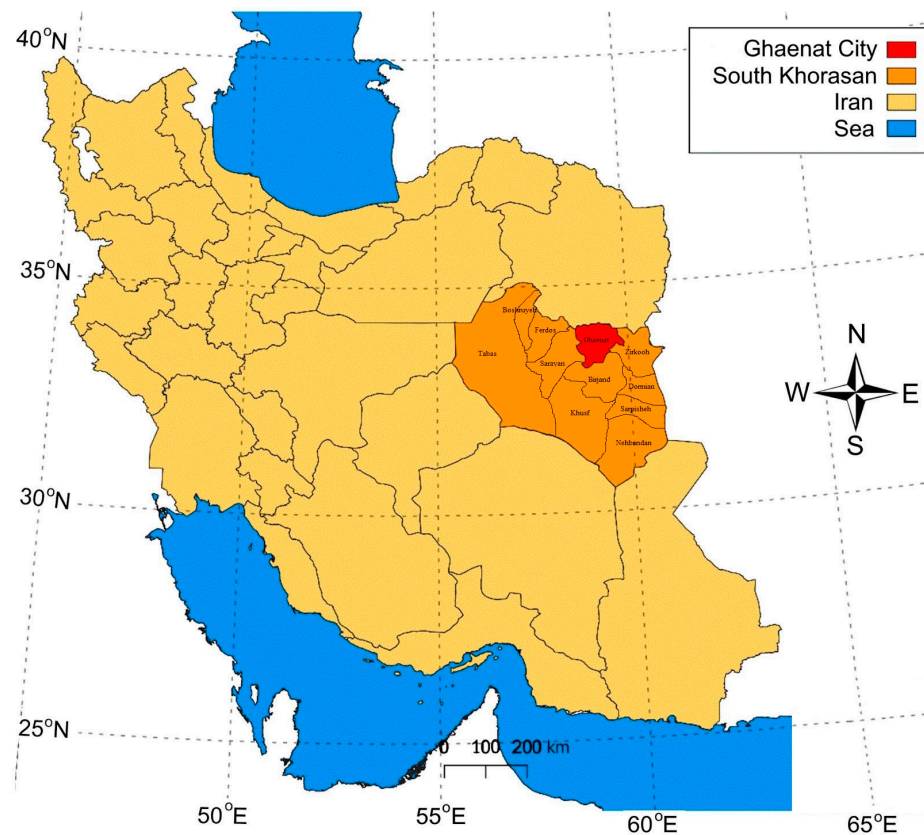


Figure 1. Shows the geographic location of the study area and indicates Qaen together with the major nearby urban centers for spatial reference.

Ghaenat County has an arid to semi-arid climate characterized by low and irregular annual precipitation. Mean annual precipitation is approximately 150–200 mm, with marked seasonal temperature variations between hot summers and cold winters ([24,25]. These climatic conditions, together with high evaporation rates, have resulted in a strong dependence on groundwater for agricultural and domestic water supply [26]. Agriculture represents an important component of the local economy, with saffron, barberry, and jujube among the major cultivated products. Intensive groundwater extraction for agricultural and domestic uses has been associated with substantial groundwater-level decline, potentially increasing the susceptibility of the county's alluvial plains to land subsidence.

From a geological and geomorphological perspective, the Qaen Plain is located between surrounding mountainous units and is predominantly covered by young alluvial deposits. Such deposits may contain compressible fine-grained materials that can undergo compaction in response to changes in groundwater conditions. Local fault systems may additionally influence subsurface hydrogeological and structural conditions across the study area. Overall, the combination of arid climatic conditions, strong dependence on groundwater resources, intensive agricultural activity, and the geological characteristics of the alluvial plain makes Ghaenat County a relevant setting for regional land-subsidence assessment.

2.2. InSAR Data and LiCSBAS2(1.9.2) Software

In this study, ready-to-use interferometric products from the LiCSAR system were used. The datasets cover the period from 31 December 2020, to 31 December 2022. For

the ascending orbit, 59 Sentinel-1 acquisitions were available, corresponding to 257 interferograms, whereas the descending dataset comprised 56 acquisitions and 182 interferograms (Table 1). The ascending and descending datasets corresponded to LiCSAR frames 086A_05609_131313 and 093D_05675_131313, respectively. The interferometric networks were generated within the standard LiCSAR processing framework; therefore, image selection and interferogram generation followed the predefined LiCSAR strategy. Atmospheric phase delays were corrected using GACOS-derived atmospheric delay products before time series inversion to reduce tropospheric artefacts.

Table 1. Sentinel-1 geometry parameters used for LOS decomposition.

Orbit Direction	Number of Sentinel-1 Acquisitions	Mean Incidence Angle (°)	Heading Angle (°)
Ascending	59	33.8912	10.2153
Descending	56	33.7998	169.7649

Time series analysis was performed using LiCSBAS [27], an open-source SBAS-based framework designed for processing LiCSAR-generated Sentinel-1 interferometric products. The LiCSAR-provided unwrapped interferograms and coherence products were processed without altering the original interferometric network to generate deformation time series and line-of-sight (LOS) velocity products. During processing, quality masking was applied using the avg_coh criterion. Pixels with avg_coh values below 0.05 were excluded, whereas pixels satisfying $\text{avg_coh} \geq 0.05$ were retained for generation of the deformation time series and velocity products.

A stable reference area was selected based on geological and geomorphological stability and velocities close to zero. Pixels within this area were used to define the zero-deformation reference level for the deformation products. The ascending and descending LOS velocity fields were subsequently combined through the decomposition procedure described in Section “LOS-to-Vertical Displacement Decomposition” to derive the final vertical displacement velocity field.

Following LOS decomposition, the resulting vertical displacement velocity product and all conditioning-factor datasets were harmonized to a common regular grid with a cell size of 500 m $\times$ 500 m. This grid served as the common analysis and data-integration framework for subsequent susceptibility modelling. The vertical deformation product was then combined with the common valid-data mask of the predictor variables, and only pixels containing valid deformation information and complete predictor values were retained for model development.

All raster preprocessing, spatial-data manipulation, machine-learning analyses, and visualization procedures were conducted in Python (3.9). NumPy and Pandas were used for numerical and tabular data processing, GDAL and Rasterio for geospatial raster operations, and scikit-learn for implementation of Logistic Regression and Random Forest. LightGBM was implemented using the LightGBM package, while Matplotlib (3.9.2) and Seaborn (0.13.2) were used for visualization and diagnostic plots.

LOS-to-Vertical Displacement Decomposition

The deformation velocities derived from ascending and descending Sentinel-1 observations were decomposed into vertical and east–west components using a two-dimensional LOS decomposition approach. Each line-of-sight (LOS) velocity represents the projection of

the three-dimensional ground-motion vector onto the radar viewing direction and can be expressed as:

$$v_{\text{LOS}} = -\sin(\theta)\cos(\alpha)v_E - \sin(\theta)\sin(\alpha)v_N + \cos(\theta)v_U \quad (1)$$

where v_{LOS} is the ground-deformation velocity measured along the radar line of sight, and v_E , v_N , and v_U represent the east–west, north–south, and vertical velocity components, respectively. The parameters θ and α denote the radar incidence angle and satellite heading angle, respectively.

Because Sentinel-1 InSAR observations have relatively limited sensitivity to the north–south component of ground motion, the north–south velocity was assumed to be negligible ($v_N \approx 0$). Under this assumption, the ascending and descending LOS velocity observations were jointly used to solve for the east–west and vertical velocity components. The resulting vertical component was subsequently used as the deformation product for the land-subsidence susceptibility analysis.

A stable reference area was selected based on geological and geomorphological stability together with pixels exhibiting velocities close to zero. This area was used to define the zero-deformation reference level for the deformation products prior to generation of the final vertical velocity map.

A separate uncertainty layer for the decomposed vertical velocity was not generated. Instead, data quality was controlled through coherence-based masking and stable reference-area selection. Groundwater-level observations were used only to evaluate the hydrogeological consistency of the detected deformation patterns and were not treated as an independent validation of InSAR measurement accuracy.

2.3. Predictive Variables

In this study, a set of predictor variables was compiled and generated to characterize the spatial susceptibility to land subsidence and provide the required inputs for the machine-learning models. The predictor variables were selected within an integrated hydrogeological–geological–climatic framework, based on the physical mechanisms governing subsidence in alluvial plains. In particular, the dataset was designed to represent pore-pressure changes associated with groundwater withdrawal, the mechanical properties of subsurface deposits, and environmental factors related to climate, surface hydrology, and geomorphological conditions. These variables were intended to capture spatial heterogeneity in sediment compressibility, aquifer yield and recharge, and geological structures that may influence subsurface flow, thereby providing a physically informed basis for regional susceptibility modelling.

Among the predictor variables, groundwater-level decline was considered an important factor because declining groundwater levels are physically associated with changes in effective stress within compressible sediments and may contribute to aquifer-system compaction and ground deformation [28].

Groundwater-level decline was derived from observations collected from 62 piezometric wells distributed across the study area. The spatial distribution of the selected wells is shown in Figure 2. The groundwater-level observations covered the same study period as the InSAR analysis, from December 2020 to December 2022, thereby maintaining temporal consistency between the groundwater and deformation datasets.

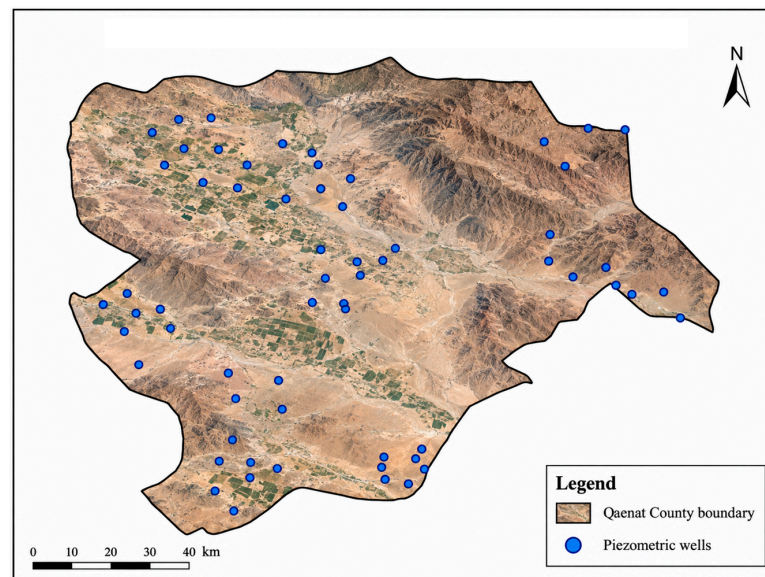


Figure 2. Spatial distribution of the 62 piezometric wells used to derive the groundwater-level decline predictor in Qaenat County.

For each well, the temporal trend in groundwater level was estimated using all available observations during the study period. A linear regression model was fitted to the groundwater-level time series of each well as follows:

$$H_t = a + b_t \quad (2)$$

where H_t represents the groundwater level at time t , a is the intercept, and b is the temporal trend coefficient representing the rate of groundwater-level change. The groundwater-level change over the study period was estimated from the fitted temporal trend coefficient. For wells exhibiting a decreasing groundwater-level trend, the magnitude of groundwater-level decline was calculated as the absolute value of the estimated negative change over the study period. Wells exhibiting stable or increasing groundwater levels were assigned a groundwater-level decline value of zero because no decline occurred during the study period.

The well-based groundwater-level decline values were subsequently spatially interpolated using the inverse distance weighting (IDW) method to generate a continuous groundwater-level decline surface. The IDW interpolation was performed using a power parameter of 2.5, 16 neighboring wells, and a maximum search distance of 30 km.

To evaluate interpolation accuracy, leave-one-out cross-validation (LOOCV) was performed using the 62 piezometric wells. In each iteration, one well was excluded from the interpolation dataset, and its groundwater-level decline value was predicted using the remaining 61 wells with the same IDW parameter settings used for the final interpolation. The predicted value was then compared with the well-derived groundwater-level decline value at the withheld location. This procedure was repeated for all 62 wells, and interpolation accuracy was quantified using the root mean square error (RMSE), mean absolute error (MAE), and mean error (ME).

To represent the spatial influence of groundwater extraction, “Distance From Production Wells” was generated as a Euclidean distance layer (Figure 3). This variable was included because proximity to production wells may reflect spatial variations in groundwater-withdrawal pressure and associated hydraulic gradients. In areas of intensive extraction, shorter distances to production wells may be associated with greater drawdown and potentially higher susceptibility to compaction. In addition, “Distance From Rivers”

was included as an indicator of hydrological conditions and surface-water–groundwater interactions. Rivers may locally act as recharge sources or drainage pathways and may also influence depositional environments and grain-size distributions in alluvial plains. Therefore, river proximity may capture spatial variability related to localized recharge and sedimentological conditions relevant to subsidence susceptibility.

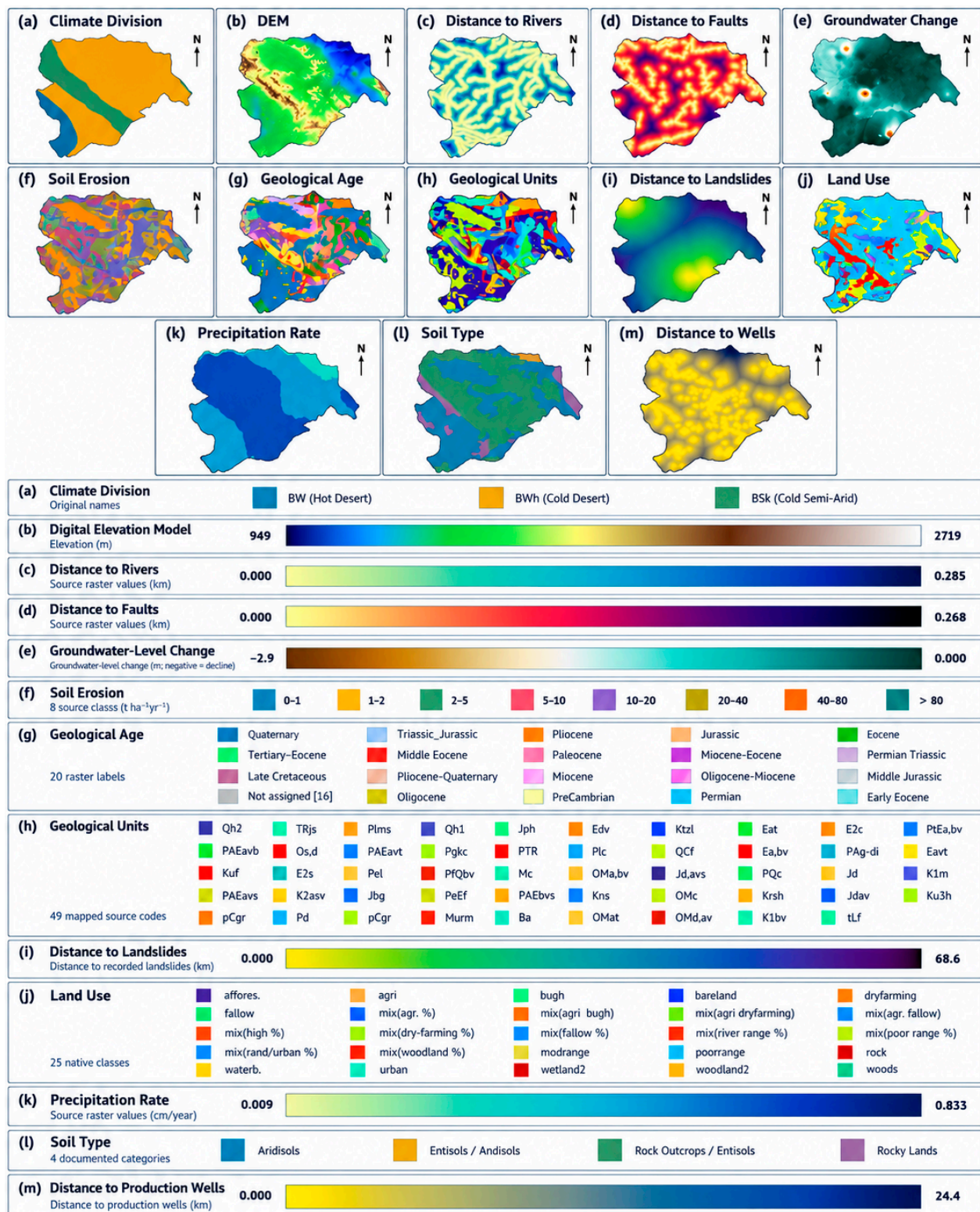


Figure 3. Predictor Raster images used in models.

To account for the role of geological substrate and lithological contrasts, “Geological Units” and “Geological Age” layers were incorporated into the modelling procedure. Geological units reflect variations in lithology and depositional facies and thus represent spatial differences in porosity, permeability, fine-fraction content, and mechanical behavior of the strata, all of which may influence subsidence susceptibility.

Geological age, in turn, may be related to the degree of consolidation, cementation, and diagenetic evolution of deposits. In alluvial environments, younger deposits are generally less consolidated and may have a greater tendency toward compaction and settlement under increasing effective stress. Furthermore, “Distance From Faults” was considered a structural–tectonic predictor. Faults can act as hydraulic and mechanical boundaries, alter preferential subsurface flow paths, control subsurface heterogeneity and sediment-thickness variations, and/or compartmentalize aquifers, thereby potentially modifying compaction behavior at the local scale. Accordingly, proximity to faults may be associated with variations in subsidence patterns and localized deformation concentrations, and including this variable allows potential structural controls on subsidence susceptibility to be represented within the modelling framework.

To represent topographic and geomorphological conditions, the Digital Elevation Model (DEM) was included as a continuous predictor. Elevation can influence drainage patterns, surface-water redistribution, sediment accumulation, and the spatial organization of alluvial environments and may therefore indirectly reflect variations in depositional and hydrogeological conditions relevant to subsidence susceptibility. The DEM was derived from the Shuttle Radar Topography Mission (SRTM) dataset with an original spatial resolution of 90 m. It was reprojected to the common coordinate reference system, clipped to the study area, and resampled to the common 500 m × 500 m modelling grid using bilinear interpolation.

The “Soil Type” layer was included as a categorical predictor to represent spatial differences in near-surface material properties, including texture and composition. Variations in soil characteristics may reflect differences in moisture retention, mechanical behavior, and the occurrence of fine-grained materials relevant to compaction susceptibility.

“Soil Erosion” was additionally included as an indicator of surface erodibility and geomorphic conditions. This variable may indirectly reflect spatial variations in slope, vegetation cover, and soil characteristics that influence surface stability and sediment redistribution.

To represent anthropogenic and land-surface influences, “Land Use” was included as a categorical predictor. Land use may serve as a proxy for spatial variations in water demand, groundwater extraction, and surface conditions affecting infiltration and runoff, particularly in agricultural areas.

The land-use dataset was originally produced by the National Land Affairs Organization of Iran, affiliated with the Ministry of Agriculture Jihad, and was obtained for this study through GeoDatas.ir, a data-distribution platform. According to the available dataset provenance information, the source organization prepares land-use maps by integrating satellite imagery analysis with field observations. The supplied shapefile contained 2128 polygon records and 40 distinct land-use classes, encoded in the ‘lable_talf’ attribute field. Following clipping to Ghaenat County, the dataset comprised 283 polygons representing 25 land-use categories.

The original classification was retained, and no independent land-use classification was performed in this study. Although the dataset was produced by a governmental organization using remote-sensing and field-based information, no official quantitative assessment of classification accuracy was available for the specific dataset used in this research. Consequently, neither an overall accuracy value nor class-specific accuracy statistics could be reported. This limitation was considered when interpreting the modelling results.

Because the original dataset was a vector polygon product, it did not have a single native pixel resolution. The layer was harmonized with the common coordinate reference system and study extent, and the categorical class labels were preserved as discrete classes during rasterization. The resulting categorical land-use raster was generated on the common $500\text{ m} \times 500\text{ m}$ modelling grid, and the nearest-neighbor method was used to preserve the original discrete class identities and avoid the creation of artificial intermediate class values.

To complete the climatic characterization, “Precipitation Rate” and “Climate Division” were included as predictors representing spatial variations in hydroclimatic conditions. Precipitation influences aquifer recharge and groundwater availability and may therefore contribute to spatial differences in groundwater-level variability. Climate Division was included as a regional background variable representing broader climatic contrasts across the study area. Finally, the “Landslide” layer was incorporated to represent areas potentially affected by slope-instability processes. Its inclusion allows the modelling framework to account for locations where observed deformation may be associated with mass movement rather than exclusively with aquifer-system compaction.

To ensure spatial consistency among datasets with different native spatial resolutions and map scales, all conditioning factors were harmonized to a common coordinate reference system, spatial extent, and analysis grid. The native spatial resolution or map scale of each predictor is reported individually in Table 2. Vector datasets were first rasterized on the common analysis grid, whereas raster datasets were spatially aligned to the same grid origin and extent.

A common cell size of $500\text{ m} \times 500\text{ m}$ was selected for susceptibility modelling as a compromise between retaining spatial variability relevant to county-scale subsidence susceptibility and avoiding artificial fine-scale precision when integrating predictor datasets with heterogeneous native resolutions and map scales. Therefore, the 500 m cell size represents the common analysis and data-integration grid rather than the native spatial resolution of the original datasets.

The final resampling to the $500\text{ m} \times 500\text{ m}$ grid was performed in Python. Continuous variables, including elevation, mean annual precipitation, groundwater-level decline, and distance-based variables, were resampled using bilinear interpolation. Categorical variables, including climatic classes, geological age, geological units, land use, soil type, soil-erosion classes, and landslide classes, were resampled using the nearest-neighbor method to preserve their discrete class identities and avoid the generation of artificial intermediate values. NoData and out-of-domain cells were subsequently excluded, and only pixels containing valid values for the response variable and all conditioning factors were retained for construction of the final feature matrix.

During spatial preprocessing and rasterization, categorical predictors, including geological units, geological age, land use/land cover, soil type, climate division, soil-erosion classes, and landslide classes, were retained as discrete class labels and were not interpreted as ordinal numerical measurements. Continuous predictors were retained as numerical variables. The categorical predictors were subsequently converted into numerical effect scores using the training-derived target-based effect encoding procedure described below.

After spatial preprocessing, categorical predictors, including geological units, geological age, land use, soil type, climate division, soil-erosion classes, and landslide classes, were transformed using a target-based effect encoding procedure.

Table 2. Predictor datasets used for land-subsidence susceptibility modelling.

Predictor	Source	Resolution/Scale	Acquisition Date/Period	Processing Method	Spatial Coverage	Final Modelling Grid	Resampling
Climate Division	Geodatas.ir (commercial geospatial dataset)	Vector polygon map	2021–2022	Raster conversion; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Digital Elevation Model (DEM)	SRTM DEM	90 m	Acquisition period: 2000	Reprojection, clipping, and resampling to the common modelling grid	Study area	500 m × 500 m	Bilinear interpolation
Distance from Faults	Geological fault map [Geodatas.ir (commercial geospatial dataset)]	Vector	2021	Euclidean distance calculation followed by alignment to the common modelling grid	Study area	500 m × 500 m	Bilinear interpolation
Distance from Rivers	River network [Geodatas.ir (commercial geospatial dataset)]	Vector	2021	Euclidean distance calculation followed by alignment to the common modelling grid	Study area	500 m × 500 m	Bilinear interpolation
Groundwater-Level Decline	62 piezometric wells	Point data	2021–2022	Temporal trend estimation; decline calculation; IDW interpolation; LOOCV assessment	Study area	500 m × 500 m	Bilinear interpolation
Soil Erosion	Geodatas.ir (commercial geospatial dataset)	Vector	2021	Rasterization; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Geological Age	Geodatas.ir (commercial geospatial dataset)	Vector polygon dataset	2020	Raster conversion; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Geological Unit	Geodatas.ir (commercial geospatial dataset)	Vector polygon dataset	2020	Raster conversion; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Landslide	Geodatas.ir (commercial geospatial dataset)	Vector inventory	2021–2022	Binary rasterization; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Land Use	Geodatas.ir (commercial geospatial dataset)	Vector polygon dataset	2020	Raster conversion; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Precipitation Rate	Geodatas.ir (commercial geospatial dataset)	Raster	2021–2022	Reprojection, clipping, and resampling to the common grid	Study area	500 m × 500 m	Bilinear interpolation
Soil Type	Geodatas.ir (commercial geospatial dataset)	Vector polygon dataset	2020	Raster conversion; target-based effect encoding during model training	Study area	500 m × 500 m	Nearest-neighbor
Distance from Production Wells	Geodatas.ir (commercial geospatial dataset)	Point data	2022	Euclidean distance calculation followed by alignment to the common modelling grid	Study area	500 m × 500 m	Bilinear

For each categorical predictor, the mean binary response was calculated separately for each class using only the training pixels within each cross-validation fold. Because the response variable was coded as 1 for significant subsidence and 0 for non-significant subsidence, this class-level mean represents the proportion of significant-subsidence pixels within each categorical class. The resulting class-specific means were then used to replace the corresponding categorical labels in the training and validation data within each fold. The class-level mean subsidence values were subsequently normalized to the 0–1 interval using min–max normalization, and the resulting effect scores were assigned to pixels according to their corresponding categorical class.

During cross-validation, the encoding mapping was recalculated independently for each fold using only the training portion of that fold and was then applied to the corresponding validation portion. For the final train–test analysis, the encoding was derived exclusively from the training data and subsequently applied to the independent test data. This procedure ensured that information from the validation or test data was not used to construct the categorical predictor encodings, thereby minimizing information leakage during model evaluation.

For a categorical class c , the normalized effect score was calculated as:

$$E_c = \frac{S_c - S_{\min}}{S_{\max} - S_{\min}} \quad (3)$$

where E_c is the normalized effect score assigned to categorical class c , S_c is the mean binary response for class c , calculated using only the relevant training data, and $S_{\min}$ and $S_{\max}$ are the minimum and maximum class-level mean response values, respectively, within the training data. Because the binary response was coded as 1 for significant subsidence and 0 for non-significant subsidence, S_c represents the proportion of significant-subsidence pixels within class c .

Prior to Logistic Regression modelling, the resulting numerical predictor matrix was standardized using z-score standardization. The mean and standard deviation used for scaling were estimated exclusively from the training data within the modelling pipeline and subsequently applied to the corresponding validation or independent test data. No feature scaling was applied to the Random Forest or LightGBM models because tree-based algorithms are generally insensitive to differences in predictor scale.

Furthermore, time-dependent predictors, particularly groundwater-level decline, were synchronized with the InSAR observation period to maintain temporal consistency and avoid the inadvertent use of information from outside the observation period during model development. Overall, the selected predictor set represents hydrogeological, climatic, geological, geomorphological, and anthropogenic conditions potentially associated with the spatial distribution of land-subsidence susceptibility. This common predictor framework allowed the three modelling approaches to characterize these relationships according to their respective statistical structures.

Prior to model development, predictor dependency and multicollinearity were evaluated to identify potential redundancy among the conditioning factors. Pearson correlation analysis was performed for continuous predictors, while variance inflation factor (VIF) analysis was applied to the numerical predictor set used in the modelling framework. These analyses were used to identify potentially strong dependencies among predictors and assess their implications for model stability and interpretation, particularly for Logistic Regression.

2.4. Response Variable Definition and Machine Learning Models

2.4.1. Binary Response Definition and Threshold Selection

The response variable used for land-subsidence susceptibility modelling was derived from the InSAR-based mean deformation velocity. Under the adopted sign convention, negative velocity values represent downward ground motion, whereas positive values represent upward motion. Because small velocity values may reflect background variability and residual uncertainty in the InSAR observations rather than appreciable ground subsidence, an operational velocity threshold was defined to distinguish significant subsidence from non-significant deformation.

To provide a measurement-based basis for threshold selection, the velocity distribution within a stable reference area was examined. The reference area was selected based on geological and geomorphological stability, with near-zero deformation velocities used as an additional criterion for identifying stable pixels. Within this area, the median deformation velocity was 0.56 mm/yr, the standard deviation was 3.98 mm/yr, and the lower 2.5th percentile of the velocity distribution was -7.75 mm/yr. These statistics were used to characterize the background variability of the InSAR velocity field. The selected threshold of -10 mm/yr is more negative than the lower 2.5th percentile of this background distribution and was therefore considered a conservative operational criterion for identifying appreciable downward deformation.

The sensitivity of model performance to the response threshold was additionally evaluated using alternative velocity thresholds of 0, -5 , -10 , -15 , -20 , and -25 mm/yr. For each candidate threshold, the binary response variable was reconstructed, and Logistic Regression, Random Forest, and LightGBM were evaluated using the same predictor dataset and validation procedure. The -10 mm/yr threshold produced the highest ROC-AUC values across all three models and was therefore retained for the final susceptibility analysis. Importantly, threshold selection was supported jointly by the background variability of the InSAR velocity field and the sensitivity analysis, rather than by model performance alone. The -10 mm/yr value should therefore be interpreted as a study-specific operational threshold rather than a universal physical boundary for land subsidence.

Accordingly, for each valid pixel (i), the binary response variable was defined as:

$$y_i = \begin{cases} 1, & v_i \leq -10 \frac{\text{mm}}{\text{yr}}, \\ 0, & v_i > -10 \frac{\text{mm}}{\text{yr}}, \end{cases} \quad (4)$$

where (v_i) is the InSAR-derived mean deformation velocity at pixel i . Class 1 represents significant subsidence, whereas Class 0 represents non-significant deformation. After applying the common valid-data mask to the response and all predictor layers, 30,681 pixels were retained for modelling. Of these, 8675 pixels (28%) were assigned to the significant-subsidence class and 22,006 pixels (72%) to the non-significant-deformation class.

To assess the spatial robustness of susceptibility hotspots across alternative subsidence thresholds, the Jaccard similarity coefficient was calculated for each modelling approach. For each threshold-specific susceptibility map, the top 10% of pixels with the highest predicted probabilities were identified as principal hotspots. Their spatial overlap was then assessed against the corresponding hotspots identified using the reference threshold of -10 mm/yr. The Jaccard coefficient was calculated as the ratio of the intersection to the union of the two hotspot sets, with values ranging from 0 (no overlap) to 1 (complete overlap).

2.4.2. Logistic Regression

Logistic Regression (LR) was employed as an interpretable baseline classifier to estimate the probability of significant subsidence based on the selected conditioning factors.

The model was trained using the binary response variable defined in Section 2.4.1 and the common valid-data mask applied consistently across all modelling approaches. The predictor matrix consisted of continuous variables and target-based effect-encoded categorical predictors after spatial preprocessing.

The probability of significant subsidence was modelled as:

$$P(Y = 1 | X) = \frac{1}{1 + \exp\left[-\left(\beta_0 + \sum_{i=1}^p \beta_i X_i\right)\right]} \quad (5)$$

where $P(Y = 1 | X)$ is the predicted probability of significant subsidence, β_0 is the intercept, β_i denotes the coefficient associated with predictor X_i , and p is the number of predictors.

Model fitting was performed in Python using scikit-learn. Hyperparameter optimization was conducted using GridSearchCV within a stratified five-fold cross-validation framework applied to the training data. The evaluated parameters included the regularization penalty (L1 or L2), compatible solvers (lbfgs, sag, saga, and liblinear), and the inverse regularization-strength parameter C (0.1, 0.3, 1, 3, and 10). The parameter combination yielding the highest mean ROC-AUC was selected. Class imbalance was addressed using `[class_weight = "balanced"]`.

Numerical predictors were standardized using StandardScaler within the modelling pipeline. Scaling parameters were estimated exclusively from the training data and subsequently applied to the corresponding validation or test data, thereby preventing information leakage.

The complete modelling dataset was divided into stratified training (80%) and testing (20%) subsets while preserving the proportions of the significant-subsidence and non-significant-deformation classes. Model development and hyperparameter tuning were performed using stratified five-fold cross-validation within the training subset. Predictive performance was evaluated using the area under the receiver operating characteristic curve (ROC-AUC). Because significant subsidence represented the minority class, precision–recall performance was additionally assessed using average precision (AP). Probability calibration was evaluated using the Brier score, with lower values indicating better calibration.

The fitted Logistic Regression model generated probabilities ranging from 0 to 1, which were subsequently used to construct the LR-based land-subsidence susceptibility map. The signs and magnitudes of the fitted coefficients were also examined to characterize the direction and relative strength of the model-based associations between the predictors and predicted subsidence probability. These coefficients were interpreted as predictive associations within the fitted model rather than as direct evidence of causal relationships.

2.4.3. Random Forest

Random Forest (RF) is an ensemble learning algorithm that combines multiple decision trees and introduces randomness through bootstrap sampling and random predictor selection at each split, thereby improving predictive stability and reducing overfitting [29]. This structure enables RF to capture nonlinear relationships and interactions among conditioning factors.

In this study, RF was employed as a nonlinear probabilistic classifier to estimate the probability of significant subsidence. The model was trained using the binary response variable defined in Section 2.4.1, where Class 1 represented significant subsidence and Class 0 represented non-significant deformation. The predictor matrix consisted of the harmonized conditioning factors after spatial preprocessing, target-based effect encoding of categorical variables, and application of the common valid-data mask. The same predictor dataset and response definition were used for all machine-learning models to ensure a consistent comparison framework.

The RF model was implemented in Python using the RandomForestClassifier available in the scikit-learn package. The model generated probability estimates ranging from 0 to 1 by averaging the class-probability estimates across the ensemble of decision trees. These probabilities were subsequently used to construct the RF-based land-subsidence susceptibility map.

Because RF is a tree-based algorithm, feature scaling is not required; therefore, no predictor standardization was applied before model training. Model evaluation followed the same stratified training–testing and five-fold cross-validation framework used for the other modelling approaches, allowing predictive performance to be compared under a common validation procedure.

To characterize variability in model performance, ROC-AUC values were recorded for each validation fold. Precision–recall performance and probability calibration were additionally evaluated using average precision (AP) and the Brier score, respectively. Mean ROC-AUC, standard deviation, and 95% confidence intervals were calculated from the fold-wise results. Because RF and LightGBM were evaluated using the same validation folds, their fold-wise AUC values and associated variability were examined to assess whether the observed difference in mean predictive performance was substantial relative to the variability across folds.

RF hyperparameters were predefined prior to model fitting. The model used 500 decision trees ($n_estimators = 500$), with no imposed maximum tree depth ($max_depth = None$). The minimum numbers of samples required for splitting an internal node and forming a terminal leaf were set to 2 and 1, respectively ($min_samples_split = 2$ and $min_samples_leaf = 1$). At each split, the number of candidate predictors was set to the square root of the total number of predictors ($max_features = "sqrt"$), thereby promoting diversity among the individual trees. Class imbalance was addressed using $class_weight = "balanced_subsample"$, whereby class weights were recalculated for each bootstrap sample.

2.4.4. Light Gradient Boosting Machine (LightGBM)

Light Gradient Boosting Machine (LightGBM) was employed as a gradient-boosted decision tree (GBDT)-based classifier capable of representing nonlinear relationships and interactions between subsidence occurrence and the conditioning factors. Unlike linear models, LightGBM can capture complex nonlinear responses, including threshold-like behavior, and interactions among predictors without requiring these relationships to be explicitly specified [30].

In this study, LightGBM was used as a probabilistic classifier to estimate the probability of significant subsidence. The model was trained using the same binary response variable defined in Section 2.4.1, where Class 1 represented significant subsidence and Class 0 represented non-significant deformation. The predictor matrix consisted of the harmonized conditioning factors after spatial preprocessing and target-based effect encoding of categorical variables. The same valid-data mask, predictor dataset, response definition, and validation framework were used across all three machine-learning models to ensure consistent comparison.

Model fitting was performed in Python using the lightgbm package. The hyperparameters were predefined prior to model fitting. The model was configured with 1000 boosting iterations and a learning rate of 0.03. The maximum tree depth was left unrestricted ($max_depth = -1$), with 31 leaves per tree ($num_leaves = 31$) and a minimum of 100 samples per leaf ($min_child_samples = 100$) to control model complexity. Feature subsampling was applied using $colsample_bytree = 0.8$. L1 and L2 regularization parameters

were set to 0 and 1, respectively ($\text{reg_alpha} = 0$; $\text{reg_lambda} = 1$). The binary classification objective was used to generate probability estimates of significant subsidence.

LightGBM was evaluated using the same stratified training–testing and five-fold cross-validation framework applied to Logistic Regression and Random Forest. ROC-AUC, average precision, and Brier score were used to evaluate discrimination, minority-class identification, and probability calibration, respectively. The predicted probabilities were subsequently mapped across the study area to generate the LightGBM-based land-subsidence susceptibility surface, with higher probability values indicating greater predicted susceptibility.

2.4.5. Susceptibility Classification and Feature Contribution Analysis

To convert the continuous susceptibility probability outputs into categorical susceptibility maps, a common equal-interval classification scheme was applied to the probability surfaces generated by Logistic Regression, Random Forest, and LightGBM. Because all three models produced probability values ranging from 0 to 1, fixed thresholds were applied consistently across the models. Five susceptibility classes were defined as Very Low (0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0). This common classification scheme facilitates direct visual comparison among the three modelling approaches while preserving the quantitative interpretation of the underlying predicted probabilities. These classes are operational susceptibility categories and should not be interpreted as equal-probability intervals with identical physical meaning across models.

In addition to susceptibility mapping, feature contribution analysis was performed separately for each modelling approach using model-specific importance measures. For Logistic Regression, predictor importance was derived from the absolute values of the fitted standardized coefficients and normalized by the sum of all absolute coefficient values. For Random Forest, feature importance based on mean decrease in impurity (MDI) was extracted and normalized by the total importance across predictors. For LightGBM, gain-based feature importance was used, representing the cumulative contribution of each predictor to reductions in the objective function during boosting, and was normalized by the total gain across predictors.

For each model, normalized feature contributions were expressed as percentages to indicate the relative predictive importance of the conditioning factors within that modelling framework. These values represent model-specific measures of predictive relevance rather than direct evidence of causal relationships. Higher contribution values indicate greater relative importance for distinguishing significant-subsidence and non-significant-deformation classes within a given model, although the estimated importance may also reflect shared information among predictors and interactions captured by the modelling algorithm.

Because Logistic Regression, Random Forest, and LightGBM derive feature importance from different mathematical principles—standardized regression coefficients, impurity reduction, and gain-based loss reduction, respectively—the normalized percentages should be interpreted primarily for comparing predictors within each individual model. Direct numerical comparison of feature-contribution percentages across the three algorithms should therefore be treated with caution and should not be interpreted as directly comparable measures of physical effect magnitude.

2.4.6. Model Training and Validation Strategy

To ensure a consistent comparison among Logistic Regression, Random Forest, and LightGBM, model performance was evaluated using stratified five-fold cross-validation across the complete modelling dataset. In each outer fold, 80% of the observations were used for training and the remaining 20% for testing. Hyperparameter optimization was conducted using an inner five-fold cross-validation procedure restricted to the training

subset of each outer fold. Predictive performance was evaluated using the area under the receiver operating characteristic curve (ROC-AUC), average precision (AP), and Brier score. No separate, fixed hold-out test set was used.

Model performance was summarized from the fold-wise validation results using mean ROC-AUC and its standard deviation. Average precision and the Brier score were additionally used to assess precision–recall performance and probability calibration, respectively. The same validation folds were used for all three models to facilitate comparison of their predictive performance under identical data partitions.

Class imbalance was handled according to the configuration of each modelling algorithm without altering the original class distribution. Logistic Regression used `class_weight = "balanced"`, whereas Random Forest used `class_weight = "balanced_subsample"`. No explicit class-weighting scheme was applied to LightGBM. Predictor standardization was applied only to Logistic Regression within the modelling pipeline, with scaling parameters estimated exclusively from the corresponding training data. Random Forest and LightGBM were trained directly on the numerical predictor values after categorical effect encoding and therefore did not require feature standardization.

To further evaluate the spatial generalization capability of the models and account for potential spatial autocorrelation, spatial block cross-validation (Spatial Block CV) was additionally employed. Empirical variogram analysis indicated a spatial correlation range of approximately 21–22 km for the binary subsidence response; accordingly, the study area was divided into 20 km × 20 km spatial blocks. The blocks were assigned to five geographically contiguous folds, with four folds used for training and the remaining fold reserved for spatial validation in each iteration. The same predictor variables, response definition, and modelling configurations were maintained for Logistic Regression, Random Forest, and LightGBM. To prevent information leakage, categorical target encoding and model-specific preprocessing were performed exclusively on the training data within each iteration, and hyperparameter selection was restricted to the corresponding training partitions. Model performance was evaluated using ROC-AUC, average precision (AP), and the Brier score. Fold-wise results were summarized and compared with those obtained using random cross-validation to assess the influence of spatial dependence on predictive performance. The workflow of the present study is illustrated in Figure 4.

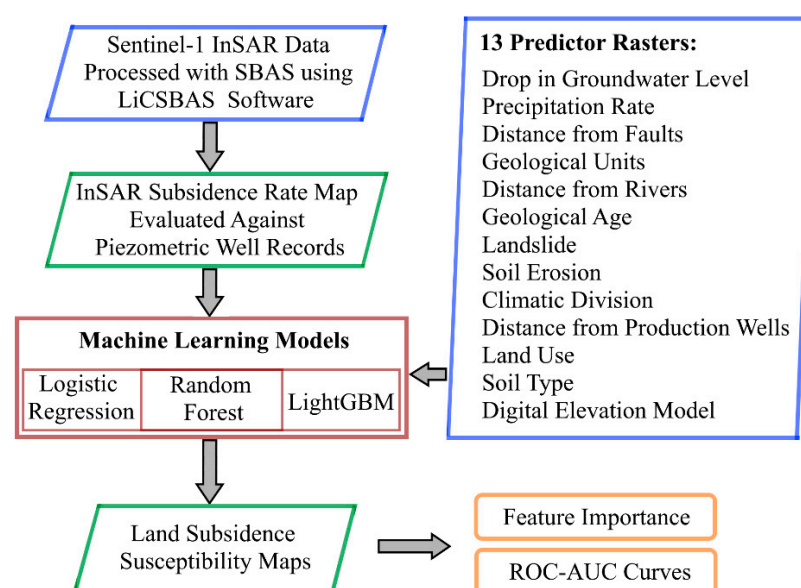


Figure 4. The workflow of the present study.

3. Results

The integrated SBAS-InSAR and machine-learning framework produced spatially explicit land-subsidence susceptibility estimates for Ghaenat County. Logistic Regression (LR), Random Forest (RF), and LightGBM identified spatial patterns associated with significant subsidence, although differences were observed in their predictive performance and in the spatial distribution of predicted susceptibility. The following sections present the InSAR-derived deformation patterns, hydrogeological consistency assessment, model validation results, predictor contributions, and resulting susceptibility maps.

3.1. LiCSBAS-Derived LOS Velocity Maps and Vertical Displacement Velocity After Decomposition

The LOS velocity maps derived from the ascending and descending Sentinel-1 datasets are presented in Figure 5. These maps represent the intermediate deformation products obtained prior to LOS decomposition and show the spatial distribution of line-of-sight deformation rates along the respective radar viewing directions.

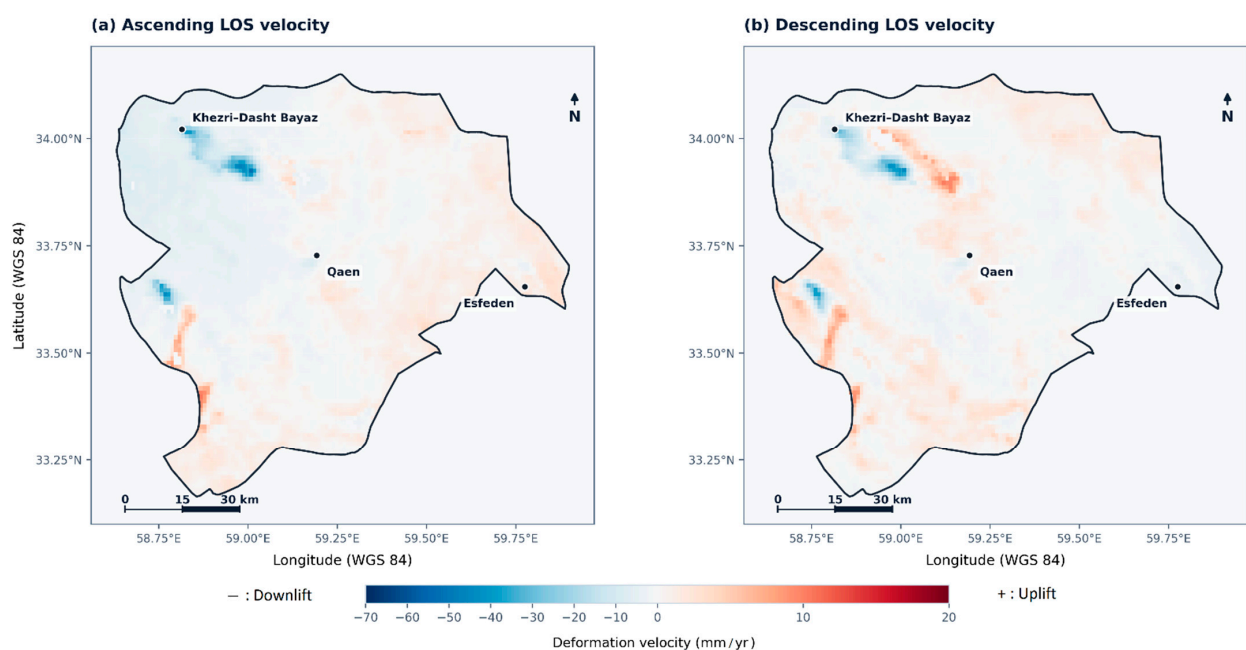


Figure 5. Ascending and descending LOS deformation velocity maps derived from Sentinel-1 observations: (a) ascending LOS velocity and (b) descending LOS velocity.

Figure 5 illustrates the ascending and descending LOS velocity fields, respectively. Although the two LOS velocity maps exhibit broadly similar spatial patterns, local differences are evident because each viewing geometry records a different projection of the ground-motion vector. Assuming that the north–south displacement component was negligible, the ascending and descending LOS velocity fields were jointly decomposed to estimate the east–west and vertical velocity components.

The decomposition of the ascending and descending LOS velocity fields yielded both east–west and vertical ground-deformation velocity components. The east–west velocity field, presented in Figure 6, ranges from approximately -6.95 to $+11.70$ mm/year across Ghaenat County. The corresponding vertical velocity field is presented in Figure 7 and was used as the deformation basis for the subsequent land-subsidence susceptibility analysis.

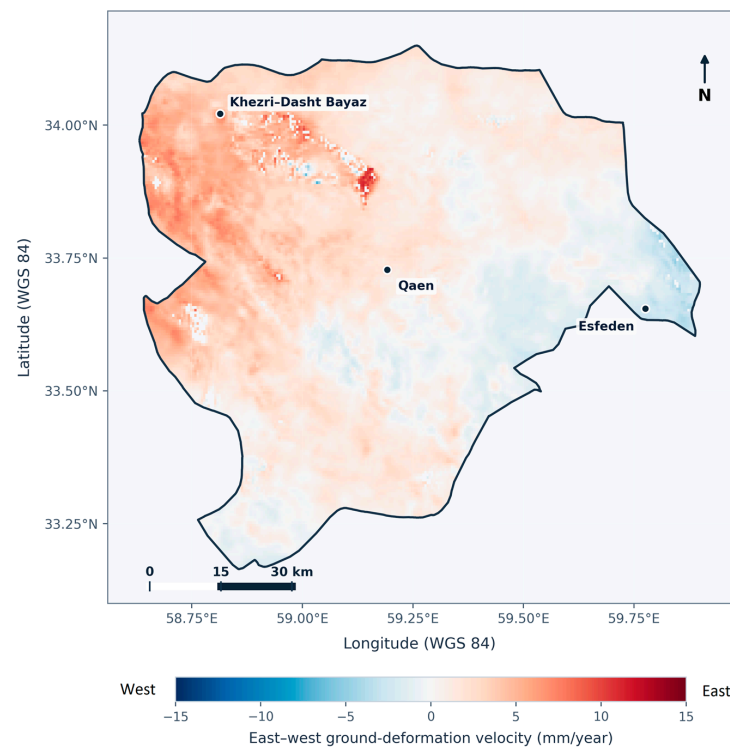


Figure 6. Spatial distribution of the east–west ground-deformation velocity derived from the decomposition of ascending and descending Sentinel-1 SBAS-InSAR LOS velocity measurements in Ghaenat County, assuming negligible north–south ground motion. Positive and negative values represent eastward and westward motion, respectively, under the adopted sign convention. The map includes geographic coordinates, major settlement locations, a north arrow, and a 30-km scale bar.

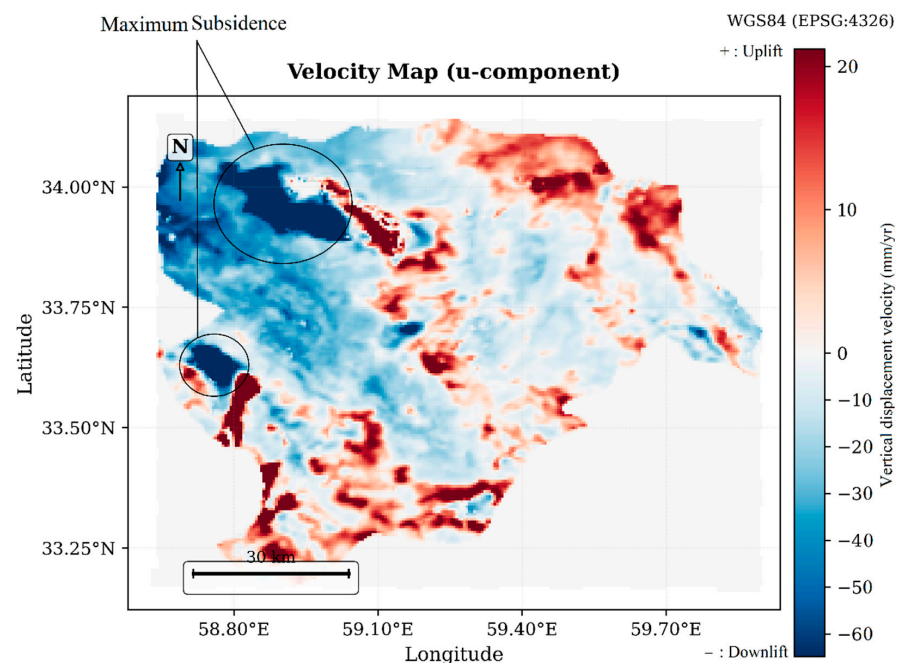


Figure 7. Vertical deformation velocity map derived from Sentinel-1 SBAS-InSAR processing in Ghaenat County. The vertical displacement velocity was obtained by decomposing ascending and descending LOS velocity measurements under the assumption of negligible north–south ground motion. The color scale represents vertical deformation velocity in mm/yr, where negative values indicate surface subsidence and positive values indicate uplift.

The color scale in Figure 7 shows the spatial variation in vertical ground-motion velocity, with negative values indicating subsidence and positive values indicating upward ground motion. The strongest downward velocities are concentrated mainly in the western and northwestern parts of the study area, where localized zones of subsidence are evident. In contrast, positive vertical velocities occur in several scattered areas, indicating spatially heterogeneous ground-motion patterns across Ghaenat County. The resulting vertical velocity field was subsequently used as the deformation basis for defining the binary response variable and developing the land-subsidence susceptibility models.

3.2. Hydrogeological Consistency and Assessment of Groundwater-Level Decline Interpolation

Hydrogeological consistency was first assessed using 62 paired observations, with each pair representing groundwater-level decline and the corresponding InSAR-derived deformation value extracted at the same piezometric-well location. Pearson correlation analysis indicated a strong spatial association between groundwater-level decline and subsidence magnitude ($(r = 0.71)$, $(p < 0.001)$). This relationship was further supported by Spearman rank correlation analysis ($(\rho = 0.65)$, $(p < 0.001)$), indicating that locations experiencing greater groundwater-level decline generally exhibited greater subsidence.

The interpolation accuracy of the groundwater-level decline surface was additionally evaluated using leave-one-out cross-validation (LOOCV) based on the same 62 piezometric wells. In each iteration, one well was withheld and its groundwater-level decline value was estimated using IDW interpolation based on the remaining 61 wells. Across the 62 validation iterations, the interpolation yielded an RMSE of 0.0821 m, an MAE of 0.0547 m, and a mean error (ME) of -0.005 m, indicating close agreement between the well-derived and interpolated groundwater-level decline values at the withheld locations. The final groundwater-level decline surface used as a predictor in the susceptibility models was subsequently generated using all 62 wells.

To further examine the temporal consistency between groundwater dynamics and surface deformation, InSAR-derived deformation time series obtained from LiCSBAS were compared with groundwater-level time series from two representative piezometric wells with continuous observations during the overlapping monitoring period from January 2021 to March 2022. For each well, groundwater-level measurements were expressed as changes relative to the initial observation, while InSAR deformation values were referenced to the first acquisition date. This normalization emphasized temporal variations and facilitated comparison of the evolution of the two datasets.

This temporal analysis was not intended to provide an independent validation of InSAR deformation accuracy, but rather to assess whether the temporal evolution of surface deformation was consistent with observed groundwater-system variations. Figure 8 illustrates the temporal evolution of cumulative ground deformation and groundwater-level fluctuations at the two selected locations.

At both locations, periods of continued groundwater-level decline during the first half of 2021 coincided with progressive accumulation of surface deformation, reaching approximately 15–17 mm of cumulative subsidence. The period of pronounced groundwater-level decline in late 2021 also occurred during an interval of continued deformation accumulation in the InSAR time series. In contrast, partial groundwater-level recovery during early 2022 coincided with a reduction in the rate of deformation accumulation and smaller fluctuations in the subsidence trend (Figure 8).

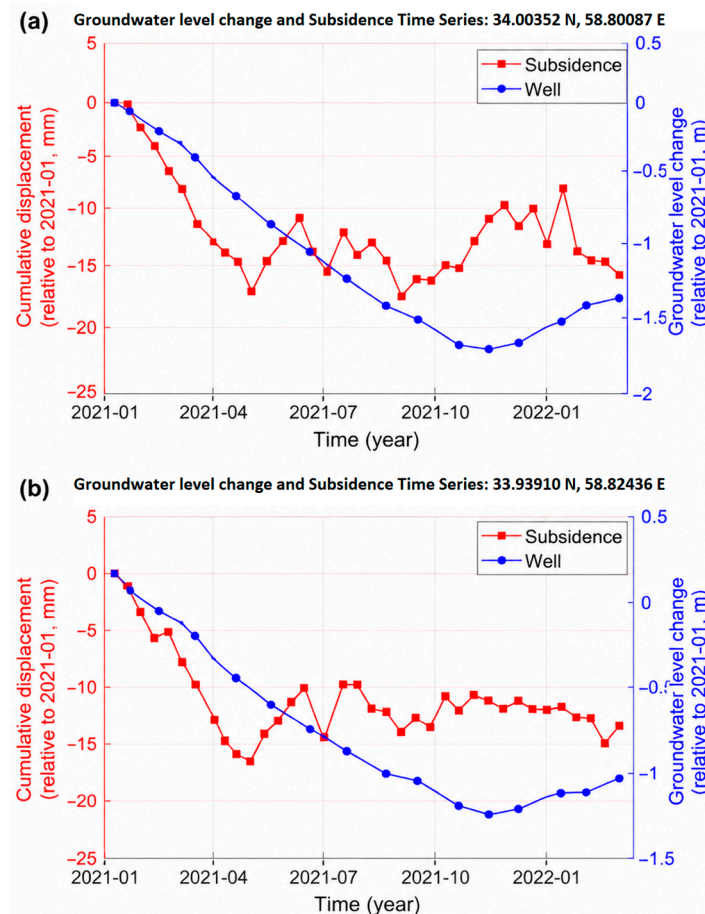


Figure 8. Time-series variations in cumulative ground displacement and groundwater levels at two monitoring locations: (a) 34.00352° N, 58.80087° E; (b) 33.93910° N, 58.82436° E. Red squares represent cumulative ground displacement (mm, left vertical axis), while blue circles indicate groundwater-level changes (m, right vertical axis). Both time series are referenced to January 2021, with negative values indicating ground subsidence and groundwater-level decline, respectively.

Overall, the observed spatial and temporal correspondence between groundwater-level variations and InSAR-derived deformation indicates hydrogeological consistency between the two datasets. However, the available observations were not sufficiently dense or temporally continuous to support a robust quantitative estimation of possible time-lagged deformation responses. Therefore, no formal lag analysis was performed, and the temporal comparison was interpreted solely as a consistency assessment rather than evidence of a quantified delayed response or a causal relationship.

Because the temporal comparison was limited to wells with sufficiently continuous overlapping observations, these results should be interpreted as a local hydrogeological assessment rather than a regional causal determination.

3.3. Binary-Response Threshold Sensitivity and Class Distribution

The sensitivity of model performance to the InSAR velocity threshold used to define the binary response variable was evaluated using six candidate thresholds ranging from 0 to −25 mm/yr (Table 3).

As the threshold became progressively more negative, the proportion of pixels classified as significant subsidence decreased from 31% at 0 mm/yr to 20% at −25 mm/yr, while the proportion of pixels classified as non-significant deformation correspondingly increased from 69% to 80%.

Table 3. Sensitivity of model performance and class distribution to the InSAR velocity threshold used to define the binary response variable.

Velocity Threshold (mm/yr)	Significant Class <i>n</i> (%)	Non-Significant Class <i>n</i> (%)	LR AUC	RF AUC	LightGBM AUC
0	9511 (31)	21,170 (69)	0.8257	0.8733	0.8669
−5	8897 (29)	21,784 (71)	0.8315	0.9015	0.8682
−10	8675 (28)	22,006 (72)	0.8824	0.9123	0.9092
−15	7670 (25)	23,011 (75)	0.8809	0.9056	0.9089
−20	7057 (23)	23,624 (77)	0.8721	0.9063	0.8897
−25	6136 (20)	24,545 (80)	0.8558	0.8911	0.8901

Model discrimination varied systematically with the selected velocity threshold. At the 0 mm/yr threshold, ROC-AUC values were 0.8257 for Logistic Regression, 0.8733 for Random Forest, and 0.8669 for LightGBM. Model performance improved as the threshold was shifted toward more pronounced downward deformation, reaching the highest ROC-AUC values at −10 mm/yr for all three modelling approaches: 0.8824 for Logistic Regression, 0.9123 for Random Forest, and 0.9092 for LightGBM. No alternative threshold produced a higher ROC-AUC for any of the three models.

At more restrictive thresholds, model discrimination generally declined. For example, at −15 mm/yr, ROC-AUC values were 0.8809, 0.9056, and 0.9089 for Logistic Regression, Random Forest, and LightGBM, respectively, while further decreases were observed at −20 and −25 mm/yr. These results indicate that the −10 mm/yr threshold provided the strongest discriminatory performance across all three modelling approaches while retaining a substantial proportion of pixels classified as significant subsidence.

Accordingly, −10 mm/yr was retained as the operational threshold for defining significant subsidence in the subsequent susceptibility analysis. Following application of this threshold and the common valid-data mask, the final modelling dataset contained 30,681 pixels, of which 8675 pixels (28%) were classified as significant subsidence (Class 1) and 22,006 pixels (72%) as non-significant deformation (Class 0).

To further investigate the spatial robustness of the susceptibility predictions, the overlap of principal susceptibility hotspots was assessed across alternative InSAR velocity thresholds using the Jaccard similarity coefficient. For each model, the top 10% of pixels with the highest predicted susceptibility probabilities were identified as hotspots and compared with those obtained at the reference threshold of −10 mm/yr. The resulting Jaccard coefficients for LR, RF, and LightGBM are presented in Table 4.

Table 4. Spatial overlap of the top 10% susceptibility hotspots across alternative InSAR velocity thresholds, measured using the Jaccard similarity coefficient relative to the −10 mm/yr reference threshold.

Velocity Threshold (mm/yr)	LR Jaccard	RF Jaccard	LightGBM Jaccard
0	0.76	0.82	0.81
−5	0.80	0.90	0.81
−10	1.00	1.00	1.00
−15	0.91	0.92	0.93
−20	0.89	0.92	0.86
−25	0.84	0.86	0.88

The Jaccard analysis revealed substantial spatial consistency in principal susceptibility hotspots across the alternative velocity thresholds. Similarity coefficients ranged from 0.76 to 0.93 across the three models, with the highest agreement consistently observed at −15 mm/yr. Random Forest showed the highest mean Jaccard similarity across the

five alternative thresholds (0.884), followed by LightGBM (0.858) and Logistic Regression (0.840). These results indicate that the principal susceptibility hotspots were largely preserved across different definitions of significant subsidence, although some spatial variation remained.

3.4. Land Subsidence Susceptibility Maps

The land-subsidence susceptibility maps generated by Logistic Regression (LR), Random Forest (RF), and LightGBM are presented in Figure 9. For all three models, the continuous predicted probabilities were classified using the same fixed probability intervals: Very Low (0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0). The use of identical class boundaries enables direct spatial comparison among the three modelling approaches.

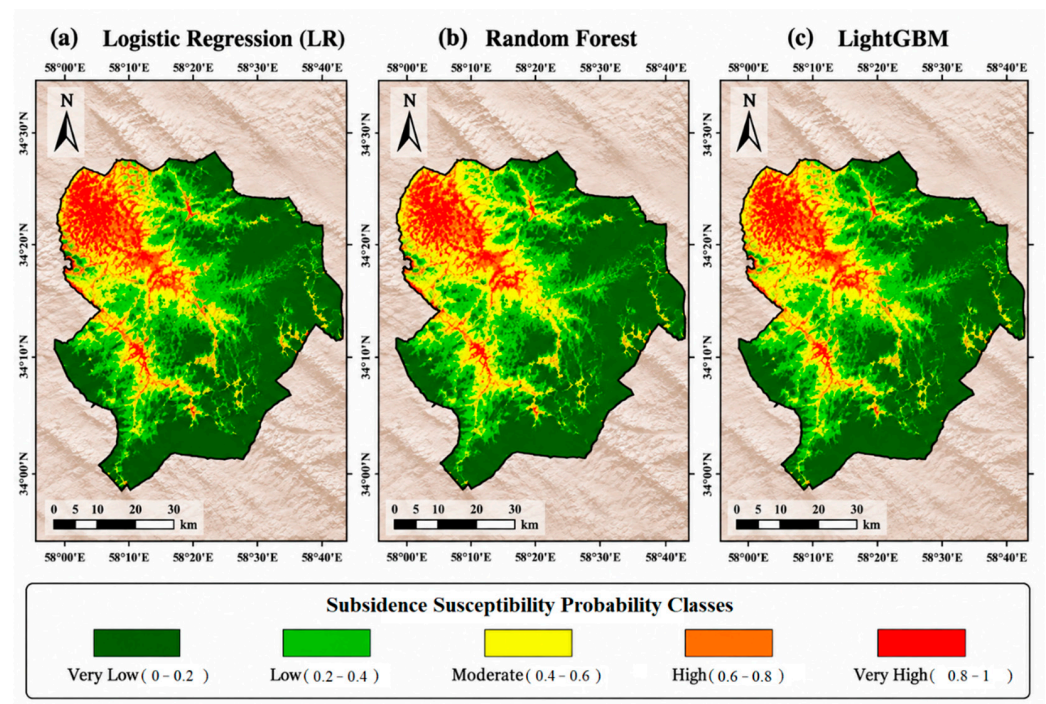


Figure 9. Land-subsidence susceptibility maps generated by (a) Logistic Regression, (b) Random Forest, and (c) LightGBM. Predicted probabilities were classified using common fixed intervals: Very Low (0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0).

All three models exhibited broadly consistent spatial patterns. Areas of High to Very High susceptibility were concentrated predominantly in the western and northwestern parts of Ghaenat County and along several central corridors, whereas much of the eastern and southeastern parts of the study area was classified as Low or Very Low susceptibility. Moderate-susceptibility zones generally occurred as transitional areas between higher- and lower-susceptibility regions.

Despite this overall spatial agreement, local differences were observed in the extent, continuity, and boundaries of the susceptibility classes produced by the three models. These differences reflect the distinct statistical structures of the modelling approaches and their different capacities to represent nonlinear relationships and interactions among the conditioning factors. In particular, the tree-based RF and LightGBM models produced locally different patterns of High and Very High susceptibility compared with LR, while the major susceptibility zones remained broadly consistent across all three models.

The mapped classes represent operational intervals of predicted susceptibility probability rather than equal-area categories or universally calibrated susceptibility levels.

Therefore, differences in the spatial extent of each class among the models reflect differences in their predicted probability distributions rather than differences imposed by the classification procedure.

3.5. ROC Curves

The mean cross-validation ROC curves for Logistic Regression, Random Forest, and LightGBM are presented in Figure 10. All three models showed substantial discriminatory ability, with their ROC curves clearly above the random-classification reference line. Logistic Regression achieved a mean ROC-AUC of 0.882, indicating good discrimination between the significant-subsidence and non-significant-deformation classes.

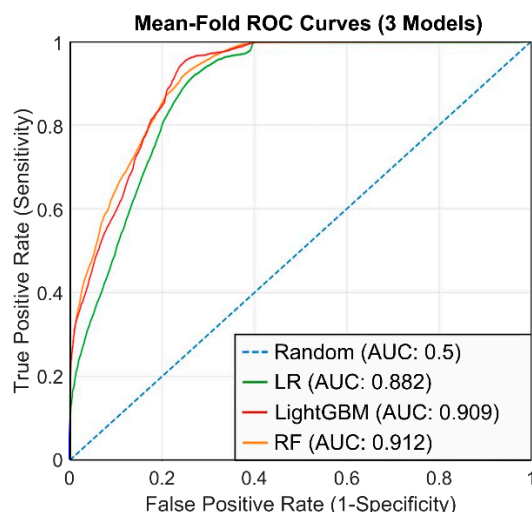


Figure 10. Mean five-fold cross-validation ROC curves for Logistic Regression (LR), Random Forest (RF), and LightGBM. The dashed diagonal line represents random classification (AUC = 0.5). Mean ROC-AUC values were 0.882, 0.909, and 0.912 for LR, LightGBM, and RF, respectively.

The two tree-based models showed stronger discrimination, with mean ROC-AUC values of 0.912 for Random Forest and 0.909 for LightGBM. Random Forest yielded the highest mean ROC-AUC; however, the difference between RF and LightGBM was only approximately 0.003. Given the fold-to-fold variability observed during cross-validation, this small difference does not provide evidence of meaningful superiority of RF over LightGBM. Rather, the two models demonstrated comparable and consistently strong discriminatory performance, while both achieved higher mean ROC-AUC values than Logistic Regression.

3.6. Statistical Parameters and Performance Indicators of the Models

To ensure a consistent comparison of predictive performance, Logistic Regression (LR), Random Forest (RF), and LightGBM were evaluated using the same stratified five-fold cross-validation framework. Model performance was assessed using the area under the receiver operating characteristic curve (ROC-AUC), average precision (AP), and the Brier score. ROC-AUC measured the ability of the models to discriminate between significant-subsidence and non-significant-deformation classes, whereas AP evaluated precision–recall performance for the significant-subsidence class. The Brier score quantified probabilistic prediction error, with lower values indicating better agreement between predicted probabilities and observed outcomes. Table 5 summarizes the mean ROC-AUC, fold-to-fold standard deviation (SD), approximate 95% confidence intervals (CIs), AP, and Brier scores.

Table 5. Predictive performance of Logistic Regression (LR), Random Forest (RF), and LightGBM based on stratified five-fold cross-validation, including mean ROC-AUC, standard deviation (SD), approximate 95% confidence intervals (CI), average precision (AP), and Brier score.

Model	Random ROC-AUC	Random ROC-AUC SD	95% CI	Average Precision	Brier Score
LR	0.8824	0.052	0.8178–0.9470	0.75	0.13
RF	0.9123	0.033	0.8713–0.9533	0.82	0.10
LightGBM	0.9092	0.030	0.8720–0.9464	0.82	0.10

All three models demonstrated good discriminatory performance under stratified random cross-validation. Random Forest (RF) achieved the highest mean ROC-AUC (0.9123), closely followed by LightGBM (0.9092), whereas Logistic Regression (LR) yielded a lower value of 0.8824. Fold-to-fold variability was lowest for LightGBM (SD = 0.030), followed by RF (SD = 0.033) and LR (SD = 0.052). Given the small difference in mean ROC-AUC between RF and LightGBM relative to the observed fold-to-fold variability, their performance was broadly comparable, with no clear evidence of superiority of either tree-based model.

The precision–recall and probabilistic error metrics supported this overall pattern. RF and LightGBM achieved identical average precision values (AP = 0.82), exceeding that of LR (AP = 0.75), indicating better precision–recall performance for the significant-subsidence class. Both tree-based models also yielded lower Brier scores (0.10) than LR (0.13), indicating lower probabilistic prediction errors. Overall, the combined metrics suggest that RF and LightGBM provided similarly strong predictive performance under stratified random cross-validation, while LR remained a useful and interpretable linear baseline.

To further assess spatial generalization, five-fold spatial block cross-validation was performed, and the results were compared with those obtained using stratified random cross-validation (Table 6). The mean ROC-AUC values under spatial validation were 0.8147, 0.8619, and 0.8579 for LR, RF, and LightGBM, respectively, corresponding to absolute decreases of 0.0677, 0.0504, and 0.0513, respectively, relative to random cross-validation. The corresponding fold-to-fold standard deviations were 0.05, 0.04, and 0.04, respectively.

Table 6. Comparison of Logistic Regression (LR), Random Forest (RF), and LightGBM performance under stratified random and spatial block cross-validation.

Model	Random ROC-AUC	Spatial ROC-AUC (±SD)	95% CI	Average Precision	Brier Score	AUC Reduction
LR	0.8824	0.8147 (0.05)	0.7526–0.8768	0.60	0.16	0.0677
RF	0.9123	0.8619 (0.04)	0.8122–0.9116	0.71	0.13	0.0504
LightGBM	0.9092	0.8579 (0.04)	0.8082–0.9076	0.69	0.13	0.0513

Although spatial validation yielded lower ROC-AUC values for all three models, RF and LightGBM maintained relatively high and comparable discriminatory performance, with a difference of only 0.0040 in mean ROC-AUC. Both models also achieved higher average precision (0.71 and 0.69, respectively) and lower Brier scores (0.13 for both) than LR (AP = 0.60; Brier score = 0.16). These findings indicate that the two tree-based models retained stronger predictive performance under spatially separated validation, while the observed reductions in ROC-AUC highlight the influence of validation design on estimated model performance.

The predictor-dependency assessment showed no evidence of severe multicollinearity among the variables included in the modelling framework. The highest absolute Pearson correlation coefficient among the continuous predictors was 0.64, while variance inflation factor (VIF) values ranged from 1.12 to 2.91, indicating low levels of linear redundancy among the predictors.

The results presented in Table 7 show that Groundwater-Level Decline had the highest relative predictive contribution in all three modelling approaches. In Logistic Regression, Groundwater-Level Decline accounted for 41.30% of the normalized contribution, followed by Precipitation Rate (17.32%), Landslide (7.56%), Distance from Production Wells (6.35%), and Digital Elevation Model (DEM) (5.84%).

Table 7. Relative contribution of predictor variables derived from Logistic Regression (LR), Random Forest (RF), and LightGBM models.

Features	LR%	RF%	LGBM%
Drop In Groundwater Levels	41.30	13.61	33.16
Digital Elevation Model (DEM)	5.84	3.15	2.74
Precipitation Rate	17.32	12.55	12.05
Distance From Faults	2.05	11.20	16.12
Geological Units	2.01	10.60	2.69
Distance From Rivers	4.63	10.25	9.26
Geological Age	2.62	7.47	2.42
Landslide	7.56	6.51	8.67
Soil Erosion	2.75	6.53	1.87
Climatic Division	3.95	5.95	1.88
Distance From Production Wells	6.35	5.61	5.90
Land Use	1.81	3.83	2.21
Soil Type	1.81	2.74	1.03

In Random Forest, the contribution of Groundwater-Level Decline was 13.61%, followed by Precipitation Rate (12.55%), Distance from Faults (11.20%), Geological Units (10.60%), and Distance from Rivers (10.25%). Compared with LR, predictor contributions in RF were distributed more broadly across multiple conditioning factors.

In LightGBM, Groundwater-Level Decline again showed the highest relative contribution (33.16%), followed by Distance from Faults (16.12%), Precipitation Rate (12.05%), Distance from Rivers (9.26%), and Landslide (8.67%).

Overall, Groundwater-Level Decline consistently emerged as the most influential predictor within each modelling framework, while Precipitation Rate and Distance from Faults also showed substantial predictive relevance, particularly in the tree-based models. These contribution values represent model-specific measures of predictive importance and should not be interpreted as direct evidence of causal effects.

The comparative results presented in Table 8 show differences in the distribution of susceptibility probability classes among the three modelling approaches. Because the susceptibility maps were derived from continuous predicted probabilities, the five classes represent predefined probability intervals—Very Low (0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0)—rather than equal proportions of the study area.

Table 8. Spatial distribution of land subsidence susceptibility classes derived from the model output probabilities. The continuous susceptibility probabilities were classified into five categories using the equal-interval classification method.

Model	Very Low% (0–0.2)	Low% (0.2–0.4)	Moderate% (0.4–0.6)	High% (0.6–0.8)	Very High% (0.8–1)
LR	50.55	16.19	12.49	2.41	18.36
RF	49.07	15.80	16.85	2.26	16.02
LightGBM	49.25	16.08	15.21	2.13	17.33

The three models showed broadly similar distributions across the susceptibility classes, although differences were observed in the proportions assigned to individual probability intervals. Logistic Regression assigned 50.55% of pixels to the Very Low class and 18.36% to the Very High class, compared with 49.07% and 16.02% for Random Forest and 49.25% and 17.33% for LightGBM, respectively. All three models assigned relatively small proportions of pixels to the High susceptibility class, ranging from 2.13% to 2.41%. These differences reflect variations in the predicted probability distributions of the models rather than differences in the classification thresholds.

4. Discussion

4.1. Comparison of Results with Literature

The results of the present study are broadly consistent with previous InSAR-based susceptibility studies showing that land subsidence reflects the combined influence of hydrogeological, geological, structural, and anthropogenic conditions, although the relative importance of these controls varies among study areas. In Ghaenat County, groundwater-level observations were compared with InSAR-derived deformation to assess hydrogeological consistency rather than to provide independent geodetic validation. The spatial analysis showed a strong association between groundwater-level decline and subsidence magnitude, while the temporal comparison at two representative piezometric wells showed that periods of groundwater-level decline generally coincided with progressive deformation accumulation, reaching approximately 15–17 mm of cumulative subsidence.

The three susceptibility models showed different levels of predictive discrimination. RF achieved the highest mean ROC-AUC (0.9123), followed very closely by LightGBM (0.9092), whereas LR yielded a lower but still good ROC-AUC of 0.8824. Given the small difference between RF and LightGBM relative to the observed cross-validation variability, the two tree-based models should be regarded as having broadly comparable predictive performance rather than as demonstrating a clear superiority of RF. Predictor-contribution analysis showed that Groundwater-Level Decline had the highest relative contribution within all three modelling frameworks. Precipitation Rate also showed substantial predictive relevance, whereas Distance from Faults was particularly important in the RF and LightGBM models. These contribution measures represent model-specific predictive associations and should not be interpreted as direct evidence of causal control.

The spatial block cross-validation results further clarify the spatial generalization capability of the models. Compared with stratified random cross-validation, ROC-AUC decreased by 0.0677, 0.0504, and 0.0513 for LR, RF, and LightGBM, respectively. These reductions suggest that spatial dependence among neighboring observations may have contributed to optimistic performance estimates under random partitioning. Nevertheless, RF and LightGBM maintained relatively strong discriminatory performance under spatial validation (ROC-AUC = 0.8619 and 0.8579, respectively), with only a marginal difference between them. This suggests that their comparable predictive performance was largely maintained when evaluated on geographically distinct blocks. These findings highlight the importance of accounting for spatial structure when assessing land-subsidence susceptibility models. However, spatial block validation does not guarantee complete independence between training and validation regions or ensure transferability to other geographical settings.

Comparison with the Quetta City study of Hussain et al. [31] reveals both similarities and important differences. That study reported pronounced ground deformation in the central urban area, with an average vertical subsidence velocity of approximately −166 mm/yr and uplift of about 48 mm/yr in the surrounding elevated terrain. Their LR-based susceptibility model achieved an AUC of approximately 0.92, and Quaternary

lithology, built-up areas, and fault-related conditions were identified as important controls on susceptibility. Importantly, Hussain et al. [31] interpreted tectonic activity as the principal cause of ground movement in Quetta, while anthropogenic influences, including intensive groundwater extraction, were considered important secondary contributors. This contrasts with Ghaenat, where groundwater-level decline emerged as the most influential predictive variable across all three models. The comparison therefore suggests that similar modelling frameworks can identify substantially different dominant controls depending on the hydrogeological, tectonic, and urban setting of the study area.

The results also show similarities with the Kashan Plain study of Eghrari et al. [32]. That study used RF and XGBoost with 291 subsidence samples divided into 70% training and 30% testing subsets. XGBoost achieved higher predictive performance than RF, with R^2 values of 0.9032 and 0.8355, respectively, together with lower RMSE and MAE values. Their feature-importance analysis identified Distance to Fault (DtF), elevation, and Groundwater Drawdown (GWD) as the most influential variables. These findings are broadly consistent with the present study in highlighting the importance of groundwater conditions and structural factors, although their relative ranking differed among models and study areas.

Differences in spatial resolution and modelling scale should also be considered when comparing the present results with previous studies. The present study used Sentinel-1 InSAR observations but deliberately harmonized all predictor and deformation layers to a common 500×500 m modelling grid. This relatively coarse grid was adopted as a conservative data-integration scale for combining datasets with heterogeneous native resolutions and map scales and should therefore not be interpreted as the native spatial resolution of the InSAR observations. In the Kashan study, several topographic predictors were derived from 12.5 m ALOS PALSAR data, Sentinel-2 variables were available at 10 m resolution, and several thematic layers were derived from 1:100,000-scale maps. In the Quetta study, Sentinel-1 data were combined with a 90 m SRTM-3 DEM during InSAR processing. These differences in spatial support and input resolution should be considered when comparing the spatial detail and apparent predictive performance of susceptibility maps across studies.

Methodological differences also extend to the classification of susceptibility maps. In the present study, the continuous predicted probabilities from all three models were classified using the same fixed equal-interval thresholds: Very Low (0–0.2), Low (0.2–0.4), Moderate (0.4–0.6), High (0.6–0.8), and Very High (0.8–1.0). Consequently, the susceptibility classes do not represent equal proportions of the study area, and the differences in class extent among LR, RF, and LightGBM reflect differences in their predicted probability distributions. In contrast, Hussain et al. [31] used a natural-break classification scheme for the Quetta susceptibility map and reported approximately 13% of the study area as Very High susceptibility, with larger proportions assigned to lower classes. Direct comparison of class percentages between the two studies should therefore be made cautiously because the classification procedures differ.

Overall, the comparison with previous studies indicates that land-subsidence susceptibility is controlled by a combination of hydrogeological, structural, geological, and anthropogenic factors rather than by a single universally dominant mechanism. In Ghaenat County, groundwater-level decline showed the strongest predictive association with subsidence susceptibility, whereas the Quetta study emphasized tectonic, lithological, and urban controls, and the Kashan study highlighted fault proximity, elevation, and groundwater drawdown. These differences emphasize the importance of interpreting model-derived predictor contributions within the physical and hydrogeological context of each study area.

4.2. Limitations

A key consideration in this study is the scale and spatial resolution of the datasets. The common ~500 m analysis grid used to integrate the InSAR-derived vertical displacement products and conditioning factors is appropriate for regional-scale susceptibility assessment and planning, but it can smooth or generalize highly localized subsidence signals, especially those associated with localized groundwater extraction areas, small geomorphic units, or narrow structural features [33,34]. As a result, the susceptibility maps should primarily be interpreted as county-level decision-support products that highlight broad high-susceptibility zones and relative spatial patterns, rather than as inputs for site-specific engineering design, building safety assessment, or micro-zonation around critical infrastructure.

It should be emphasized that the susceptibility maps generated in this study represent the spatial probability of significant subsidence occurrence based on observed deformation patterns and environmental conditioning factors. These outputs should not be interpreted as complete risk maps because exposure and vulnerability components, such as population, infrastructure, and socioeconomic conditions, were not incorporated into the modelling framework.

A second limitation relates to the temporal window of the observations. While the two-year InSAR time series (2020–2022) provides a robust characterization of the observed deformation trend, land subsidence in arid and semi-arid aquifer systems can respond to multi-year hydroclimatic variability, delayed compaction, and changes in groundwater abstraction regimes.

The predictive validity of the susceptibility models is therefore limited to the environmental and deformation conditions represented by the observation period. Although the models identify spatial relationships between subsidence occurrence and conditioning factors, their performance under future hydrogeological conditions, climate variability, or changes in groundwater abstraction regimes requires further temporal validation.

Therefore, longer-term monitoring, including continued InSAR observations and consistent groundwater measurements, would be valuable for evaluating the influence of prolonged wet–dry cycles, drought persistence, and potential recovery periods on both deformation rates and susceptibility patterns.

Uncertainty in the groundwater-level decline predictor is associated with the spatial interpolation of piezometric observations. Although the IDW interpolation was evaluated using leave-one-out cross-validation (RMSE = 0.0821 m, MAE = 0.0547 m, and ME = −0.005 m), interpolation uncertainty may still vary spatially depending on well density, hydrogeological heterogeneity, and local groundwater gradients. Therefore, the groundwater-level decline surface should be interpreted with greater caution in areas with limited observation coverage.

Although this represents the best regional information accessible for the study area, the interpolated drawdown field may be less reliable in zones with sparse well coverage, complex hydrogeological boundaries, or strong local gradients induced by intensive pumping. In addition, some conditioning factors (e.g., land use/land cover, soil and lithological maps, or climate layers) may not perfectly match the InSAR observation period, and resampling to a common grid can introduce further generalization.

Although the land-use dataset was derived from satellite imagery and field-based information by a national governmental organization, the absence of publicly available quantitative classification-accuracy statistics introduces uncertainty regarding the reliability of individual land-use categories. This limitation should be considered when interpreting the contribution of land use to the susceptibility predictions.

Finally, InSAR-derived deformation estimates can be affected by atmospheric artifacts, decorrelation, and unwrapping errors, and the interpretation of “vertical” deformation depends on the adopted projection/decomposition strategy. Moreover, susceptibility modelling is inherently spatial; if training and test samples are not fully separated in space, model performance can be slightly optimistic because of spatial autocorrelation.

To account for potential spatial autocorrelation and further assess model generalization, spatial block cross-validation was additionally performed. This approach provided a more conservative evaluation of predictive performance under geographically separated training and validation folds, although further testing in independent geographical regions is still needed to establish broader model transferability.

Despite these common limitations in regional studies, the combination of a multi-year InSAR dataset, a comprehensive set of hydrogeological, geological, climatic, and environmental conditioning factors, and a rigorous validation strategy provides confidence in the main spatial patterns, the relative ranking of controlling factors, and the comparative performance of the tested models. In addition, rapid advances in unmanned aerial vehicle (UAV) technology enable large-scale monitoring of land subsidence, including deformation rates that exceed the maximum detectable limits of InSAR [35].

The binary response used in this study necessarily depends on an operational deformation-velocity threshold. Although the selected threshold of -10 mm yr^{-1} was supported by the locally estimated background variability of the InSAR velocity field and by sensitivity testing across alternative thresholds, it should not be interpreted as a universal physical boundary between stable and subsiding terrain. The magnitude at which deformation becomes distinguishable from background variability may differ among regions and InSAR processing configurations. Accordingly, the threshold adopted here is specific to the present dataset and study area.

Importantly, although the Jaccard analysis demonstrated substantial spatial consistency among the principal susceptibility hotspots across alternative subsidence thresholds, this consistency reflects the spatial overlap of the highest-ranked susceptibility pixels rather than equivalence in their predicted probability values. Because each subsidence-velocity threshold defines a different binary response, predicted probabilities should be interpreted relative to their respective thresholds and should not be directly compared across threshold-specific models.

An independent geodetic validation of the InSAR-derived deformation using GNSS, leveling, or other ground-based deformation measurements was not possible because such datasets were not available for the study area during the investigated period. Therefore, the comparison with groundwater-level observations should be interpreted as a hydrogeological consistency assessment supporting the physical plausibility of the detected deformation patterns, rather than as an independent validation of InSAR measurement accuracy.

4.3. Recommendations and Future Directions

Given the arid to semi-arid climate of Ghaenat County, its limited and irregular precipitation, and its dependence on groundwater resources, the susceptibility framework developed in this study can support county-scale screening, monitoring prioritization, and groundwater-management planning. The resulting maps should be used as decision-support products for identifying areas that warrant closer investigation rather than as complete risk maps, because exposure and vulnerability components were not included in the modelling framework.

Future monitoring should focus on areas consistently identified as having High or Very High susceptibility across the modelling approaches. In these zones, more frequent groundwater-level observations would improve understanding of the relationship between

aquifer dynamics and surface deformation. Where feasible, the existing piezometric network could be complemented by a limited number of geodetic control observations, such as permanent or campaign-based GNSS measurements, to provide independent constraints on InSAR-derived deformation rates.

Extending the InSAR observation period beyond the current two-year window would also improve the temporal interpretation of subsidence processes. Continued multi-year monitoring would help determine whether the observed deformation patterns persist, intensify, stabilize, or partially recover under changing groundwater and hydroclimatic conditions. Seasonal and annual updates of both InSAR deformation and groundwater observations would be particularly valuable for examining longer-term wet–dry cycles and changes in groundwater abstraction.

Improvements in the groundwater-monitoring network should also address spatial uncertainty in the interpolated groundwater-level decline surface. Areas with sparse well coverage or strong hydrogeological gradients could be explicitly identified as zones of higher interpolation uncertainty and prioritized for additional observations. Similarly, targeted higher-resolution investigations around major pumping centers, critical infrastructure, and localized deformation hotspots would complement the regional 500×500 m modelling framework and reduce the risk of overlooking fine-scale subsidence signals.

From a modelling perspective, future studies should supplement categorical susceptibility maps with probability-threshold maps, model-agreement maps, and spatial uncertainty products. These outputs can provide a clearer indication of where predictions are consistent across models and where additional field investigation may be required. Although spatial block cross-validation was performed in the present study, further evaluation using geographically independent validation areas and alternative spatial partitioning strategies is recommended to assess broader model transferability and the sensitivity of performance estimates to spatial dependence.

From a management perspective, the susceptibility results can help prioritize locations for more detailed groundwater assessment and monitoring. Measures such as improved abstraction monitoring, more efficient irrigation practices, and locally appropriate recharge-management strategies may be considered in areas where groundwater decline is persistent, provided that their feasibility is evaluated against local hydrogeological and land-use conditions. Such measures should therefore be regarded as potential management options rather than direct prescriptions derived solely from the susceptibility models.

Overall, future development of the framework should emphasize longer observation periods, improved groundwater and geodetic monitoring, spatially explicit uncertainty assessment, higher-resolution local investigations, and more spatially independent validation. These improvements would strengthen the use of land-subsidence susceptibility mapping as a practical regional tool for evidence-based monitoring and groundwater-management planning in Ghaenat County.

5. Conclusions

This study developed an integrated framework for monitoring and mapping land-subsidence susceptibility in Ghaenat County, Iran, by combining Sentinel-1 SBAS-InSAR deformation analysis, groundwater observations, and machine-learning modelling. Sentinel-1 time series interferometry processed using LiCSBAS was used to derive deformation time series and velocity products. Comparison with piezometric-well observations indicated spatial and temporal consistency between groundwater-level variations and InSAR-derived deformation, supporting the hydrogeological plausibility of the detected subsidence patterns rather than providing independent geodetic validation.

The InSAR-derived deformation information was subsequently integrated with 13 hydrogeological, geological, climatic, geomorphological, and anthropogenic conditioning factors to generate probability-based land-subsidence susceptibility maps using Logistic Regression (LR), Random Forest (RF), and LightGBM. RF and LightGBM demonstrated comparable and consistently strong predictive performance, with mean ROC-AUC values of 0.9123 and 0.9092, respectively, whereas LR achieved lower but still good discrimination performance (ROC-AUC = 0.8824). The susceptibility maps showed broadly consistent spatial patterns, with higher susceptibility concentrated mainly in the western and north-western parts of the county and along several central zones, although the spatial extent and sharpness of predicted hotspots varied among models.

Predictor-contribution analysis showed that Groundwater-Level Decline had the highest relative predictive contribution within all three modelling frameworks, while Precipitation Rate and Distance from Faults also showed substantial predictive relevance. These contributions should be interpreted as model-specific associations rather than direct evidence of causal control.

Overall, the results demonstrate the utility of integrating InSAR-derived deformation with environmental and hydrogeological predictors within a machine-learning framework for regional land-subsidence susceptibility assessment. The resulting probability-based maps can support county-scale screening, monitoring prioritization, groundwater assessment, and identification of areas requiring more detailed investigation. Because the outputs represent susceptibility rather than complete risk, they should not be interpreted as direct estimates of exposure, consequences, or vulnerability.

The predictive capability of the framework remains constrained by the spatial and temporal characteristics of the available datasets, including the two-year InSAR observation period, the 500×500 m modelling grid, and the lack of independent geodetic validation. Future applications should therefore incorporate longer deformation time series, denser groundwater monitoring, spatially independent validation, and higher-resolution local investigations to evaluate the temporal and spatial transferability of the susceptibility patterns identified in this study.

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