

Article

Optimized Geo-Environmental Modeling and Deep Learning for Predictive Sinkhole Susceptibility Mapping Along the Southeastern Coast of the Dead Sea

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Abstract

The quick drop of the water level in the Dead Sea has expedited the formation process of dissolution depression (DDs) along the southeastern coast, which brings about serious dangers with it. The objective of this research is to create a model that will allow us to forecast the risks of DD formation by means of a unique framework based on deep learning-segmented imaging of the earth in combination with multi-criteria geospatial susceptibility modeling. The research created a dependable geospatial database containing information on 668 identified DDs. Seven geo-environmental conditions were studied using the Analytic Hierarchy Process (AHP) and were combined through weighted overlay analysis. The results show that almost 10% of the area under study falls into zones with a very high risk of DD occurrence; thus, the appropriate data were derived at the end of the study that can be used in forming an effective danger prediction tool.

Keywords: dissolution depressions; geo-environmental modeling; deep learning; susceptibility mapping

1. Literature Review

The DS shoreline has undergone one of the most rapid geomorphological transformations recorded in evaporitic environments worldwide. Since 1970, the lake level has declined from approximately −397 m to −439 m in 2025, representing a cumulative drop of nearly 42 m as a consequence of upstream freshwater diversion, reduced inflow from the Jordan River system, and intensive industrial mineral extraction [1–5]. This unprecedented hydrological imbalance has exposed extensive areas of previously submerged land, generating highly unstable coastal conditions and accelerating the development of dissolution-related depressions throughout the Dead Sea littoral zone [6–9].

Recent estimates indicate that approximately 28.5 km² of new land has emerged along the receding Dead Sea shoreline since 1970 [6]. This newly exposed coastal plain contains thick evaporitic sediments that are highly susceptible to subsurface dissolution. As groundwater adjusts to the declining base level, relatively less saline groundwater dissolves buried halite deposits, forming underground cavities that eventually collapse into sinkholes (DDs) [10–12]. Consequently, sinkhole activity has increased markedly, posing



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a major geohazard to infrastructure, agriculture, tourism, and future land-use planning across the Dead Sea region [13].

Previous investigations have identified the spatial distribution of Dead Sea sinkholes (DDs) as the result of a complex interaction among hydrological, geological, geomorphological, and anthropogenic factors. The continuous decline in the Dead Sea water level induces groundwater migration toward the receding shoreline, whereas recharge through ephemeral drainage networks and alluvial fan systems enables undersaturated groundwater to dissolve subsurface halite layers, leading to sinkhole formation [8,14]. Geological and tectonic controls associated with the Dead Sea Transform (DST) further enhance sinkhole development by creating preferential groundwater flow pathways and structural weaknesses that promote localized dissolution and collapse. Moreover, the occurrence of existing DDs may increase the likelihood of additional collapses in adjacent areas through progressive cavity enlargement and the propagation of subsurface instability.

Previous studies have employed diverse approaches to detect Dead Sea sinkholes (DDs), monitor their evolution, and characterize their spatial distribution [1,15–18]. Despite these advances, most investigations have primarily focused on sinkhole formation mechanisms, shoreline retreat, or local-scale hydrogeological processes. Consequently, comprehensive predictive frameworks integrating the major geo-environmental factors controlling DD development remain limited. This study addresses this gap by analyzing DDs within an 18.94 km² area using two complementary extraction methods: manual digitization from Google Earth Pro imagery and deep learning-based semantic segmentation. The resulting sinkhole inventory was integrated with key geo-environmental variables in ArcGIS Pro based framework to identify the principal factors controlling sinkhole development and spatial susceptibility.

To evaluate spatial susceptibility in environments influenced by multiple interacting factors, ArcGIS Pro integrated with multi-criteria analysis (MCA) have become widely used for hazard assessment and environmental suitability modeling. Among these approaches, the AHP developed by Saaty (1980, 2008) provides a systematic framework for quantifying the relative importance of conditioning factors through pairwise comparisons. Therefore, this study aims to identify and quantify the geo-environmental controls governing Dead Sea sinkhole (DD) development and to delineate areas susceptible to future collapse using an integrated ArcGIS–AHP framework. Seven conditioning factors were incorporated into the weighted overlay model: elevation, slope, distance to the hydrological network, distance to faults, lithology/soil type, land use/land cover (LULC), and proximity to existing DDs mapped from the 2025 inventory. These variables were selected based on previous studies and field validation to represent the principal controls on sinkhole development, with particular emphasis on topography, structural faults, and drainage networks, which play a fundamental role in accelerating subsurface dissolution and sinkhole formation [4,14,19]. The resulting susceptibility model classifies the study area into five hazard levels, providing a robust scientific basis for hazard assessment, land-use planning, infrastructure management, and long-term monitoring of geomorphological instability along the rapidly evolving Dead Sea shoreline.

2. Description of the Study Area

The study area extends between 31°15′–31°25′ N and 35°28′–35°38′ E, covering 18.94 km² along the southern Jordanian shoreline of the Dead Sea (Figure 1). It encompasses the Ghor Al-Mazra'ah coastal plain, situated immediately west of the Lisan Peninsula within the tectonic regime of the Dead Sea Transform (DST) [20]. The area exhibits a pronounced topographic gradient, descending from elevations exceeding 277 m above sea level in the eastern highlands to approximately −439 m (BMSL) at the present shoreline.

Since 1970, the Dead Sea water level has declined from approximately -397 m to -439 m, resulting in the loss of nearly 38% of its surface area and the complete desiccation of the southern basin. This regression exposed a broad corridor of unconsolidated, salt-rich lacustrine sediments. Controlled by the tectonic framework of the DST, structural discontinuities facilitate the infiltration of undersaturated groundwater into subsurface halite deposits, accelerating salt dissolution and promoting the rapid proliferation of DDs. Consequently, the zone between the 1970 and 2025 shorelines has evolved into a highly unstable geomorphological environment. Owing to its exceptionally high concentration and continuous expansion of DD, the study area represents one of the most hazardous sectors along the eastern Dead Sea shoreline, making it a priority region for susceptibility assessment and geohazard management [1,2,17,18].

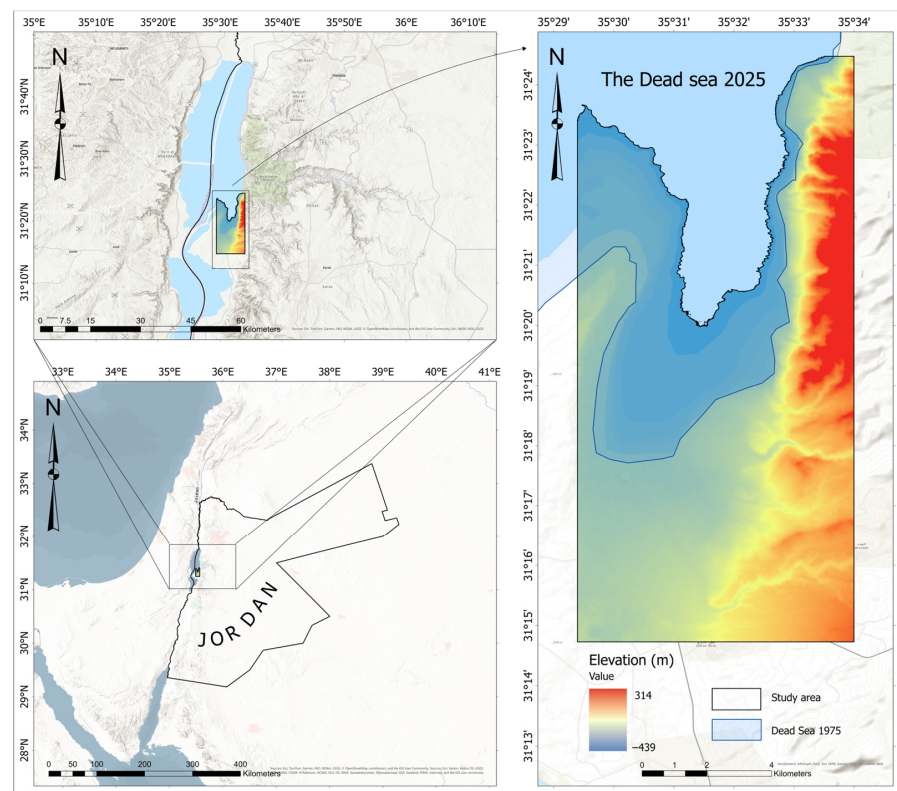


Figure 1. Location map of the study area showing the southeastern Dead Sea region, topographic layers (DEM), and historical shoreline fluctuations between 1970 and 2025.

3. Data Sources and Methodology

3.1. Data Sources and Geo-Environmental Conditioning Factors

To identify and quantify the geo-environmental factors controlling the initiation and spatial distribution of dissolution depressions (DDs) along the southeastern shoreline of the Dead Sea, an integrated remote sensing, ArcGIS Pro and deep learning framework was established. Seven distinct geo-environmental conditioning factors were selected based on their direct physical influence on subsurface dissolution and sinkhole development, including Digital Elevation Model (DEM)-derived elevation, terrain slope, distance to the drainage network, distance to tectonic faults, lithology and soil formations, land use/land cover (LULC), and proximity to previously mapped dissolution depressions. All collected spatial datasets were projected to the WGS 1984 UTM Zone 36 N coordinate system and standardized to a common spatial resolution to ensure geometric consistency for subsequent raster overlay analysis. Topographic variables, specifically elevation and slope, along with the drainage networks, were derived from NASA DEM datasets using the Surface and

Hydrology toolsets within the ArcGIS Pro Spatial Analyst extension. Geological formations, structural tectonic fault networks, and baseline soil maps were acquired from the Jordanian Natural Resources Authority and the Ministry of Agriculture. The LULC dataset was mapped from Google Earth Pro imagery using a supervised support vector machine (SVM) classifier followed by manual refinement to differentiate four major thematic classes.

To construct the baseline inventory, a comprehensive dataset of documented DDs was compiled through visual interpretation and manual digitization of high-resolution Google Earth Pro imagery. This inventory was further validated via field investigations to secure ground-truth positional accuracy. For automated feature extraction, a deep learning semantic segmentation workflow was implemented using a U-Net architecture with a ResNet-34 backbone. Training samples were generated as (512×512) pixel image tiles with 50% overlap using the Export Training Data for Deep Learning tool, and the trained network was deployed via the Classify Pixels Using Deep Learning tool to generate the pixel-level sinkhole inventory.

Finally, the seven conditioning factors were standardized and weighted utilizing the AHP to quantify their relative contribution to sinkhole development. This step provided the necessary inputs for the subsequent weighted overlay susceptibility modeling and hazard exposure analysis within the active Dead Sea retreat zone (Figures 2 and 3 and Table 1).

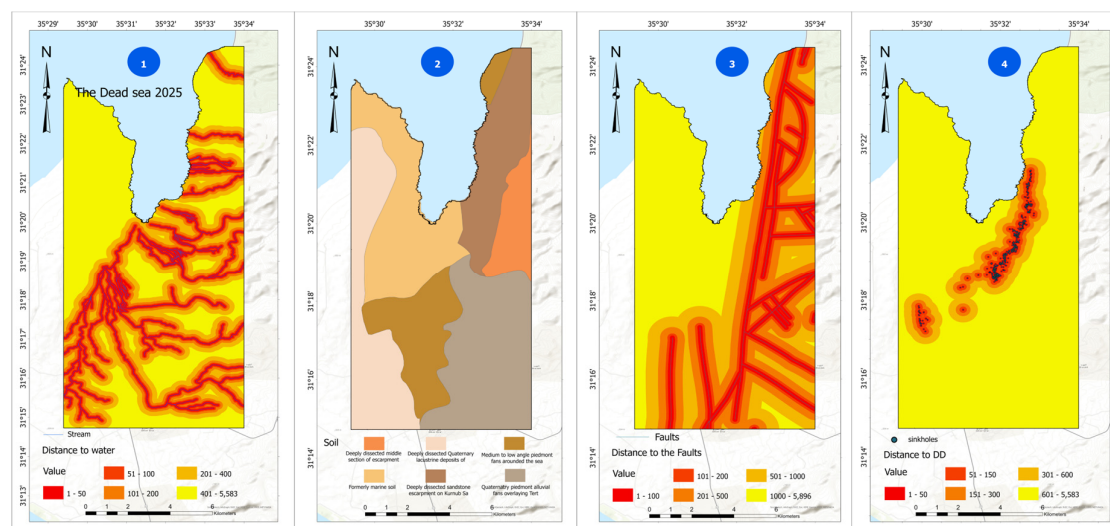


Figure 2. Geo-environmental factor maps (distance to water network, soil, faults, and distance to sinkholes) standardized and reclassified for ArcGIS Pro-based multi-criteria susceptibility modeling.

Table 1. Geo-environmental variables and conditioning factors utilized in the AHP-based DD susceptibility model.

Field	Description	Range/Categories	Unit
SQM	DD area	8–21,399	km ²
DEM	Elevation (DEM)	−423 to −361	M (BMSL)
Slope	Terrain gradient	1.0–38.9°	Degrees
Hydrological network	Distance to hydrological network	0.5–806.9	M
Faults	Distance to fault lines	1.1–1954.7	M
LULC	Land use/land cover	Barren, Water, Agriculture, Urban	Category
Soil	Soil/lithology type	5 geological units	Category
DD proximity	Distance to existing DD	Derived from DD centroids	M

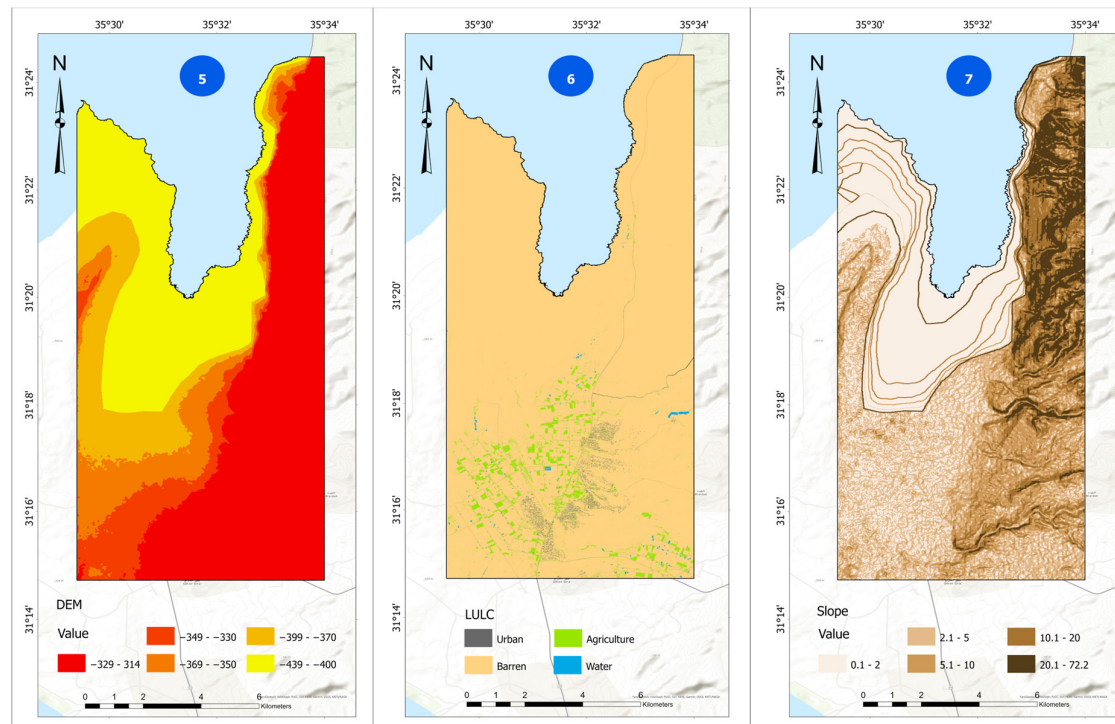


Figure 3. Standardized and reclassified thematic factor maps (elevation, LULC, and slope), prepared for multi-criteria evaluation and ArcGIS Pro-based susceptibility modeling.

3.2. Research Methodology

A comprehensive geospatial framework integrating remote sensing, deep learning, ArcGIS Pro, and multi-criteria decision analysis (MCDA) was developed to identify the geo-environmental conditions governing the initiation and spatial distribution of dissolution depressions (DDs) and to delineate future sinkhole susceptibility zones along the southeastern shoreline of the Dead Sea. The methodological workflow comprises four sequential stages: (1) sinkhole inventory generation via deep learning and field validation, (2) geospatial database preparation and environmental factor preprocessing, (3) factor weight assignment using the analytic hierarchy process (AHP), and (4) spatial susceptibility modeling and risk exposure mapping through weighted overlay analysis.

3.2.1. Sinkhole Inventory Generation Using Deep Learning

A reliable sinkhole inventory is essential for susceptibility modeling because dissolution depressions (DDs) provide the primary evidence for identifying and classifying hazard zones. In this study, DDs were first delineated by manual interpretation of high-resolution Google Earth Pro imagery (1.0–1.2 m, 2025) and verified through field surveys, resulting in an inventory of 668 DDs. To improve extraction consistency and efficiency, a deep learning semantic segmentation workflow was implemented in ArcGIS Pro using a U-Net model with a ResNet-34 encoder. Training was performed on 512×512 pixel image tiles (50% overlap) for 50 epochs using GPU acceleration. The model achieved stable convergence (loss: 0.0407–0.0402), with an overall accuracy of 98.81% and precision of 81.5%. Although recall was lower (14.7%), the conservative detection strategy minimized false positives, providing a robust inventory for subsequent sinkhole susceptibility mapping.

3.2.2. Geospatial Database Preparation

To investigate the environmental controls dictating sinkhole occurrence, a comprehensive geospatial database was constructed. Seven geo-environmental conditioning factors known to influence subsurface karst dissolution were incorporated: digital elevation model

(DEM)-derived elevation, terrain slope, distance to the drainage network, distance to tectonic faults, lithology/soil formations, land use/land cover (LULC), and proximity to previously mapped DDs.

All datasets were projected to the WGS 1984 UTM Zone 36 N coordinate reference system and resampled to a common spatial resolution to secure spatial compatibility and pixel-level correspondence. Continuous vector datasets, including drainage networks, tectonic faults, and mapped dissolution depressions, were transformed into continuous raster surfaces using the Euclidean distance algorithm. This transformation effectively modeled spatial influence gradients, facilitating the quantitative evaluation of proximity-dependent geomorphological processes. Subsequently, all thematic layers were standardized and reclassified into a common dimensionless susceptibility scale to ensure absolute compatibility within the multi-criteria evaluation framework.

3.2.3. Weighting of Geo-Environmental Conditioning Factors

The relative contribution of each conditioning factor to sinkhole initiation was quantified using the AHP. Pairwise comparison matrices were constructed based on established AHP principles, integrating expert geomorphological knowledge with empirical site conditions.

To verify the mathematical reliability and eliminate subjective bias within the weighting scheme, a consistency analysis was performed. The calculated principal eigenvalue ($\lambda_{\max} = 7.32$), Consistency Index ($CI = 0.053$), and Consistency Ratio ($CR = 0.040$) demonstrated a highly robust judgment matrix. Because the CR value remained substantially below the critical threshold of 0.10, the weighting procedure was confirmed to be internally consistent, thereby minimizing epistemic uncertainty and enhancing the reproducibility of the susceptibility model.

3.2.4. Sinkhole Susceptibility Modeling

The standardized environmental layers and their corresponding AHP-derived weights were integrated using the weighted overlay technique in ArcGIS Pro, V.3.7 to generate a spatially explicit sinkhole susceptibility model. This analysis delineated the synergistic combinations of geological, geomorphological, hydrological, and anthropogenic factors that represent the optimal settings for future DD initiation.

The resulting susceptibility map stratifies the coastal zone into distinct hazard-potential classes. Finally, to translate susceptibility into actionable risk metrics, the final map was intersected with infrastructure and regional land-use datasets. This step allowed for a detailed spatial exposure and vulnerability assessment of roads, buildings, agricultural land, and critical anthropogenic assets within the highly dynamic Dead Sea retreat zone. The final criterion weights utilized in the weighted overlay framework are structured and presented in Table 2.

3.3. Final Results of AHP Weights

The weights shown in Table 2 were generated based on the spatial distribution and size of the 668 documented of DDs, using AHP to determine the relative influence or weight that should be assigned to each criterion. These weights will be applied directly in the ArcGIS Pro Weighted Overlay tool. The matrix utilizes Saaty's 1–9 scale. Values placed above the diagonal indicate that the row criterion has more influence. Ranking fourth, the newly introduced criterion (DD proximity) exhibits a moderate influence; it yields lower weight than the primary geological and hydrological drivers, yet surpasses elevation, LULC, and slope in terms of susceptibility contribution.

Table 2. Pairwise comparison matrix, criteria priorities, and relative weights of the seven geo-environmental factors within the AHP-based dissolution depression (DD) susceptibility model, including consistency check parameters (CR).

Criterion	Stream	Soil	Faults	DD	DEM	LULC	Slope	Weight
Distance to Hydrological Network	1	2	2	2	3	4	6	0.26
Soil/Lithology	1/2	1	2	2	2	3	5	0.21
Distance to Fault	1/2	1/2	1	2	2	2	4	0.18
DD proximity	1/2	1/2	1/2	1	2	2	3	0.14
Elevation (DEM)	1/3	1/2	1/2	1/2	1	2	3	0.10
LULC	1/4	1/3	1/2	1/2	1/2	1	2	0.07
Slope	1/6	1/5	1/4	1/3	1/3	1/2	1	0.04

Consistency check: $\lambda_{\max} = 7.32$ | $CI = 0.053$ | $RI (n = 7) = 1.32$ | $CR = 0.040$ Accepted (threshold: $CR < 0.10$).

3.3.1. Rationale for Each Criterion Weight, Ordered According to Its Importance in Determining the Susceptibility/Hazard Level

The relative importance of the seven geo-environmental conditioning factors was quantified using the analytic hierarchy process (AHP), integrating expert knowledge, published evidence on Dead Sea sinkhole development, and statistical analysis of the spatial distribution of the 668 mapped dissolution depressions (DDs). The assigned weights reflect the relative contribution of each factor to sinkhole initiation and development within the study area.

Distance to the hydrological network was identified as the most influential conditioning factor and assigned the highest weight (26%). Inventory analysis revealed that 41.6% of all documented DDs occur within 100 m of a drainage channel, while the largest sinkholes (XL class) are located at a mean distance of only 46 m. This spatial relationship reflects the fundamental role of drainage systems in concentrating surface runoff and promoting freshwater infiltration into subsurface evaporite layers, thereby accelerating salt dissolution and cavity formation. Compared with previous six-factor models, the weight was slightly reduced to accommodate the newly introduced proximity-to-DDs criterion.

Lithology and soil received the second-highest weight (21%) because they define the geological conditions controlling sinkhole development. The study area is dominated by highly soluble lacustrine deposits containing evaporitic sediments that became exposed following the progressive retreat of the Dead Sea. Quaternary alluvial fan deposits exhibit the greatest susceptibility, with a mean DD area of 467 m², whereas sandstone outcrops remain comparatively stable due to their low solubility. Consequently, lithological variability governs both the spatial distribution and the potential intensity of subsurface dissolution.

Distance to tectonic faults was assigned a weight of 18%, reflecting the structural influence of fault systems on groundwater circulation. Spatial analysis showed that 14.4% of mapped DDs occur within 100 m of major faults, while approximately 50% are located within 500 m. Fault zones enhance rock permeability and provide preferential pathways for freshwater migration into buried evaporite sequences, thereby increasing localized dissolution and collapse potential.

Proximity to existing dissolution depressions received a weight of 14% to account for the pronounced spatial clustering of sinkholes. Areas located near existing DDs are likely to share similar subsurface geological conditions, including evaporite distribution, groundwater dynamics, and pre-existing dissolution cavities. This factor was generated using the Euclidean Distance algorithm in ArcGIS Pro and subsequently reclassified into standardized susceptibility classes. Although highly predictive, its weight was intentionally

kept lower than those of the primary geological and hydrological factors because its spatial influence is largely controlled by these underlying processes.

Elevation was assigned a weight of 10%, owing to its relationship with shoreline retreat and groundwater-table decline. Approximately 65% of the documented DDs occur at elevations below −400 m below mean sea level (BMSL), corresponding to the zone most strongly affected by the continuous recession of the Dead Sea. As lake levels decline, newly exposed evaporite deposits become increasingly vulnerable to freshwater infiltration from ephemeral streams and lateral groundwater flow, creating favorable conditions for accelerated sinkhole formation.

Land use/land cover (LULC) was assigned a weight of 7% because it primarily represents surface environmental conditions and hazard exposure rather than directly controlling dissolution processes. Although 84% of the mapped DDs occur on barren coastal surfaces, the largest sinkholes (mean area = 640 m²) are concentrated near water-related land-cover classes. Higher susceptibility ratings were therefore assigned to urban and agricultural areas to reflect their greater exposure and potential socioeconomic consequences.

Terrain slope received the lowest weight (4%) because it primarily characterizes surface morphology rather than acting as a direct driver of dissolution. Inventory analysis indicated that 62.6% of all documented DDs occur on gentle slopes of less than 2°, which are typical of the flat coastal plain. While low-gradient terrain does not directly induce dissolution, it favors sediment accumulation, surface-water retention, and groundwater infiltration, thereby creating geomorphological conditions conducive to sinkhole development. In contrast, steeper slopes generally correspond to more competent bedrock with comparatively lower susceptibility to rapid karstification.

3.3.2. Reclassification Scores for ArcGIS Pro, V. 3.7

Prior to the weighted overlay analysis, each raster layer was reclassified into a standardized hazard scale from 1 (Low) to 5 (Very High), Parameter weights were established according to Saaty's methodology [19,20] with mathematical consistency verified via the Consistency Ratio (CR < 0.1). Finally, the reclassified thresholds and final hazard zones were calibrated and validated using rigorous field verification data. To create the Proximity Raster, the 668 recorded DD records were combined in ArcGIS Pro using the exported X-Y coordinate data of the DD records as a Point Feature Class. Using the Spatial Analyst Extension, a Euclidean Distance Analysis was then conducted to determine the shortest line distance from every cell to the closest pit, creating a continuous distance surface. The proximity raster created from this analysis was finally used as input for reclassification based on threshold values to classify the study area into discrete proximity-based susceptibility zones based on the values specified, as detailed in Table 3 and Figures 4 and 5.

Table 3. Reclassification for the seventh criteria hazard-weighting scores for DD Susceptibility mapping used throughout the study area.

Distance to Hydrological Network	Score	Hazard Level
<50 m	5	Very high
50–100 m	4	High
100–200 m	3	Moderate
200–400 m	2	Low
>400 m	1	Very low
Distance from Faults	Score	Hazard Level
<100 m	5	Very high
100–200 m	4	High
200–500 m	3	Moderate

Table 3. Cont.

Distance to Hydrological Network	Score	Hazard Level
500–1000 m	2	Low
>1000 m	1	Very low
Distance from Nearest DD	Score	Hazard Level
<50 m	5	Very high—active cluster
50–150 m	4	High
150–300 m	3	Moderate
300–600 m	2	Low
>600 m	1	Very low—isolated area
Elevation m (bmsl)	Score	Hazard Level
<−400 m	5	Very high
−400 to −370 m	4	High
−370 to −350 m	3	Moderate
−350 to −330 m	2	Low
>−330 m	1	Very low
Slope (degrees)	Score	Hazard Level
<2°	5	Very high
2–5°	4	High
5–10°	3	Moderate
10–20°	2	Low
>20°	1	Very low
Soil/Lithology Type	Score	Hazard Level
Deeply dissected sandstone escarpment (Kurnub Sandstone)	5	Very high
Formerly marine soil	5	Very high
Quaternary piedmont alluvial fans (overlying Tertiary)	4	High
Medium to low angle piedmont fans (Dead Sea area)	3	Moderate
Deeply dissected Quaternary lacustrine deposits	2	Moderate
Deeply dissected middle section of escarpment	1	Low
LULC Class	Score	Notes
Water	5	
Urban	4	Critical infrastructure exposure
Agriculture	4	Active land-use exposure
Barren	3	84% of all DDs background class

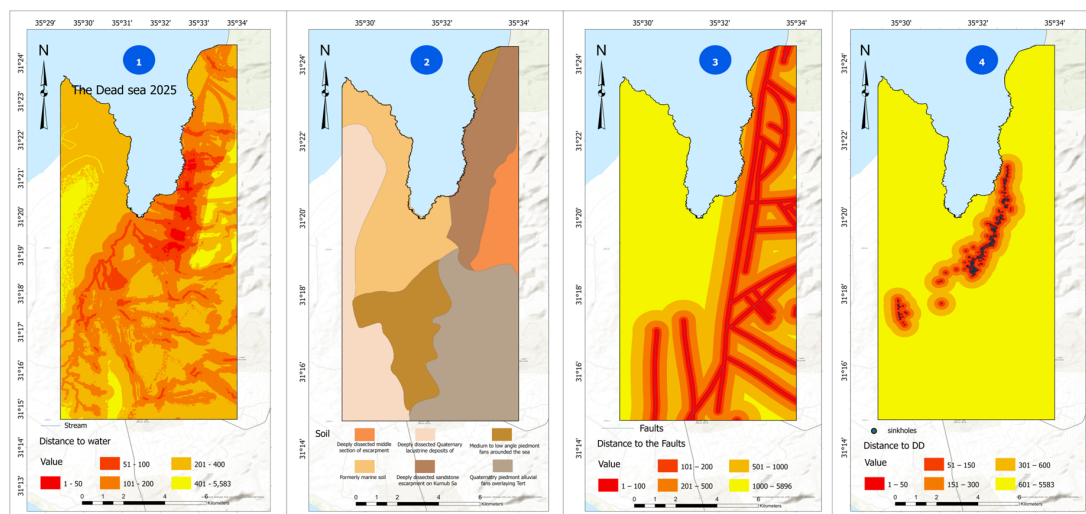


Figure 4. Susceptibility mapping and infrastructure exposure assessment along the southeastern Dead Sea coast using weighted overlay of geo-environmental factors (distance to water networks, soil, faults, and distance to DD).

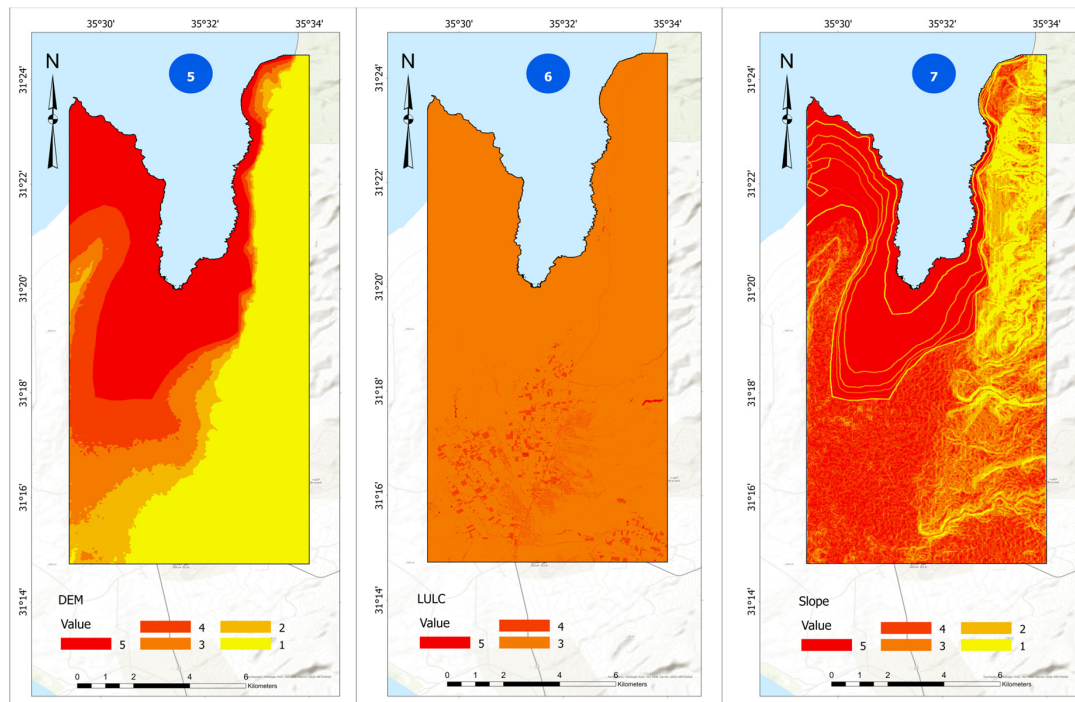


Figure 5. Susceptibility mapping and infrastructure exposure assessment along the southeastern Dead Sea coast using weighted overlay of geo-environmental factors (elevation, LULC and slope).

3.4. Apply Weighted Overlay

Parameter weights were assigned via Saaty's method—distance to streams (26%), soils/lithology (21%), distance to faults (18%), proximity to DD (14%), elevation (10%), LULC (7%), and terrain slope (4%)—using a 1–5 evaluation scale.

4. Results and Discussion

4.1. Results

4.1.1. Deep Learning-Based Sinkhole Extraction Results

The U-Net model with a ResNet-34 backbone successfully generated a high-resolution pixel-level inventory of dissolution depressions (DDs) from the 1 m satellite imagery, providing the spatial foundation for the subsequent susceptibility analysis. The training process exhibited rapid convergence followed by stable optimization, with no evidence of significant overfitting throughout the 50 training epochs. Final training and validation losses reached 0.0407 and 0.0402, respectively, indicating excellent agreement between the learning and validation datasets. Independent evaluation yielded an overall accuracy of 98.81%, precision of 81.5%, recall of 14.7%, and an F1-score of 25.0%. The high overall accuracy and precision demonstrate that the model effectively distinguished well-defined dissolution depressions from the surrounding landscape while maintaining a low false-positive rate. Consequently, the extracted sinkhole inventory represents a reliable and spatially consistent dataset for analyzing the environmental controls governing sinkhole occurrence.

The model performance further demonstrates the suitability of deep learning semantic segmentation for automated sinkhole mapping in the rapidly evolving Dead Sea coastal environment. The relatively low recall indicates that some small, incipient, or spectrally ambiguous dissolution depressions remained undetected, primarily because their surface expression is weak or partially obscured by alluvial deposits and complex geomorphological conditions. Nevertheless, the conservative detection behavior substantially reduced false-positive predictions, thereby improving the reliability of the inventory used for susceptibility modeling. Rather than constituting the primary objective of this study, the deep

learning model served as a robust preprocessing tool for generating an accurate sinkhole inventory, which enabled objective evaluation of the relationships between the 668 mapped dissolution depressions and the seven geo-environmental conditioning factors. This integration of deep learning with GIS-based multi-criteria analysis significantly enhances the robustness, reproducibility, and predictive capability of the proposed sinkhole susceptibility model, as shown in (Figures 6 and 7).

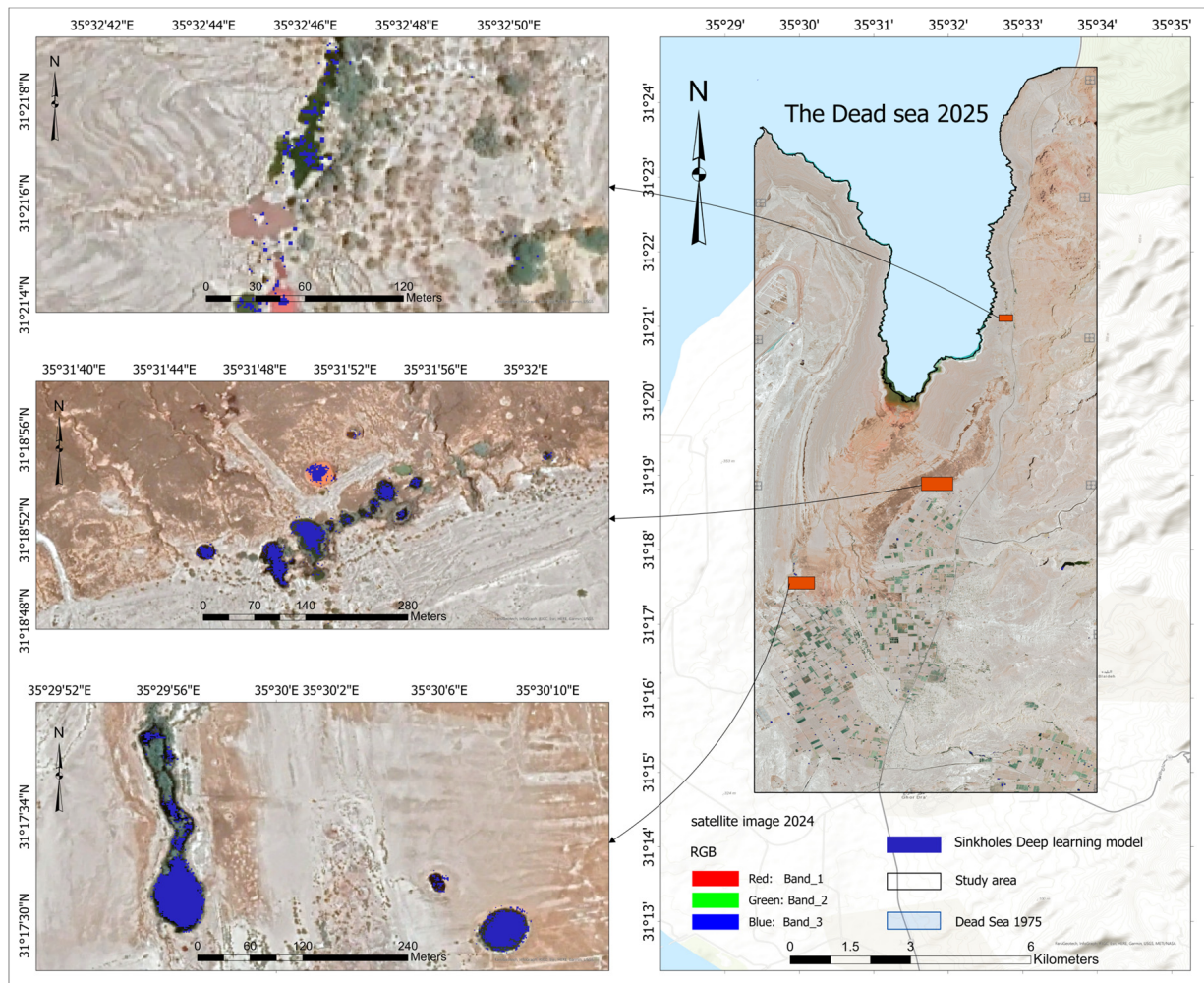


Figure 6. Deep learning-derived dissolution depression inventory along the southeastern Dead Sea shoreline. The map presents the pixel-level extraction of dissolution depressions generated by the U-Net (ResNet-34) semantic segmentation model from 1.2 m, with enlarged insets illustrating representative detection results.

4.1.2. The Spatial Susceptibility Results and Model Validation

The integration of seven environmental and geological factors using multi-criteria spatial analysis generated a DD susceptibility map in the study area. The AHP produced a consistency ratio (CR) of 0.040, which is well inside the scientifically accepted upper limit of $CR < 0.10$. The final susceptibility indices ranged from 1.3 to 4.9, and high and very high hazard zones (3.1–4.9) primarily existed along the coastal strip and at the immediate retreat margins of the 1970 Dead Sea shoreline [17,21,22]. Low-hazard zones (1.3–2.7) were present in the eastern upland regions, which are composed of relatively stable lithologic units and have greater elevations than the rest of the study area. As shown in Figure 2. There is a strong spatial relationship between the locations of the 668 documented DDs and areas with the highest susceptibility scores (>3.7), demonstrating that the model has good predictive capability.

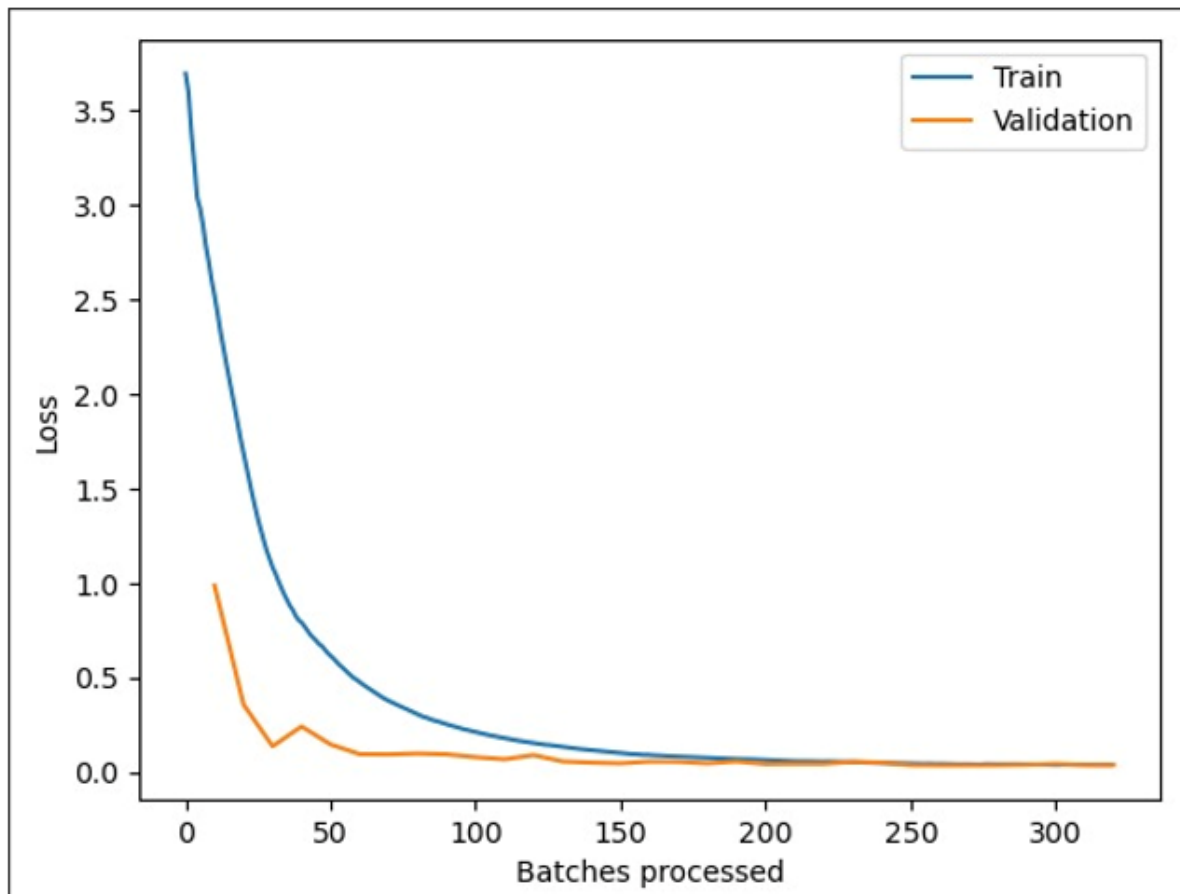


Figure 7. Convergence behavior of the U-Net (ResNet-34) deep learning model during semantic segmentation of dissolution depressions.

4.1.3. Statistical Determinates of DD Formation

An examination of the quantitative data from the 668 documented DD indicates that both hydrologic and topographic proximity play a significant role in DD Development; the main findings can be summarized as follows:

1. **Hydrologic/Tectonic Influences:** Approximately 41.6% of all DDs are located within 100 m of a linear hydrologic feature and approximately 29.3% are found within 200 m of an identified fault. These linear features appear to act as conduits for freshwater entry into the subsurface.
2. **Topographic Limitation:** DD occurrences are very sensitive to elevation/gradient; Approximately 65.3% of all DDs exist below the -400 m contour, which represents the zone of most recent Dead Sea recession and approximately 62.6% of all DDs exist on nearly flat ground having slopes less than 2 degrees.
3. **Clustering of Geomorphological Units and LULC:** LULC analysis indicates that 84% of all DDs occur on Bare Ground. It should be noted that DDs adjacent to water bodies show significantly larger mean sizes (640 m^2). Moreover, evidence exists for a spatial contagion effect, whereby new DDs tend to form proximal to existing ones; this is likely due to pre-existing subsurface voids and structural weaknesses in the surrounding area. This aligns with numerous previous studies [1,2,17,23].

4.1.4. Spatial Susceptibility Results and Model Validation

The spatial distribution and susceptibility of DDs in the southeastern Dead Sea region were established utilizing a multi-criteria decision-making (MCDM) approach combining seven environmental and geological variables. The Analytic Hierarchy Process (AHP) was

utilized to weight each variable, yielding a consistency ratio (CR) of 0.040. This ratio is well below the recommended upper threshold of (CR) < 0.10 proposed by [19,20], thereby validating the logical consistency of the developed pairwise comparison matrix. Based on the geometric stability and subsurface characteristics, the resultant susceptibility index values (ranging from 1.32 to 4.93) were reclassified into five distinct hazard categories, as presented in (Table 4).

Table 4. Statistics regarding number of documented DD hazard classifications.

Hazard Category	Index Range	Area (m ²)	Geomorphological Characteristics
Very Low	1.32–1.80	8,237,760	Stable upland regions with minimal environmental susceptibility.
Low	1.81–2.60	49,840,984	Regions with high lithological stability and low development potential.
Moderate	2.61–3.39	36,408,047	Intermediate risk zones, often situated near stabilized sediments.
High	3.40–4.20	8,811,576	Zones exhibiting significant geomorphological instability.
Very High	4.21–4.93	1,200,588	Active DD with rapid DD proliferation and recession-driven risk.

4.1.5. Hazard Level and Model Accuracy Spatial Distribution

As illustrated in the final susceptibility map (Figure 6), a distinct geographic correlation is evident; nearly all high and very high hazard zones (susceptibility index: 3.40–4.93) primarily occur within the immediate coastal zone and near the former recession margin of the 1970 shoreline. In addition, the clustering of hazard zones indicates the major influence of base-level fall in causing the movement of the fresh-salt-water interface downward thus allowing subsurface salt to dissolve [15,24–27]. On the other hand, low and very low hazard zones are mostly found in the east upland regions of the study area. In general, the east upland regions are separated from the remaining portions of the study area by relatively stable lithology and higher elevation. As such, they experience less hydrogeologic effect from events occurring at the shore line, this is consistent with the findings of previous studies [19].

In order to evaluate how well the model performed as a predictor of DD occurrence, the location of 668 documented DD occurrences were superimposed upon the susceptibility map. There existed a good correlation between many of the DD occurrences and high-scoring zones (>3.70) on the susceptibility map. The fact that nearly all of the documented DD occurrences coincide with areas classified as being highly susceptible demonstrates that the AHP-based model accurately incorporates the geomorphic influences driving land instability in this hypersaline environment and provides an effective tool for both mitigating hazards associated with DD and planning infrastructure projects.

The categorization of DD risk along the Dead Sea shoreline can be divided into five separate categories based on geomorphic stability and the properties of subsurface materials. This hierarchical classification system represents a methodical approach to assessing land susceptibility and will serve as a valuable tool for both hazard mitigation and urban planning in affected regions.

4.1.6. Spatial Distribution and Susceptibility Zonation of DD Occurrence

The susceptibility map (Figure 8) illustrates the spatial distribution of sinkholes hazards in the southeastern Dead Sea region created using the Analytic Hierarchy Process AHP. The AHP model includes multiple aspects of geomorphology and hydrology in its analysis resulting in a range of susceptibility index values from 1.30 to 4.90. It is apparent that there exists a strong association between the recession of the shoreline illustrated by

the 1970 border and a corresponding increase in the number of high-risk zones. High-risk zones (3.70–4.90) exist primarily along active drainages and newly formed mudflat areas, which correspond to areas exhibiting the highest intensity of subsurface salt dissolution. Areas exhibiting greater elevation or farther away from the present shoreline illustrate lower susceptibility values, indicating greater geological stability.

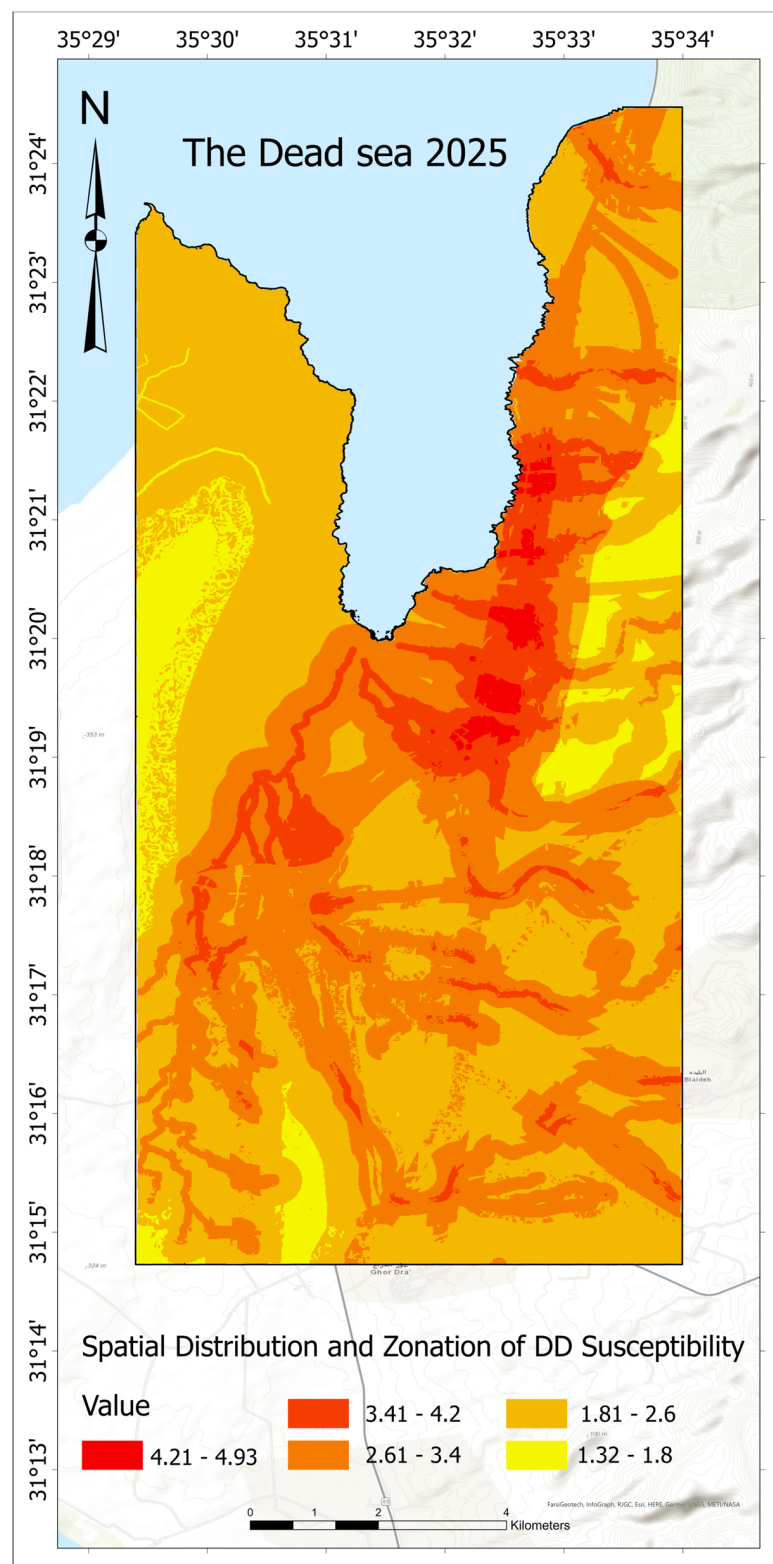


Figure 8. Spatial distribution and zonation of DD susceptibility in the southeastern Dead Sea region: AHP-based modeling and validation using documented DD locations.

5. Discussion

This research illustrates that the use of a combination of high-resolutions deep learning-based inventory generation and multi-criteria susceptibility models provides substantial improvement in the hazard assessment achievement in the Dead Sea area. The application of the U-Net semantic segmentation model as a preprocessing tool resulted in the generation of an objective and uniform dissolution depression (DD) inventory. The strong capability of this inventory ensured an accurate evaluation of geoenvironmental factors especially that of base level decrease, water connections, and tectonic structure, which are the main factors that positively influence on coastal stability.

Despite these encouraging results, the model exhibited relatively low recall (14.7%) and an F1-score of 25.0%. This performance imbalance reflects the inherent complexity of the Dead Sea coastal geomorphology, where many small, incipient, or spectrally ambiguous depressions present weak surface expressions or are partially obscured by active alluvial processes. Consequently, the model tended to adopt a conservative detection strategy, prioritizing precision over completeness. While this reduced the detection of subtle features, it also minimized false positives, which is critical for producing a reliable geomorphological inventory.

As a result, the final dataset of 668 mapped DDs represents a highly reliable and spatially consistent inventory, suitable for subsequent susceptibility modeling. In this context, the deep learning framework should not be considered a final mapping solution but rather a preprocessing tool that enhances the quality and reliability of spatial inputs used in further geospatial analysis. The integration of this AI-derived inventory with a GIS-based multi-criteria decision analysis significantly improves methodological robustness, reproducibility, and predictive accuracy in sinkhole susceptibility mapping.

From a geomorphological perspective, the results highlight a complex interaction between hydrological dynamics, structural controls, and subsurface geological conditions governing DD distribution along the southeastern Dead Sea coast. Among all conditioning factors, proximity to existing DDs emerged as the most influential predictor of future occurrences. This strong spatial dependence supports the concept of spatial contagion, where existing collapse features act as hydraulic focal points that enhance preferential flow paths for freshwater infiltration into subsurface halite layers, accelerating karstification processes.

Hydrological connectivity also plays a fundamental role in DD formation. Approximately 41.6% of mapped DDs are located within 100 m of hydrological networks, indicating that episodic flash floods and seasonal runoff significantly contribute to subsurface salt dissolution. These processes are further intensified by the continuous decline in Dead Sea water levels, which has dropped from approximately -393 m in 1970 to -439 m in 2025. This dramatic reduction alters the freshwater–brine equilibrium, enhances groundwater circulation, and promotes progressive subsurface instability across marginal coastal zones.

The most hazardous areas are concentrated within very high susceptibility zones (4.00–4.90), which contain approximately 65.3% of all documented DDs. These zones are predominantly distributed below the -400 m elevation contour and represent the core instability belt of the study area. Their development is controlled by the combined effects of freshwater–brine interaction, evaporite dissolution, fault-controlled groundwater flow, and enhanced infiltration along structural discontinuities. The co-occurrence of these processes produces highly favorable conditions for subsurface void formation and eventual surface collapse.

Given their spatial concentration and high hazard potential, these zones pose a significant threat to infrastructure, transportation corridors, and planned development projects. Therefore, they should be prioritized in future risk mitigation strategies. Recommended measures include high-resolution geophysical surveys, continuous ground deformation

monitoring, and the establishment of early warning systems. These interventions are essential for reducing uncertainty, improving hazard preparedness, and protecting human life and economic assets in the Dead Sea region.

6. Conclusions

This study provides the first comprehensive high-resolution geographic assessment of the spatial distribution and susceptibility of dissolution depressions (DDs) along the entire 18.94 km² southeastern Dead Sea shoreline. An integrated geospatial framework combining very-high-resolution Google Earth Pro imagery, field validation, U-Net (ResNet-34) deep learning, Geographic Information Systems (GISs), the Analytic Hierarchy Process (AHP), and weighted-overlay modeling was developed to produce a reliable DD susceptibility map. A total of 668 DDs were identified with an overall extraction accuracy of 98.81%, while the AHP model demonstrated strong statistical consistency (CR = 0.040).

Geo-environmental analysis revealed that drainage proximity, lithological conditions, and fault structures are the primary controlling factors, with 65.3% of DDs occurring below −400 m elevation and 41.6% within 100 m of drainage networks. The susceptibility assessment classified 9.95% (~1.88 km²) of the study area as high to very high risk, concentrated in low-relief terrain (<2°), depressed coastal zones, and areas influenced by active hydrological pathways and structural discontinuities.

Spatial patterns indicate strong clustering of DDs around pre-existing depressions and barren surfaces, suggesting progressive subsurface dissolution and increasing landscape instability. This study establishes the first high-resolution hazard zonation framework for the southeastern Dead Sea coast and provides a transferable methodology for monitoring and managing dissolution-related geohazards in evaporite–karst environments worldwide.

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