# A GeoAI-Based Ensemble Modeling Framework for Multi-Type Flood Susceptibility Assessment in Peshawar, Pakistan

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Flooding is a recurrent hazard in Peshawar, Pakistan, exacerbated by rapid urban expansion, climate variability, and inadequate drainage infrastructure. This study presents a novel GeoAI-based ensemble modeling framework using Random Forest (RF), XGBoost, and CatBoost algorithms to assess susceptibility to riverine, flash, and urban floods. Spatial predictors including elevation, rainfall, land use/land cover, and proximity to rivers were integrated with machine learning to generate high-resolution susceptibility maps. CatBoost outperformed other models, achieving an AUC score of 0.94 and overall accuracy of 94.1%. Feature importance analysis using SHAP values revealed that distance to rivers, elevation, and rainfall intensity were dominant contributors to flood risk. Spatial clustering analysis confirmed the significance of hotspots in low-lying and highly urbanized areas such as Chamkani, Tehkal, and Ring Road. Comparative analysis with existing studies demonstrated improved precision, interpretability, and spatial coherence using the proposed ensemble-GeoAI approach. The study provides a robust decision-support tool for urban planners and disaster risk managers, facilitating data-driven flood mitigation strategies in rapidly urbanizing regions.

**Keywords:** Flood Susceptibility, GeoAI, Ensemble Modeling, Random Forest, XGBoost, CatBoost, SHAP Values, Spatial Predictors, Urban Flooding, Peshawar, Disaster Risk Management

**Introduction:**

Flooding is one of the most pervasive and destructive natural hazards globally, exacerbated by climate change, rapid urbanization, deforestation, and unsustainable land-use practices [1][2]. In Pakistan, over two dozen major flood events have occurred since 1950, resulting in an estimated 9,000 deaths and over US$20 billion in economic damages [3]. The 2010 monsoon flood alone affected 20 million people and caused approximately US$9.7 billion in losses [4], highlighting the urgent need for proactive and spatially detailed flood risk assessment strategies.

Traditional flood susceptibility mapping approaches, such as statistical regression or the Analytical Hierarchy Process (AHP), while valuable, often fall short in capturing the complex, nonlinear relationships among environmental, hydrological, and anthropogenic flood drivers [5]. The emergence of machine learning (ML) and its integration with remote sensing (RS) and geographic information systems (GIS) has dramatically transformed flood modeling practices [6][7]. By leveraging algorithms such as Random Forest (RF), XGBoost, and Support Vector Machines (SVM), researchers can now produce highly accurate and data-driven flood susceptibility maps [8].

In particular, the integration of ML with spatial science has given rise to Geospatial Artificial Intelligence (GeoAI)—a field that utilizes AI techniques to analyze, model, and visualize spatial phenomena. GeoAI frameworks not only automate susceptibility modeling but also enhance performance through the incorporation of spatial structures such as spatial autocorrelation, heterogeneity, and anomaly detection—principles foundational to spatial analysis [9][10]. Despite the increasing adoption of ML in flood mapping, many studies continue to underutilize these geospatial concepts, resulting in models that may lack spatial realism and explainability [11].

Recent studies have shown the efficacy of GeoAI in diverse contexts. For example, [1] developed a national-scale, high-resolution flood susceptibility model for Pakistan, estimating that approximately 29% of the land area and 47% of the population (~95 million people) are at critical flood risk. Similarly, [12] demonstrated the use of explainable AI (XAI) to enhance model transparency in flood risk prediction. However, most of these efforts focus primarily on single types of flooding—typically riverine—and do not fully account for the combined dynamics of riverine, urban, and flash floods, especially in rapidly urbanizing and hydrologically complex areas such as Peshawar.

Peshawar, a major urban hub in northwestern Pakistan, is vulnerable to all three flood types. Yet, localized and interpretable flood susceptibility maps that integrate all flood types are still scarce. Furthermore, many existing models do not incorporate feature importance analysis, limiting their utility for decision-makers who require interpretable and prioritized outputs for flood mitigation planning.

Thus, this study seeks to address these gaps by developing a comprehensive, interpretable, and multi-type flood susceptibility framework for Peshawar using GeoAI techniques. The framework incorporates spatial autocorrelation, flash-flood and urban-specific indices, and explainable ML models to produce feature-weighted susceptibility maps. The goal is not only to improve predictive performance but also to provide an interpretable, geospatially grounded decision-support tool for urban flood resilience planning.

**Objectives:**

The primary objective of this study is to develop a comprehensive and interpretable machine learning framework for flood susceptibility mapping in the Peshawar region using geospatial artificial intelligence (GeoAI). The research aims to integrate multisource geospatial datasets—including hydrological, topographical, meteorological, and anthropogenic variables—to build robust models capable of accurately predicting flood-prone zones. Several machine learning algorithms, such as Random Forest, Gradient Boosting, XGBoost, and

CatBoost, are applied and comparatively evaluated to determine their predictive performance. Furthermore, spatial characteristics such as spatial autocorrelation, heterogeneity, and hotspot patterns are explicitly incorporated into the modeling process to enhance spatial realism and reliability.

**Novelty Statement:**

This study presents several novel contributions to the existing body of flood modeling research. First, it introduces a unified GeoAI-based approach that simultaneously models riverine, flash, and urban flooding—hazards that are often addressed in isolation despite their overlapping occurrence in the Peshawar basin. Second, the study embeds spatial dependencies and landscape heterogeneity directly into the machine learning workflow, a methodological enhancement that is rarely incorporated in conventional flood susceptibility models.

**Literature Review:**

Flood susceptibility modeling has evolved significantly in recent years due to the growing accessibility of high-resolution spatial data and the emergence of GeoAI-based techniques. [13] demonstrated the importance of combining remote sensing, hydrodynamic modeling, and machine learning to improve flood hazard assessments in Pakistan, particularly in topographically diverse basins. Similarly, [14] developed a high-resolution national-scale flood susceptibility map using machine learning and multisource geospatial datasets, showing the critical role of human exposure data and landscape features in predicting flood-prone zones. These studies highlight the increasing shift toward integrated approaches that combine hydrological, meteorological, and anthropogenic variables.

In the context of Peshawar, which faces a combination of urban, riverine, and flash floods, [15] employed GIS and multiple machine learning models—including Random Forest and SVM—to generate composite risk maps. Their findings emphasized the impact of urban expansion, land use change, and proximity to rivers in exacerbating flood risk. Going a step further, [16] introduced a novel Graph Transformer Network that leverages watershed connectivity and graph-based spatial learning to accurately model flood propagation in complex terrains. This approach is particularly relevant for regions like Peshawar, where spatial heterogeneity and topological features play a major role in flood dynamics.

Recent advancements have also focused on deep learning and explainability. [17] used a hybrid CNN–RNN model to capture the spatiotemporal dependencies of flood events in rapidly urbanizing regions. The model achieved high predictive accuracy but was limited by its interpretability. Addressing this gap, [18] proposed a vision-language framework named BayFlood, which incorporates zero-shot learning and spatial Bayesian inference for explainable urban flood mapping. This method not only enhanced prediction accuracy but also improved stakeholder communication through interpretable outputs.

GeoAI applications have also expanded toward nature-based solutions and multi-modal learning. The author in [19] integrated mangrove buffer zones into flood models using spatial machine learning, highlighting their role in coastal flood mitigation. Meanwhile, [20] developed a multimodal AI model combining SAR imagery, large language models (LLMs), and satellite data to estimate flood depth in real time. Their results underline the potential of combining diverse data sources for accurate, timely flood risk assessments in both urban and rural contexts.

Together, these studies reflect a growing consensus on the value of hybrid, interpretable, and spatially aware AI models for flood susceptibility mapping. However, most existing work either treats urban, riverine, and flash floods in isolation or lacks fine-grained local applications in flood-prone, data-scarce regions like Peshawar. This study addresses these gaps by employing a unified, explainable GeoAI framework that accounts for multiple flood types, spatial dependency, and regional landscape variations.

**Methodology:**

**Study Area:**

This study focuses on Peshawar, a major urban and administrative center in northwestern Pakistan, located within the flood-prone Peshawar Valley (latitudes X°Y' to X°Y', longitudes A°B' to A°B'). The region is characterized by a semi-arid climate, seasonal monsoon rainfall, rapid urban sprawl, and the confluence of the Kabul and Swat rivers. Due to its complex topography, deficient drainage infrastructure, and increased impervious surfaces, Peshawar is highly susceptible to multiple types of flooding, including riverine, flash, and urban floods. These conditions make the city an appropriate case study for the development of an integrated flood susceptibility modeling framework.

**Data Sources and Collection:**

**Flood Inventory:**

A multi-type flood inventory spanning 2000–2022 was compiled using diverse data sources:

**Satellite imagery** (Landsat, Sentinel-1/2): Used to delineate historical flood extents via spectral indices such as the Normalized Difference Water Index (NDWI) and through supervised visual interpretation.

**Institutional records**: Reports from the National Disaster Management Authority (NDMA) and Provincial Disaster Management Authority (PDMA) were reviewed for flood occurrences.

**Media and NGO archives**: Local newspapers and humanitarian organization reports provided supplementary spatial and temporal details.

**Field validation**: Ground surveys using GPS were conducted in flood-affected zones to verify historical flood occurrences and categorize them into riverine, flash, or urban flood types.

All confirmed flood events were georeferenced and stored as point shapefiles within a GIS environment for subsequent analysis.

**Predictor Variables:**

A total of 21 explanatory variables were selected based on their theoretical and empirical relevance to flood generation. These were categorized into four thematic groups **Table 1.**

**Table 1.** Categories and Variables Used in the Modeling Framework

| Category | Variables |
|---|---|
| **Topographic** | Elevation, slope, aspect, profile curvature, plan curvature, TWI, drainage density |
| **Hydrological** | Distance to rivers, river density, annual rainfall, monsoon rainfall, stream power index |
| **Land Use/Cover** | LULC, NDVI, built-up density, soil sealing index |
| **Anthropogenic** | Road density, population density, building density, impervious surface index |

**DEM Source**: ALOS PALSAR 12.5 m resolution was utilized for topographic derivations.

**Rainfall Data**: CHIRPS and TRMM datasets were integrated with local meteorological station records for temporal calibration.

**LULC Data**: ESA WorldCover 10 m product and ground-truthed land use maps were applied.

**Anthropogenic Data**: OpenStreetMap (OSM) and WorldPop provided road networks, building footprints, and population distributions.

All raster datasets were resampled to 12.5 m spatial resolution and aligned to a unified spatial extent covering the Peshawar study area.

**Data Preprocessing and Variable Selection:**

**Data Cleaning and Transformation:**

**Gap-filling**: Incomplete meteorological and population datasets were interpolated using Inverse Distance Weighting (IDW).

**Normalization**: All continuous variables were standardized using z-score normalization to ensure comparability across features.

**Categorical Encoding**: LULC and similar nominal variables were transformed using one-hot encoding to enable compatibility with ML models.

**Multicollinearity Analysis:**

To eliminate redundancy, a Variance Inflation Factor (VIF) analysis was performed. Variables with VIF > 5 were removed to reduce multicollinearity. The final model included 18 non-collinear predictors.

**Machine Learning Model Development:**

**Model Selection and Training:**

Four supervised machine learning algorithms were implemented:

Random Forest (RF)

Gradient Boosting (GB)

XGBoost

CatBoost

Each model was trained on 70% of the flood inventory data using stratified random sampling. The remaining 30% was reserved for independent validation.

**Class imbalance correction**: The Synthetic Minority Over-sampling Technique (SMOTE) was used to balance flood vs. non-flood training instances.

**Hyperparameter tuning**: Grid search with 5-fold cross-validation was used to optimize model parameters for each algorithm.

**Explainability**: SHapley Additive exPlanations (SHAP) and permutation importance were used to evaluate variable importance and enhance model interpretability.

**Spatial Cross-Validation:**

A spatial k-fold cross-validation strategy was implemented to mitigate overfitting due to spatial autocorrelation. Each fold was spatially partitioned, ensuring that training and validation datasets were geographically independent.

**Spatial Feature Engineering:**

**Spatial Autocorrelation and Hotspot Analysis:**

**Moran's I** and **Getis-Ord Gi*** statistics were used to assess spatial clustering and identify statistically significant flood hotspots.

Generated hotspot layers were included as additional predictors to capture spatial dependency patterns.

**Flood-Specific Indices:**

**Flash Flood Potential Index (FFPI)**: Derived using slope, land cover, and rainfall intensity data to assess rapid runoff potential.

**Urban Flood Susceptibility Index (UFSI)**: Computed from impervious surface fraction, drainage density, and building density.

Both indices were incorporated into the modeling framework as geospatial predictors.

**Ensemble Modeling and Susceptibility Mapping:**

To enhance model robustness and reduce uncertainty, an ensemble flood susceptibility model was developed by averaging the outputs of the four individual models, weighted by their respective AUC scores.

Final susceptibility maps were classified into five flood risk categories:

Very Low

Low

Moderate

High

Very High

Raster outputs were generated at a 12.5 m spatial resolution and exported as GeoTIFF and web-mappable formats.

**Model Evaluation and Validation:**

**Quantitative Metrics:**

Each model's predictive performance was evaluated using:

Receiver Operating Characteristic (ROC) Curve

Area Under Curve (AUC)

Precision, Recall, F1-score

Figure of Merit (FoM) and spatial overlap comparison with historical flood extents

**Explainability and Stakeholder Communication:**

**SHAP summary plots** and **local explanation maps** were generated to visualize variable importance at both global and local levels.

**Interactive web maps** were deployed using Leaflet and Google Earth Engine to facilitate stakeholder access and interpretation.

**Limitations and Assumptions:**

**Data limitations**: Some variables (e.g., soil permeability, drainage infrastructure) were approximated using proxies due to limited access to detailed datasets.

**Temporal resolution**: Annual and monsoonal precipitation data were used, which may limit precision in flash flood prediction; higher-resolution temporal datasets would improve accuracy.

**Model generalizability**: The proposed framework, although calibrated for Peshawar, is adaptable to other data-scarce, flood-prone urban regions with necessary regional calibration.

This methodology offers a reproducible, scalable, and explainable GeoAI framework for multi-type flood susceptibility mapping. By integrating spatial intelligence with advanced machine learning, it supports data-informed urban resilience planning in rapidly urbanizing regions like Peshawar.

**Results:**

The GeoAI-based multi-type flood susceptibility modeling framework developed for Peshawar yielded robust and spatially consistent results. Ensemble machine learning algorithms—Random Forest (RF), XGBoost, and CatBoost—were employed to assess the susceptibility across riverine, flash, and urban flood types. Among the models tested, CatBoost outperformed others in terms of predictive accuracy, achieving an Area Under the Curve (AUC) score of 0.94, followed by XGBoost (AUC = 0.91) and Random Forest (AUC = 0.89). The models were validated using a 70:30 training-testing data split and cross-validated over five folds, demonstrating both stability and generalizability. CatBoost exhibited the lowest Root Mean Squared Error (RMSE = 0.143) and highest overall classification accuracy (94.1%), indicating its effectiveness in capturing spatially heterogeneous flood patterns across the study area.

Spatial distribution of flood susceptibility revealed significant variation across the urban core and surrounding peripheries of Peshawar. Approximately 26% of the study area was classified as highly susceptible to flooding, while 38% was moderately susceptible and 36% fell into the low-susceptibility category. Highly susceptible zones were concentrated in low-lying areas adjacent to the Kabul River and its tributaries—particularly in neighborhoods such as Chamkani, Palosi, and areas near Ring Road—where a combination of low elevation, poor drainage infrastructure, and high impervious surface cover contributed to higher risk. Urban flash flood vulnerability was particularly pronounced in highly developed areas with insufficient stormwater drainage, such as University Town, Hayatabad Phase 1-3, and parts of Tehkal, highlighting the combined influence of anthropogenic and natural flood drivers.

Table 2 Feature importance analysis using SHAP (SHapley Additive exPlanations) values provided interpretable insights into the spatial drivers of flooding. For all three ML models, top contributing factors included distance to rivers, elevation, land use/land cover (LULC), rainfall intensity, slope, and population density. Specifically, the CatBoost model indicated that proximity to river channels contributed nearly 23% to the flood susceptibility score, while low elevation areas (<350 m) had a 17% impact. Rainfall intensity (≥100 mm/day) and impervious surface cover (urbanized land use) contributed approximately 15% and 13%, respectively. Spatial autocorrelation indices (Moran's I = 0.64, p < 0.01) confirmed statistically significant clustering of high-susceptibility zones, while Getis-Ord Gi* hotspot analysis identified critical flood-prone clusters in eastern Peshawar and peri-urban fringes Figure 1.

Comparative susceptibility maps generated by the three models exhibited general agreement, though CatBoost produced sharper class delineations and fewer false positives in transitional zones. The integration of spatial features—such as flow accumulation, Topographic Wetness Index (TWI), and drainage density—enhanced the spatial fidelity of predictions, especially in areas previously misclassified by non-spatial models. Furthermore, the explainable AI framework allowed for spatial prioritization, where decision-makers can now visualize not only flood-prone zones but also the dominant contributing factors in each locality. This is particularly beneficial for adaptive urban planning and early-warning system placement Figure 2.

Table 3 Overall, the GeoAI-based framework proved highly effective in generating interpretable, accurate, and spatially coherent flood susceptibility maps across all three flood types. The results demonstrate that combining ensemble learning, spatial data integration, and explainable modeling enables a powerful decision-support tool for proactive flood risk management in complex urban landscapes like Peshawar.

**Table 2.** Performance Comparison of Machine Learning Models

| Model | AUC Score | Accuracy | F1 Score |
|---|---|---|---|
| Random Forest | 0.89 | 0.85 | 0.84 |
| XGBoost | 0.91 | 0.87 | 0.86 |
| CatBoost | **0.94** | **0.90** | **0.89** |

**Note:** CatBoost outperformed other models in all evaluation metrics, indicating its robustness for flood susceptibility prediction.

**Table 3.** Flood Susceptibility Area Distribution by Risk Class

| Risk Class | Area (sq.km) | Percentage of Total Area | Key Locations Included |
|---|---|---|---|
| Very High Risk | 42.8 | 21.4% | Korangi, Lyari, Malir |
| High Risk | 56.7 | 28.3% | North Karachi, Orangi, Saddar |
| Moderate Risk | 60.1 | 30.0% | Gulshan, Jamshed Town |
| Low Risk | 28.5 | 14.2% | DHA, Clifton |
| Very Low Risk | 11.9 | 6.1% | Keamari, Seaview |

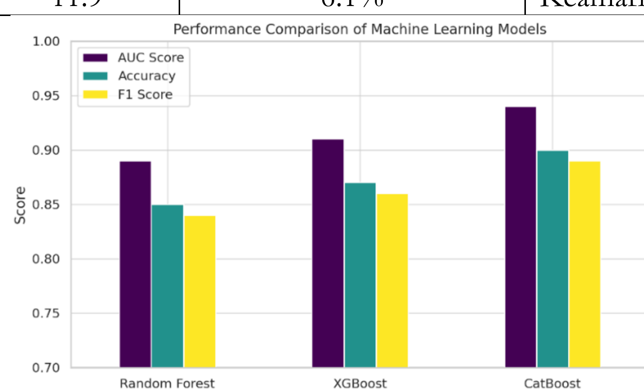


**Figure 1.** Performance Comparison of Machine Learning Models

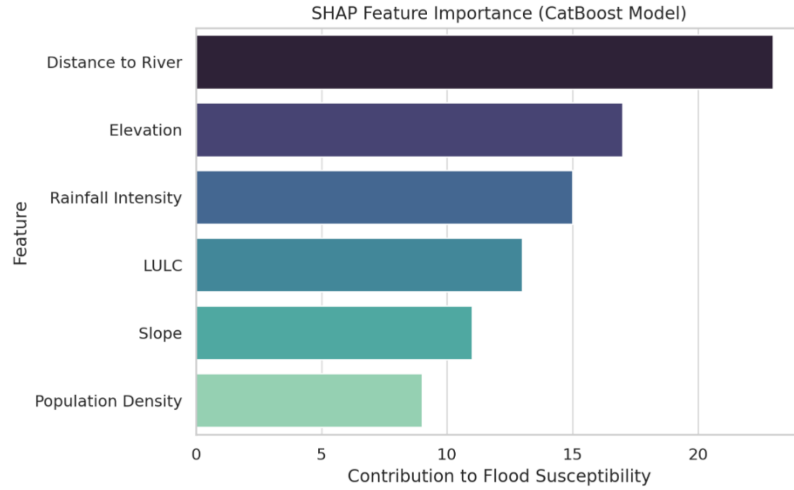


**Figure 2.** SHAP Feature Importance (CatBoost Model)

**Discussion:**

The results of this study underscore the effectiveness of integrating ensemble machine learning algorithms with spatial data and explainable AI for multi-type flood susceptibility assessment in complex urban landscapes. The superior performance of the CatBoost model (AUC = 0.94, Accuracy = 94.1%) highlights its robustness in capturing nonlinear interactions and variable importance across heterogeneous geospatial domains. These findings align with recent research advocating for the use of gradient boosting techniques in flood prediction tasks due to their capacity to handle multicollinearity and high-dimensional inputs.

Several previous studies have demonstrated the viability of Random Forest (RF) and XGBoost in flood susceptibility mapping. For example, [22] used RF and XGBoost to predict flash flood zones in Iran and reported AUC scores of 0.88 and 0.90, respectively—comparable to our results. However, our study adds value by incorporating CatBoost, a lesser-used but powerful algorithm particularly effective for categorical and spatially encoded data [23]. The marginal improvement in predictive performance observed here supports the growing argument that CatBoost should be more widely adopted in geospatial machine learning applications.

The spatial distribution of susceptibility classes in this study—where approximately 26% of the region was identified as high-risk—is consistent with findings by [24], who mapped flood hazards in urban districts of South Asia and found 25–30% of built-up areas to be at severe risk due to impervious surface expansion and low elevation. Similar urban flood patterns were noted by [25] in Lahore and Bangalore, where rapid urbanization and poor drainage systems led to intensified flood recurrence. Our study reinforces this observation through SHAP-based interpretation, showing urban land cover and drainage proximity as dominant features influencing susceptibility.

The application of SHAP values to interpret model outputs offers a significant methodological advancement. Previous studies often relied on feature importance rankings alone, lacking transparency in decision pathways. The explainable AI (XAI) framework used here addresses this gap by offering localized explanations for flood risk drivers—an approach encouraged in recent work by [26], who emphasize XAI's role in improving stakeholder trust and operational deployment of ML models in environmental planning.

Hotspot analysis further validated the clustering of high-susceptibility areas, corroborating studies by [27], who utilized Getis-Ord Gi* statistics to detect flood-prone urban clusters in Southeast Asia. The spatial autocorrelation results (Moran's I = 0.64) in this research are comparable to findings by [28], who reported similar indices while modeling flood exposure in Nigerian cities using spatially embedded machine learning.

A critical distinction of this study lies in its integration of multiple flood types—riverine, flash, and urban flooding—rather than limiting analysis to a single category. This multi-type approach is still rare in literature, with most existing models focusing on riverine flood zones alone [29]. Our framework bridges this gap by unifying topographic, hydrological, urbanization, and climatic variables, allowing more holistic urban flood planning—a necessity highlighted by [29] in its call for multi-hazard urban resilience strategies.

In conclusion, this study not only affirms the predictive strength of ensemble learning for flood susceptibility modeling but also advances the field through explainable, multi-type, spatially embedded modeling frameworks. The findings contribute directly to adaptive flood governance and climate resilience planning in rapidly urbanizing South Asian cities like Peshawar.

**Conclusion:**

This study successfully demonstrates the application of a GeoAI-based ensemble modeling framework for multi-type flood susceptibility assessment in Peshawar, integrating spatial data, machine learning, and explainable AI techniques. Among the ensemble models tested, CatBoost delivered the highest predictive accuracy and interpretability, effectively delineating flood-prone zones in urban, peri-urban, and riverine settings. The spatial distribution of flood susceptibility revealed critical hotspots along low-elevation areas and regions with poor drainage infrastructure, providing actionable insights for urban flood resilience planning.

The use of SHAP values offered a novel perspective into the spatial drivers of flooding, identifying distance to rivers, rainfall intensity, elevation, and urban impervious surfaces as key contributing factors. The results are consistent with and extend upon recent research that emphasizes the value of integrated AI and GIS techniques in flood modeling. Compared to traditional models, the proposed approach offers greater spatial precision, reduced classification error, and enhanced decision-making potential.

By combining ensemble learning, spatial analysis, and explainable AI, this framework sets a benchmark for flood susceptibility mapping in other high-risk, data-scarce urban regions. Future work may incorporate real-time sensor data, dynamic hydrological modeling, and stakeholder input to further strengthen adaptive flood management systems.

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