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Urban Waterlogging Risk Prediction Considering the Influence of Land Use Patterns: A Case Study of Shenzhen

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ABSTRACT

Predicting urban waterlogging risk influenced by land use dynamics has become increasingly important with growing urbanization. However, prior studies have scarcely considered the influence of land use patterns. The present study proposes a novel methodology for predicting waterlogging risk, while exploring the enhancement effect of incorporating landscape indices on prediction. The present study proposes an enhanced framework for predicting waterlogging risk, while exploring how incorporating landscape indices affects prediction. This framework integrates the MaxEnt and PLUS methods, which are specifically designed to incorporate landscape indices. It can enhance the predictive performance and interpretability of waterlogging risk. The integrated model was constructed using data from 2015, and its accuracy was validated with data from 2020. First, landscape indices were computed and the PLUS model was constructed based on the land use data from 2015. Subsequently, we trained two sets of MaxEnt models (with and without landscape indices) using the waterlogging data from 2015, and simulated the landscape indices and waterlogging risk in 2020 with the MaxEnt-PLUS method being utilized for this purpose. The findings indicate that the incorporation of landscape indices resulted in an enhancement of the AUC value of the MaxEnt model from 0.919 to 0.928. Furthermore, the results of the waterlogging risk simulation are more consistent with actual waterlogging hotspots. Therefore, the calibrated PLUS model was deemed appropriate for the purpose of predicting future land use change. Then, the MaxEnt-PLUS method was employed to project the waterlogging risk in 2030, and the changing patterns of the various risk areas during 2015–2030 were examined. In summary, the proposed method could enhance the reliability of waterlogging risk prediction, thereby providing decision support for sponge city planning and stormwater management.

1 | Introduction

Urban waterlogging is a consequence of accelerating global urbanization processes. This phenomenon is particularly evident in economically developed cities because of their high percentage of impervious surfaces (Zheng et al. 2016; Li et al. 2022; Xiao et al. 2024; Zhou et al. 2025). Waterlogging has far-reaching consequences that affect various aspects of urban life, including traffic, residences, and infrastructure (Paprotny et al. 2018; Hu et al. 2019; Tang, Tian, et al. 2024; Wang, Xiao, et al. 2024; Li et al. 2025). Many nations have adopted diverse strategies to address waterlogging. For instance, the "sponge city" strategy is a means of reducing waterlogging risk, with a focus on decreasing surface runoff and enhancing infiltration (Wang et al. 2018; Li et al. 2023). Nevertheless, examining only historic and current instances of waterlogging is insufficient for the effective mitigation of future risks. The ability to predict waterlogging risk with reasonable accuracy is essential, as it enables the implementation of precise measures to address the issue by targeting high-risk areas in advance. This emphasizes the urgent need for methodologies capable of predicting future waterlogging risk, which is a key concern in environmental planning and management.

Previous studies have proposed a variety of methodologies for assessing and predicting waterlogging risk. These methodologies include the analytic hierarchy process, hydrological models, and machine learning techniques (Park and Lee 2024; Tang, Wang, et al. 2024; Yang et al. 2024; Liu et al. 2025; Zeng et al. 2025). The analytic hierarchy process typically evaluates waterlogging risk by examining the connections between waterlogging occurrences and influencing factors through expert judgment (Thanvisitthpon et al. 2020; Taromideh et al. 2022). However, these methods are limited by the subjectivity of the experts involved. Conversely, hydrological models assess waterlogging risk by simulating rainfall runoff and physical processes within the drainage system (Nkwunonwo et al. 2020; Prodanovic et al. 2022). Nevertheless, the suitability of these models for simulating larger areas is typically limited because of the requirement of high-accuracy hydrological and meteorological data. In comparison, machine learning techniques are effective in capturing the nonlinear relationships between dependent and independent variables, which can eliminate the need for complex hydrographic data. Therefore, machine learning has been increasingly applied to waterlogging risk prediction in recent years. For instance, Darabi et al. (2020) utilized random forests to predict waterlogging risk by integrating remote sensing and meteorological information. Rafiei-Sardooi et al. (2021) employed support vector machines to predict areas with a high likelihood of waterlogging. Yan et al. (2024) utilized two ensemble machine learning methods to estimate urban waterlogging susceptibility. Tehrany et al. (2019) applied decision trees and support vector machines to analyze the potential factors that influence waterlogging.

Nonetheless, the training process of conventional machine learning requires accurate positive and negative samples. Given the sudden and localized nature of urban waterlogging events, the availability of data pertaining to waterlogging occurrence is often limited, particularly with regard to obtaining reliable negative samples (Chen et al. 2023; Xu et al. 2023). Maximum entropy (MaxEnt) model can address this challenge, which was originally developed for simulating species distribution. The MaxEnt model has been shown to be capable of identifying high-risk areas for disasters based on the occurrence of disasters and the associated influencing factors (Eini et al. 2020; Javidan et al. 2021; Lin et al. 2022; Pourghasemi et al. 2023; Li et al. 2024). Another advantage of MaxEnt is its ability to make accurate predictions with limited sample data (Phillips et al. 2006). The aforementioned features of the MaxEnt model render it a suitable tool for predicting waterlogging risk, a phenomenon that is neither uniform in its distribution nor abundant in occurrence.

In addition to prediction methods, the determination of factors influencing waterlogging can significantly affect prediction performance. Land use changes, particularly impervious surfaces and green spaces, are closely related to waterlogging (Berndtsson et al. 2019; Wu et al. 2022; Xu et al. 2024; Thanvisitthpon et al. 2025; Zhang et al. 2025). For instance, Wang, Zhang, et al. (2024) pointed out that land use dynamics exert a pivotal effect on the occurrence of urban waterlogging. Feng et al. (2025) highlighted that well-planned allocation of green infrastructure could enhance waterlogging control performance. Dai et al. (2024) found that land use significantly affects the absorption rate of surface runoff, which in turn exacerbates or mitigates waterlogging risk. Zhang et al. (2023) concluded that vegetation cover and impervious surface percentage have increasing effects on waterlogging over time. Zhao et al. (2025) demonstrated that optimizing the spatial distribution of impervious surfaces can effectively reduce waterlogging risk. Therefore, the utilization of land use simulation models has become increasingly prevalent in waterlogging risk prediction (Zhao et al. 2023). For instance, Wu et al. (2022) combined FLUS and SCS models to predict future changes in waterlogging risk. Lin et al. (2022) proposed an approach for predicting waterlogging risk by combining MaxEnt and FLUS. Wang, Chen, et al. (2023) employed PLUS and MaxEnt to predict waterlogging risk under different scenarios. Liu et al. (2023) utilized FLUS and multivariate linear regression models to predict flood risk.

However, a lack of consideration has been demonstrated in previous studies with regard to the influence of land use patterns. Landscape indices can effectively quantify the spatial characteristics of land use (Cushman et al. 2008; Lin et al. 2023; Han et al. 2024). Specifically, the connectivity, fragmentation degree, and dominance of land use patches have significant impacts on rainwater flow and regulation. Highly connected green spaces can effectively store surface runoff and reduce waterlogging. Conversely, the fragmentation of green and blue infrastructures can compromise their capacity to store stormwater (Miller and Brewer 2018; Zhai et al. 2021). For instance, Su et al. (2018) demonstrated that waterlogging risk positively correlates with the fragmentation of green space. Miller and Brewer (2018) highlighted that landscape indices can quantify the rainwater storage capacity of land use. Yuan et al. (2019) discovered a close correlation between the landscape patterns of land use and waterlogging. Wu et al. (2020) highlighted the impact of different landscape patterns on waterlogging disasters. Wang, Guan, et al. (2023) revealed a significant association between the landscape patterns of land use and surface runoff depth.

In light of these results, incorporating the significant impact of land use patterns into waterlogging risk prediction has the potential to enhance the rationality of the results. Therefore, the aim of the present study is to put forward a novel waterlogging risk prediction methodology that considers landscape indices of various land use types. Specifically, the impact of land use patterns on waterlogging was assessed based on the MaxEnt. Then, the PLUS method was utilized in the projection of future land use patterns. Finally, the MaxEnt and PLUS methods were integrated to explore whether the incorporation of land use patterns could enhance waterlogging risk prediction. It is anticipated that this proposed methodology will provide valuable guidance for the design of blue-green spaces, thereby providing significant contributions for the establishment of "sponge cities".

2 | Methods and Data

2.1 | Case Study

Shenzhen, a preeminent megacity in southeastern China, serves as an ideal case for validating the proposed framework (Figure 1). Owing to its climatic conditions and high degree of urbanization, Shenzhen is one of the most representative and vulnerable cities to waterlogging worldwide (Yang et al. 2022).

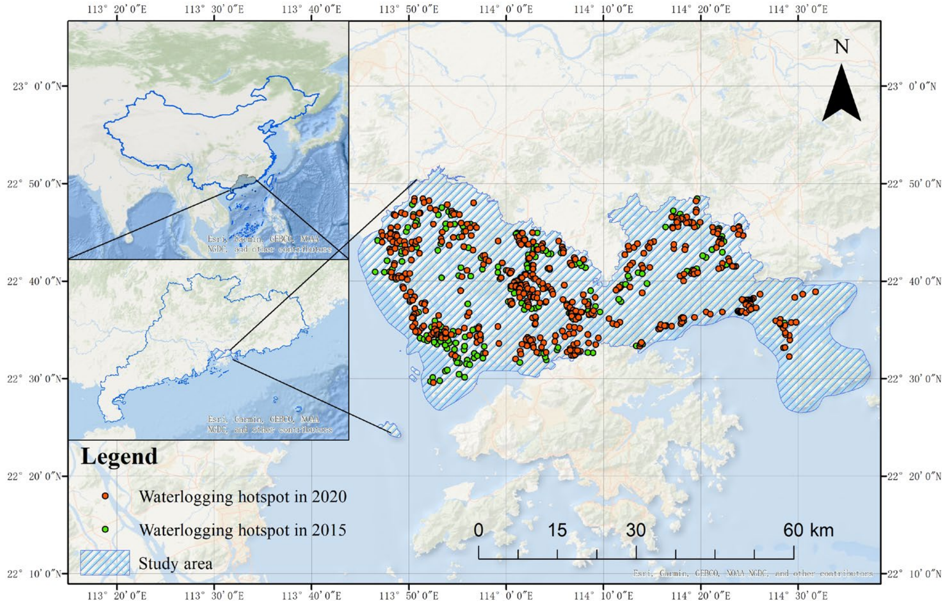

FIGURE 1 | Location of Shenzhen and distribution of waterlogging hotspots.

TABLE 1 | Data used in this study.

Data	Features	Source
Waterlogging hotspot	Point	Sponge City Planning of Shenzhen
Land use	30 m	Chinese Academy of Sciences
Road network	Line	Amap
Administrative division	Polygon	National Geomatic Center of China
DEM	30 m	Geospatial Data Cloud Platform
NDVI		
Extreme rainstorm volume	1 km	Shenzhen Municipal Bureau of Meteorology
Overpass	Point	Amap

Furthermore, the expansion of impermeable surfaces and the fragmentation of blue-green spaces result in inadequate waterlogging discharge capacity, making it challenging to manage extensive precipitation (Xu et al. 2024). Therefore, a case study of Shenzhen is highly suitable for demonstrating the applicability of the proposed MaxEnt–PLUS–landscape index framework.

2.2 | Data

The data employed in this study are presented in Table 1. The waterlogging hotspot data in 2015 and 2020 were employed for model training and validation, respectively. Land use data in 2015 and 2020 were obtained as inputs to the PLUS model. These data were also used to calculate landscape indices, land use proportions, and distances from water bodies. Furthermore, DEM was employed to calculate slope, roughness, elevation, and undulation. The extreme rainstorm volume data were also collected. Resampling and normalization were applied to all raster data, resulting in a resolution of 1 km. The selection of a 1 km spatial resolution was driven by both the study's focus on citywide spatial heterogeneity and data availability. First, 1 km is recognized as an effective scale for capturing macro-level urban land use trends while maintaining computational efficiency for multi-scenario simulations (Lin et al. 2022; Nazir et al. 2025; Cai et al. 2026). Second, this resolution aligns with the coarsest input datasets (e.g., extreme rainstorm volume), ensuring data consistency. Furthermore, the area situated 0.5 km from the risk source boundary was identified as the risk area, as this distance is generally considered the radius of daily life for residents (Lin et al. 2018). Therefore, 1 km resolution reflects the operational radius of urban functional zones, making it highly suitable for regional-level strategic planning, where the identification of citywide hotspots is imperative.

2.3 | Methods

In this study, a novel methodology for predicting waterlogging risk is proposed, incorporating the landscape indices of land use. To assess the validity of this approach, the prediction results were compared with those that did not consider landscape indices (Figure 2). First, the data in Table 1 were collated, and the landscape indices of land use were calculated. To ensure spatial alignment, all data were projected onto the same geographic coordinate system and standardized to a 1 km resolution before being entered into the models as factors. Second, the PLUS and MaxEnt models were constructed using the data from 2015 to simulate land use and waterlogging risk in 2020. The results, both with and without consideration of landscape indices, were then compared with the actual situation. Lastly, the proposed method was used to predict the waterlogging risk in 2030.

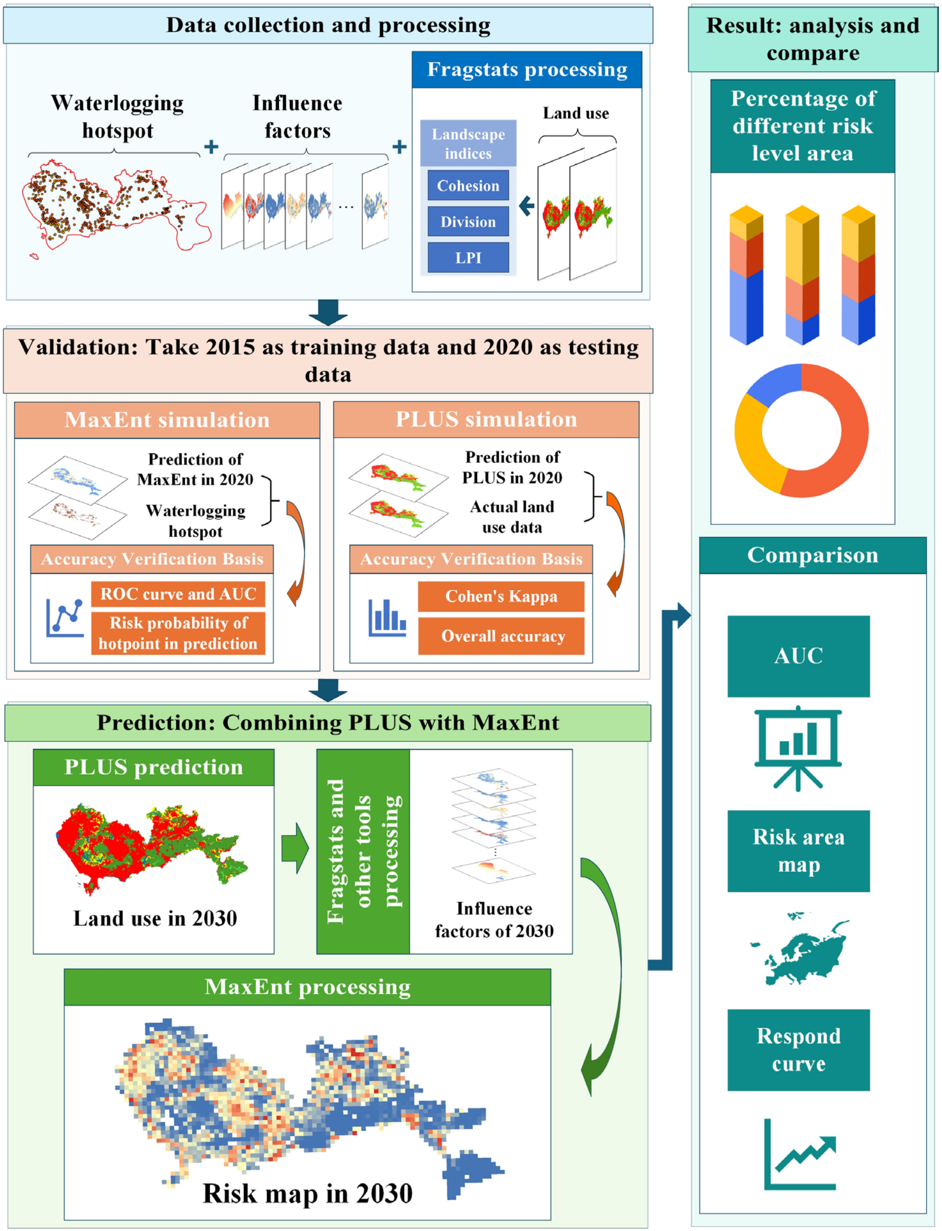

FIGURE 2 | Waterlogging risk prediction considering landscape indices.

2.3.1 | Landscape Indices

Landscape indices are useful for the quantification of spatial characteristics associated with land use. In light of previous findings (Su et al. 2018; Yuan et al. 2019; Kim et al. 2021; Yan et al. 2024) and our own experiments, three class-level landscape indices were adopted: cohesion, division, and largest patch index (LPI). It has been demonstrated that these indices could provide significant insights into the aggregation, segmentation, and dominance of land use. The landscape indices were calculated using Fragstats 4.2. To capture the landscape pattern of each land use class, the eight-cell neighborhood rule was adopted. The calculation was conducted at the class level to maintain consistency with the land use dynamics modeled in the PLUS. Aside from these specific configurations, all other parameters were maintained at their default settings to ensure comparability with previous studies (Kim and Park 2016; Amiri et al. 2018; Kim et al. 2021).

The cohesion quantifies the spatial aggregation of analogous land use patches. Higher values indicate a greater aggregation degree. Aggregated green spaces and water bodies are more effective in controlling stormwater runoff and promoting natural infiltration, thus reducing waterlogging risk. The division is tasked with the quantification of the degree to which land use patches are fragmented. Higher values indicate more segmented land use types and lower connectivity. For green spaces and water bodies, lower connectivity negatively affects their stormwater storage function. The LPI is the percentage of the largest patch for a particular land use type. Higher LPI values indicate a greater prevalence of that land use type in the landscape. Generally, a greater prevalence of green spaces and water bodies means they can store more rainwater, thereby reducing surface runoff from heavy rainfall.

The PLUS model was calibrated to simulate and project land use in Shenzhen, and then the aforementioned landscape indices were computed building upon the associated land use results.

Subsequently, the landscape indices of different land use types were utilized as influencing factors during waterlogging risk prediction.

2.3.2 | MaxEnt

MaxEnt is a species distribution model grounded in maximum entropy theory. This model was initially devised for the purpose of predicting the possible locations of species (Yang et al. 2013; Chen et al. 2024; Li et al. 2024). It has gradually become an effective tool for predicting the spatial distributions of various geographic phenomena (Elith et al. 2011). The present study utilized the MaxEnt model to assess the relationship between waterlogging occurrence and a range of driving factors (e.g., precipitation, topography, land use patterns) and to predict regions susceptible to waterlogging.

The MaxEnt model is grounded in the theoretical framework of estimating the maximum likelihood of a phenomenon occurring under known conditions (e.g., species distribution or waterlogging occurrence). This model is designed to infer probability distributions from observed data (e.g., historical waterlogging hotspots), with the aim of making predictions that are as reasonable as possible without additional information (i.e., entropy maximization). Avoiding unnecessary assumptions is important to ensure the universality of the results while satisfying the known conditions. These characteristics enable the MaxEnt model to maintain a high level of prediction accuracy despite limited samples or incomplete data. The merits of this model are particularly helpful for waterlogging prediction, given the limited sample size of waterlogging data.

In the present study, the MaxEnt model was first employed to simulate waterlogging risk in 2020 based on the waterlogging hotspots in 2015. The precision of the simulated outcomes was validated against the observed waterlogging hotspots in 2020. Following the validation process, future waterlogging risk was predicted by incorporating the future land use projections obtained from the PLUS model.

2.3.3 | Patch-Generating Land Use Simulation (PLUS)

The PLUS model is a state-of-the-art tool that combines historical land use data, spatial factors, and machine learning techniques for land use change projections (Liang et al. 2021; Zhai et al. 2021; Gao et al. 2022). The PLUS model can simulate complex patch-level spatial changes, which renders it especially suitable for predicting future landscape dynamics. This model utilizes landscape patches as the basic unit for spatial data processing, which can simulate land use patches and the corresponding landscape patterns that align with actual conditions.

To ensure the reliability of future waterlogging risk prediction, the predictive performance of the PLUS model was quantitatively evaluated. Specifically, the accuracy of the PLUS was evaluated by utilizing the land use data in 2015 and 2020, and subsequently, prediction of land use in 2030 was made. We projected land use conditions for 2020 using the land use data from 2015, and assessed the model's accuracy through comparison with the actual data from 2020. Once the desired level of accuracy was achieved, Markov chains were utilized to predict the area of every land use type in 2030. Finally, predictions regarding future land use in 2030 were made using the calibrated PLUS model.

3 | Result

3.1 | Land Use Simulation and Validation

The land use data and associated spatial factors from 2015 were imported into the PLUS model to ascertain the developmental possibilities for all land use types. The parameters of the PLUS model were established empirically with consideration of previous studies and iterative tuning (Li et al. 2021; Du et al. 2023; Wang, Hou, et al. 2023) (Table 2). The parameter tuning followed the systematic sensitivity analysis approach of Liang et al. (2021) and Du et al. (2023). In this approach, the patch generation thresholds and neighborhood sizes were iteratively adjusted to maximize the simulation accuracy, as measured by the Kappa coefficient. The model was implemented to generate the land use simulation output for 2020, with water bodies and nature reserves serving as limitations (Figure 3). To validate the model's performance, the simulated land use results were evaluated against the actual data for the same year. The findings show that the Kappa coefficient is 0.944 and the overall accuracy is 0.966, demonstrating a strong reliability of the simulation outcomes.

3.2 | Waterlogging Risk Simulation and Validation Based on MaxEnt

The MaxEnt model was utilized to simulate waterlogging risk based on the waterlogging hotspots and their potential influencing factors from 2015 (Figure 4). In accordance with previous studies and empirical testing to achieve a balance between model complexity and generalization ability (Elith et al. 2011; Wang, Hou, et al. 2023; Li et al. 2024), the parameter setting of the MaxEnt is shown in Table 3. The feature types were set to “auto”, and the regularization multiplier was initially set to 1.0, which has been widely used in risk susceptibility studies. A parameter sweep was then conducted within the range of 0–5, with an interval of 0.1. The model was repeatedly trained using different regularization multipliers, and the AUC was used to evaluate performance. The optimal AUC was achieved when the regularization multiplier was set to 0.1, which was subsequently adopted in the final modeling process.

To validate the selection of MaxEnt over other mainstream machine learning algorithms such as Random Forest, we conducted a comparative performance analysis. Both models were trained under the same conditions by 10 times. Although Random Forest

TABLE 2 | Parameter setting of PLUS model.

Parameter	Setting
Patch generation threshold	0.7
Expansion coefficient	0.1
Percentage of seeds	0.0001
Neighborhood size	15

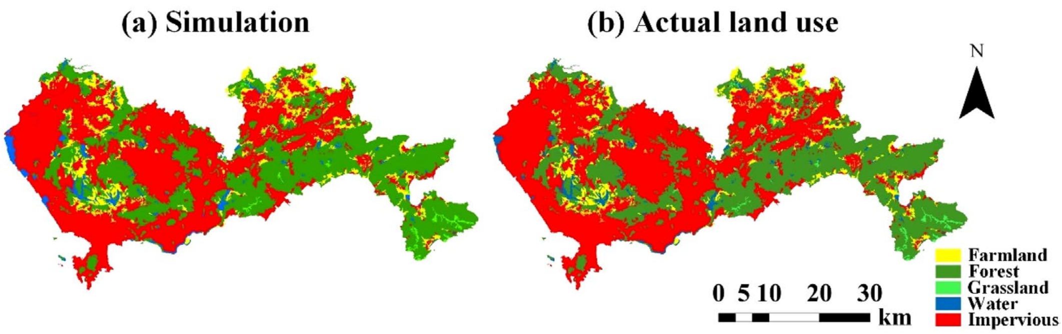

FIGURE 3 | Land use simulation results for 2020.

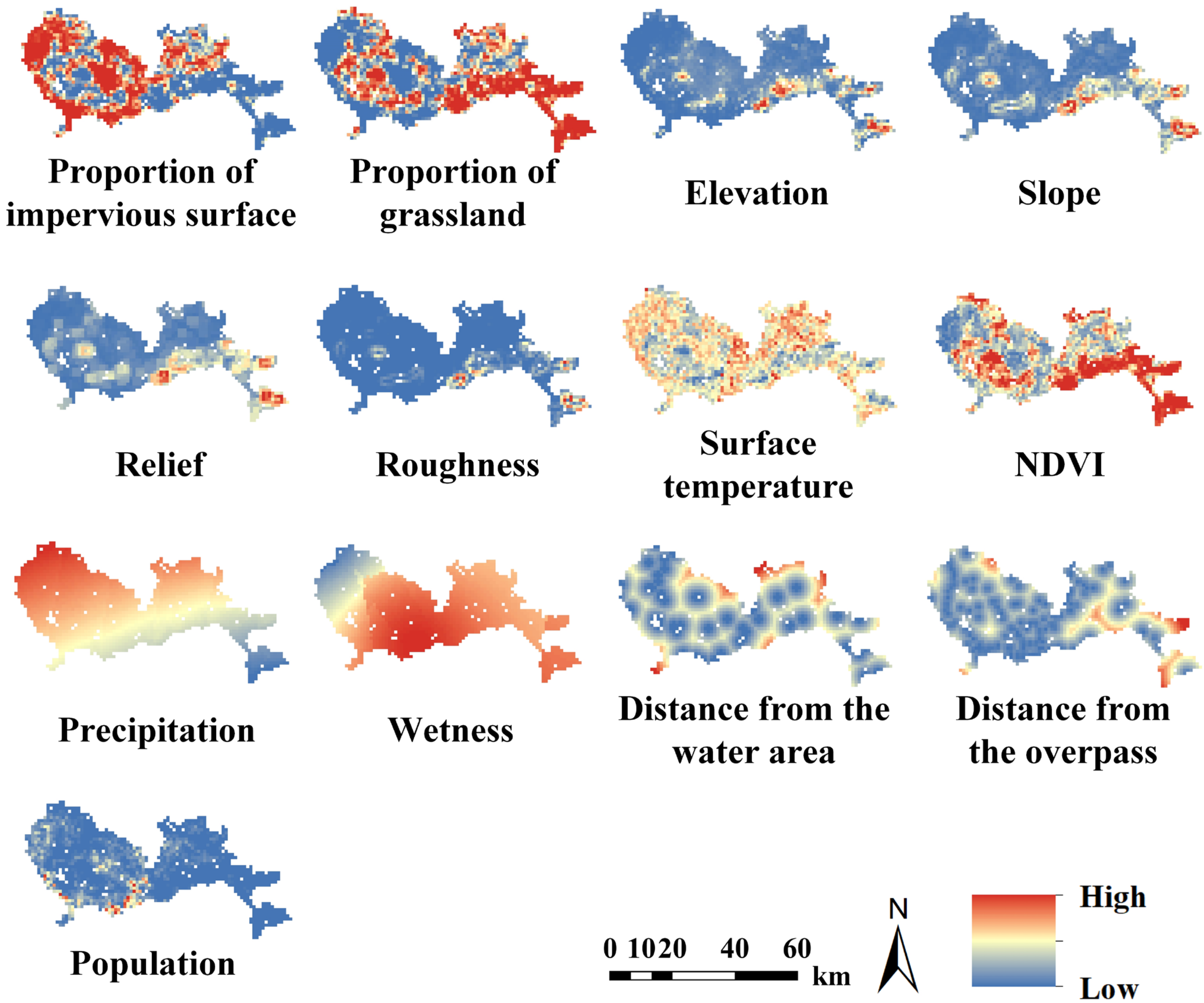

FIGURE 4 | Potential influencing factors of waterlogging.

is a powerful ensemble method, MaxEnt demonstrated higher stability and a superior average AUC (Figure 5). This advantage stems from MaxEnt's maximum entropy principle, which is inherently better suited for presence-only waterlogging events, as it avoids the biases often introduced by unreliable pseudo-absence points in other machine learning models. This methodological choice ensures that our framework remains robust even in data-scarce urban environments. First, waterlogging risk simulation results were obtained without considering landscape indices as influencing factors (Figure 6a and Figure 7a). Subsequently, the same operation was carried out by incorporating landscape indices (Figure 6b and Figure 7b). A comparison of the corresponding ROC curves reveals that the introduction of landscape indices enhances the AUC value to 0.928. As indicated by previous findings, a high level of excellence is typically achieved when the AUC exceeds 0.85 (Wei et al. 2018).

Next, the consistency between the simulated and observed waterlogging risk patterns was analyzed to assess the model's reliability. Specifically, the results were categorized into five levels (low-, lower-, medium-, higher-, and high-risk) based on a natural break method. The probability of waterlogging risk was then summarized based on actual waterlogging hotspots in 2015. Given the substantial adverse impact of waterlogging and the need for preventive measures, the proportion of waterlogging hotspots classified as medium risk and above to all hotspots was calculated, as well as the average risk probability for all waterlogging hotspots. The results indicate that most waterlogging hotspots were within the medium-risk and above levels (95.7% of the total). Furthermore, the average risk probability for all waterlogging hotspots was in the higher-risk level (43.2%), with a greater proportion of waterlogging hotspots falling into the higher- and high-risk levels. Although the average risk probability of waterlogging hotspots without considering landscape indices was also in the higher-risk level (41.5%), the proportion of waterlogging hotspots in the medium-risk and above levels was lower (94.8%). Our findings demonstrate that the waterlogging risk simulation results were generally consistent with the actual situation and were more reliable when landscape indices were included.

TABLE 3 | Parameter setting of MaxEnt.

Parameter	Setting
Feature type	Auto
Random test percentage	25
Regularization multiplier	0.1
Replicates	10
Replicates type	Bootstrap
Maximum iterations	500
Convergence threshold	0.00001
Random seed	ON

In addition, we further predicted the probability of waterlogging risk in 2020 based on the aforementioned methodology (Figure 6c). The validation results indicate that more than half of the waterlogging hotspots were at the medium-risk and above levels (60.8%). Furthermore, the average risk probability for all waterlogging hotspots was 22.5%, which falls within the medium-risk level. When the landscape indices were excluded from the prediction (Figure 6d), the average probability remained in the medium-risk level (25.7%), but the proportion of waterlogging hotspots at the medium-risk and above levels decreased to 57.3%. This finding further emphasizes the significance of incorporating landscape indices in predicting medium- and high-risk areas.

3.3 | Waterlogging Risk Prediction by Combining MaxEnt and PLUS

Next, we predicted the probability of waterlogging risk in 2030. Markov chains were utilized to project the area demand for each land use category. The calibrated PLUS model was then employed to project land use in 2030 (Figure 8a). The land use-related factors (e.g., proportions of green spaces and

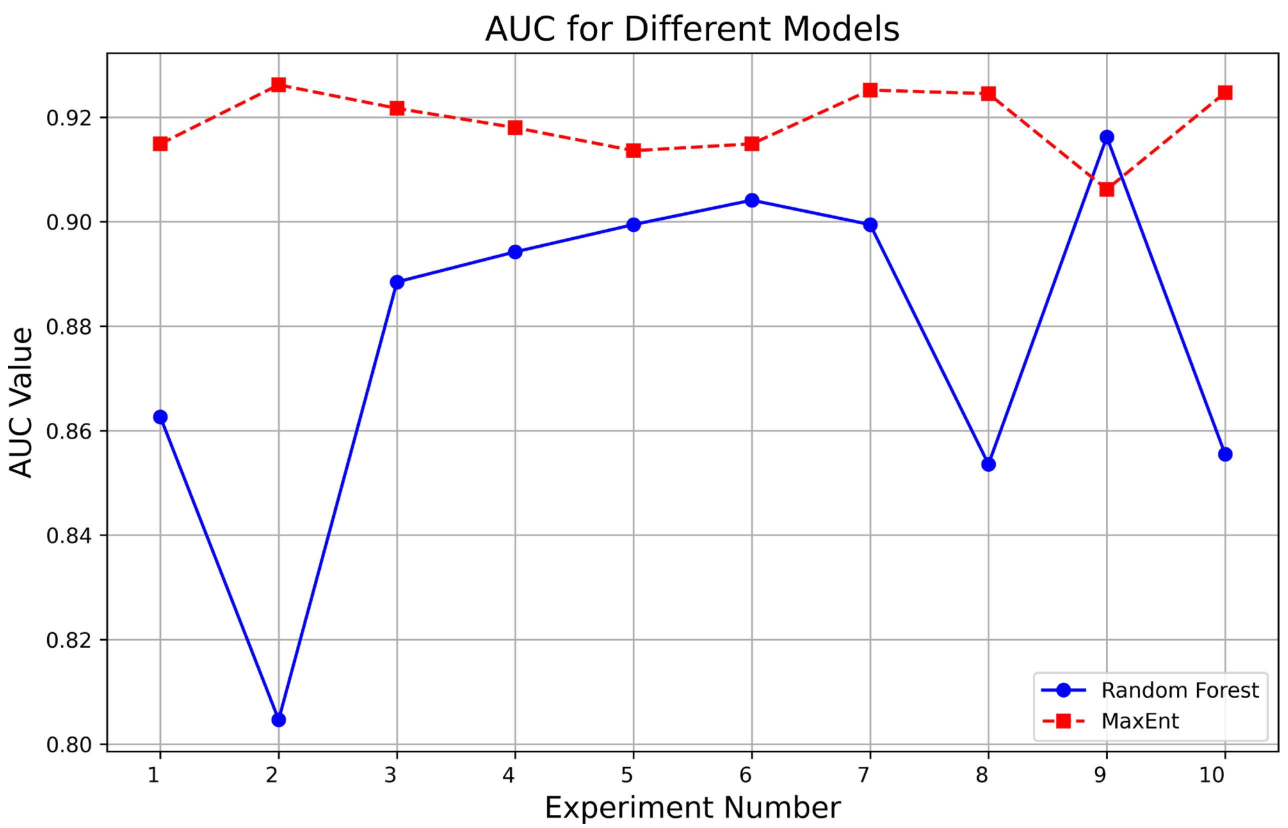

FIGURE 5 | AUC of MaxEnt and Random Forest.

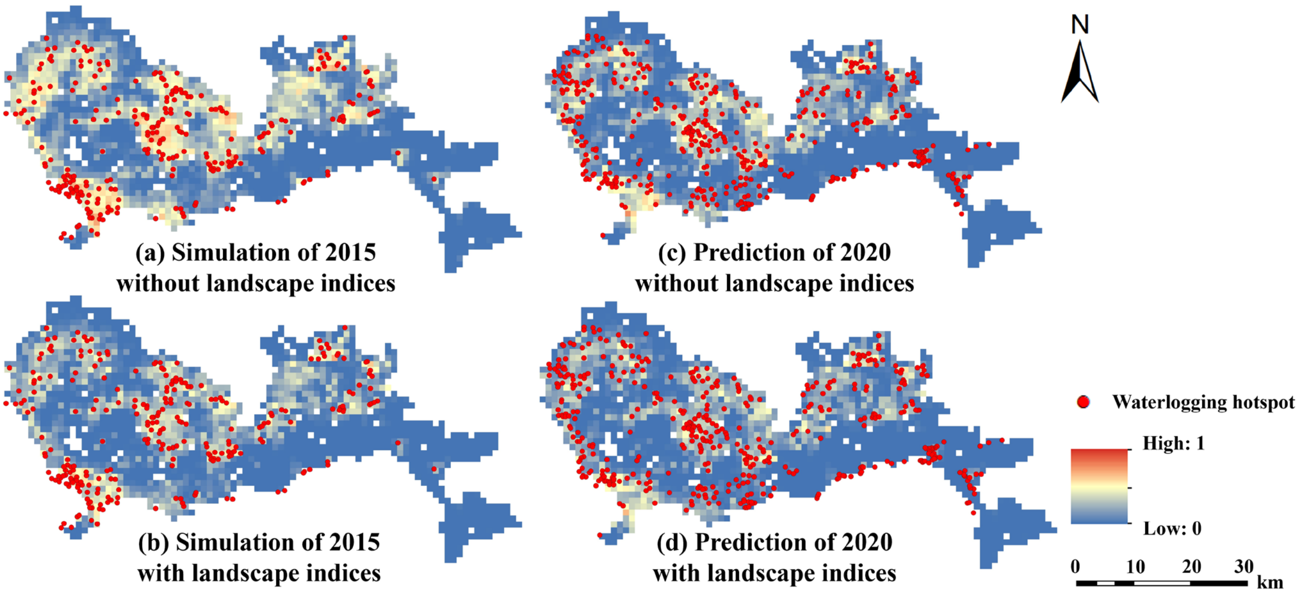

FIGURE 6 | Waterlogging risk simulation for 2015 and 2020.

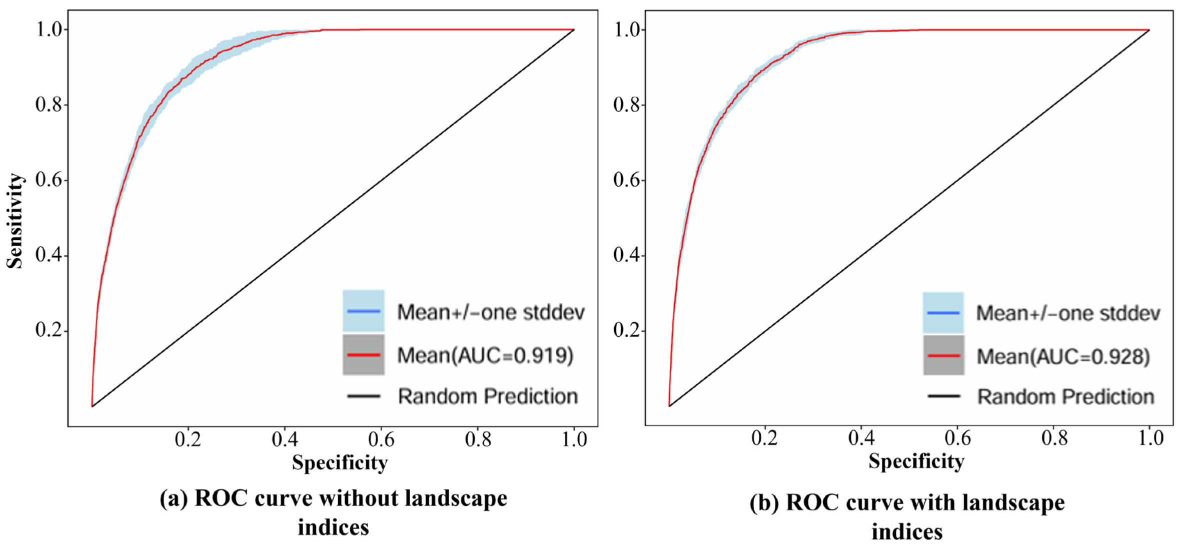

FIGURE 7 | ROC curve of MaxEnt.

impervious surfaces) and landscape indices were derived from the prediction results. Finally, all pertinent factors were incorporated into the MaxEnt model to project the probability of waterlogging risk in 2030 (Figure 8b). The results indicate that the majority of medium- to high-risk areas for waterlogging will be situated in large and contiguous urban cores and remote development areas. These areas are distinguished by a large percentage of impervious surfaces and a high concentration of human activities.

4 | Discussion

4.1 | Comparison of Results With and Without Landscape Patterns

We conducted a comparative analysis to evaluate how the inclusion of landscape pattern information affected the accuracy of waterlogging risk simulations. The findings demonstrate that the incorporation of landscape patterns enhances the AUC value, for instance, increasing from 0.919 to 0.928 in 2015. Furthermore, the modeling results of waterlogging risk probability were overlaid with the actual waterlogging hotspots for validation. Our findings indicate that the incorporation of landscape patterns reduces the proportion of medium- to high-risk areas that do not align with the actual waterlogging hotspots. This improvement is illustrated by the pink circles in Figure 9, which delineate the areas that have been better predicted. The reduction in misclassification can facilitate urban designers in minimizing the investment of financial resources and human labor in non-high-risk areas, thereby enabling a more rational allocation of resources for waterlogging prevention.

The enhancement in accuracy can be attributed to the incorporation of landscape indices (Cohesion, Division, and LPI) during the modeling process. These indices provide substantial insights regarding the spatial distribution and morphological properties of various land use categories, particularly impervious surfaces, grasslands, and water bodies. Specifically, these indices reflect the continuity, fragmentation, and dominance of land use, which can provide more detailed information for waterlogging risk simulation and prediction, thus enhancing the reasonableness of the results.

Furthermore, the incorporation of landscape indices addresses the omission of ecological regulation in conventional methods. In most previous studies, the assessment of waterlogging risk frequently relied on macro-data, including land use proportion, topography, and population. Landscape indices, however, can quantify the regulatory capacity of ecological spaces, including green spaces and water bodies. This advantage helps waterlogging risk assessment models to better identify the role of ecological spaces. For example, in regions with high LPI values, our new model can better identify the mitigation capacity of highly dominant forests and farmlands, thus improving the reasonableness of the modeling results. This information compensates for the shortcomings of using only common factors, allowing the waterlogging risk assessment model to remain highly accurate, even in complex environments.

In summary, urban designers could more reasonably identify medium- to high-risk areas for waterlogging by incorporating the landscape patterns of land use. Targeted waterlogging prevention and land management strategies can then be developed accordingly. The waterlogging risk prediction method proposed in this study could offer data support for future decision-making with regard to land use and the planning of waterlogging prevention measures.

4.2 | Analysis of Changes in Waterlogging Risk Zones

All the waterlogging risk modeling results for 2015, 2020, and 2030 were categorized into five levels using the natural break method. A comparison was then made to reveal alterations in the proportion of each level (Figure 10). The findings indicate a substantial increase in waterlogging risk levels from 2015 to 2020, with a larger proportion of medium- and high-risk areas observed. Between 2020 and 2030, no substantial alterations in waterlogging risk levels were identified. Only a slight reduction in the proportion of higher-risk zones and a minor increase in medium-risk zones occurred.

Furthermore, transfer matrix and Sankey diagram were also employed to reveal the alterations in waterlogging risk areas (Table 4 and Figure 11). The results of the transfer matrix indicate that, from 2015 to 2030, high-risk areas will mostly be

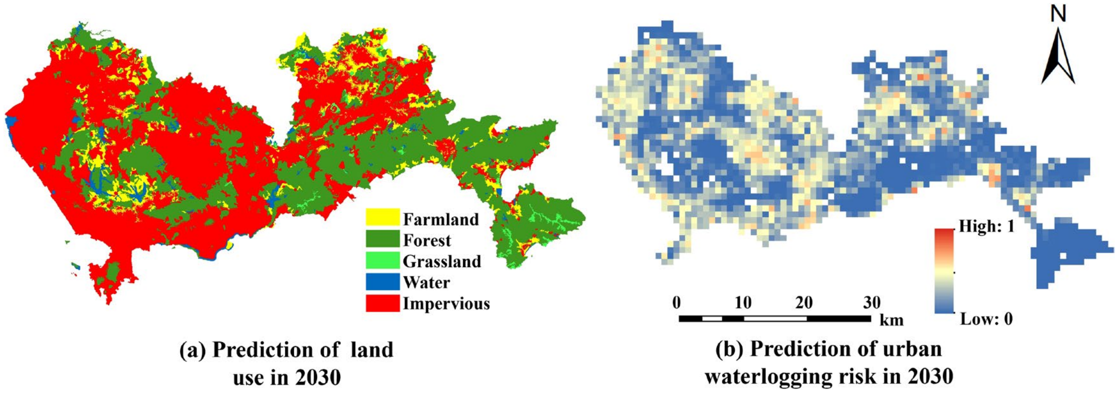

FIGURE 8 | Projection of land use and waterlogging risk in 2030.

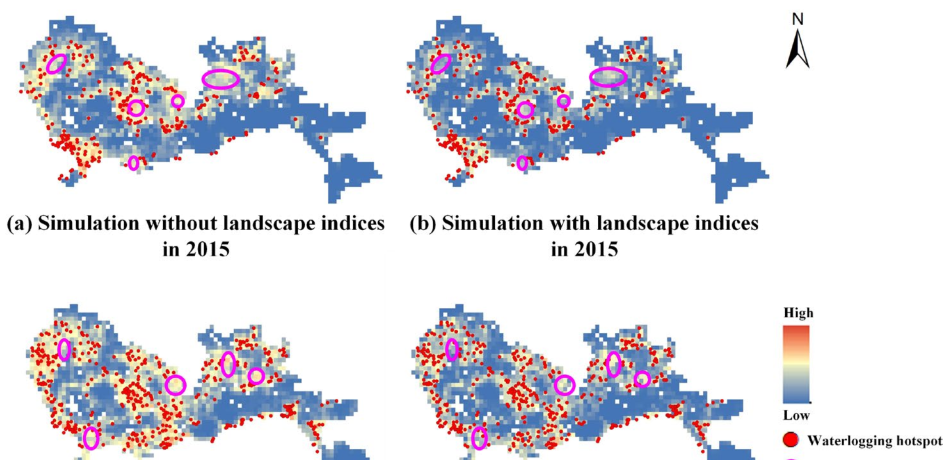

FIGURE 9 | Comparison of simulation results with actual waterlogging hotspots in 2015 and 2020.

converted to higher-risk areas, and higher-risk areas will largely be converted to medium-risk areas. However, some medium-risk areas have a tendency to become higher-risk, and some lower-risk areas have a tendency to become medium- or higher-risk areas.

Overall, the findings suggest a gradual expansion of medium- and low-risk areas, along with a slight decline of areas classified as high- and higher-risk. There will be an increase in waterlogging risk throughout Shenzhen, with a trend toward concentration in medium- and higher-risk areas.

The increase in waterlogging risk between 2015 and 2020 mainly attributes to accelerated urbanization, which has led to the replacement of natural surfaces with impervious ones. This trend was particularly pronounced in core urban areas and peri-urban regions. The expansion of impervious surfaces reduced natural infiltration and stormwater storage capacity, thereby increasing surface runoff. In particular, a rise in medium- to high-risk zones occurred due to the loss of ecological buffer areas, such as forests and farmlands.

The transition between 2020 and 2030 is characterized by a gradual shift. Most medium- and lower-risk areas will show an elevated risk level. Some low-risk areas will transition to lower- or medium-risk levels, mainly in newly urbanized fringes. This reflects that the continued expansion of impervious surfaces causes a decline in infiltration and storage capacity. These findings highlight the necessity for policymakers to monitor waterlogging trends and implement preventive measures in newly developed areas.

4.3 | Implications for Urban Waterlogging Management

The methodological framework proposed in this study, which integrates the PLUS, MaxEnt, and landscape indices, demonstrates a transferable approach for assessing urban waterlogging risks across diverse urbanizing regions. Rather than focusing on site-specific management strategies, this framework underscores the fundamental GIScience principle of incorporating spatial heterogeneity and structural landscape configuration into waterlogging risk modeling.

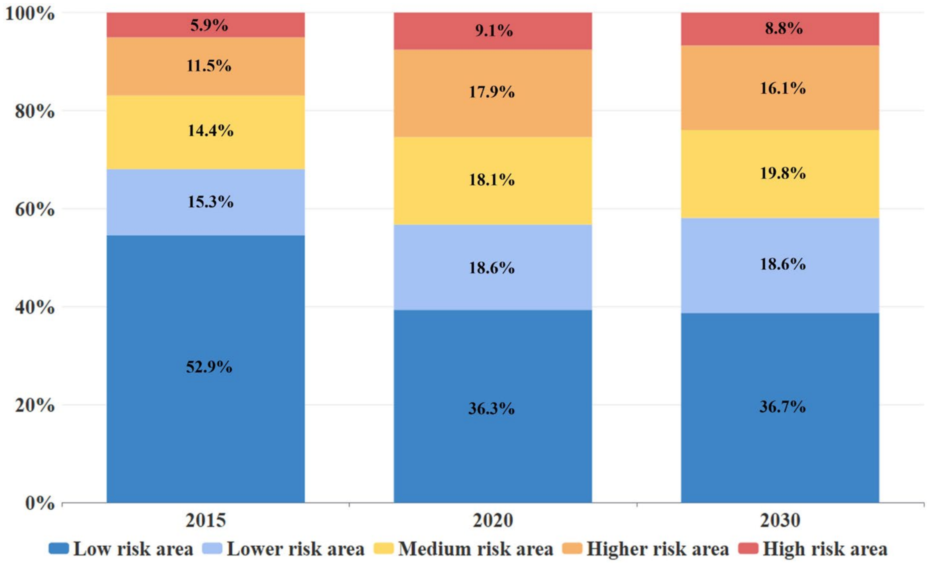

FIGURE 10 | Change in the proportion of waterlogging risk areas from 2015 to 2030.

TABLE 4 | Transfer matrix from 2015 to 2030 (Number of grid cell).

	2030					
2015	**Low-risk area**	**Lower-risk area**	**Medium-risk area**	**Higher-risk area**	**High-risk area**	**Total**
Low-risk area	564	153	84	46	32	879
Lower-risk area	30	69	85	49	21	254
Medium-risk area	12	41	80	73	34	240
Higher-risk area	4	27	54	70	37	192
High-risk area	1	19	26	30	23	99
Total	611	309	329	268	147	1664

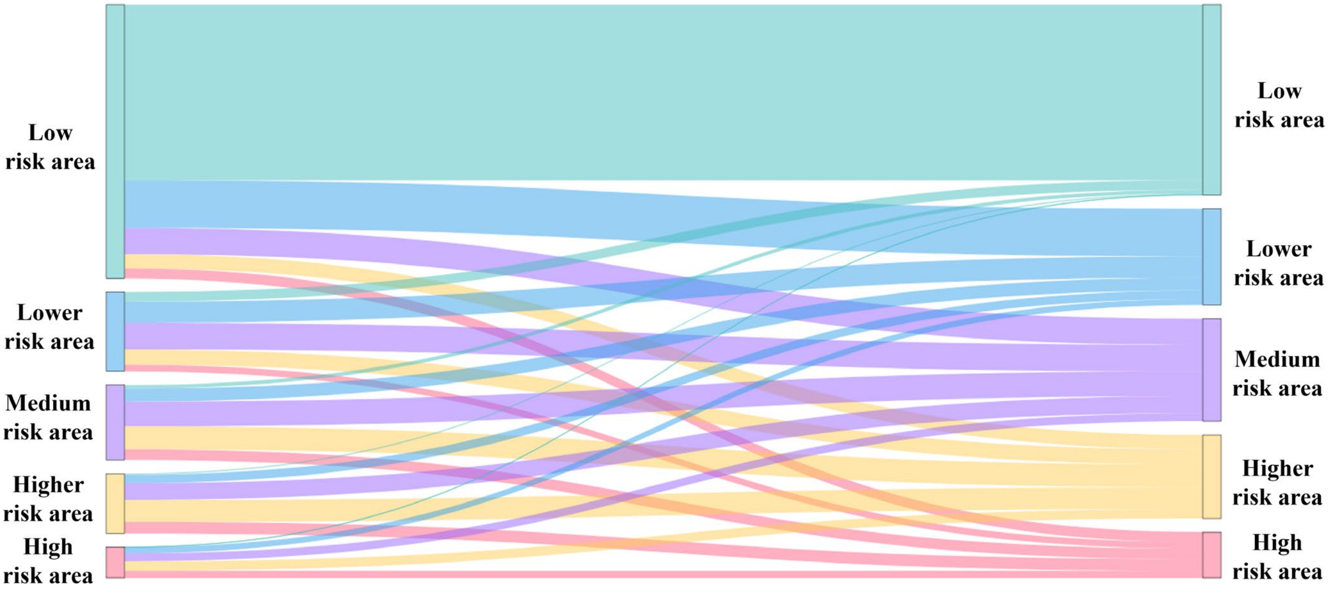

FIGURE 11 | Sankey diagram for risk area conversion from 2015 to 2030.

First, the results demonstrate the framework's efficacy in accurately identifying high-risk waterlogging zones. The proposed approach can be extended to other urban areas where land use and landscape configuration significantly affect waterlogging. Its structure and parameterization are applicable to other cities experiencing rapid urbanization. The approach is also adaptable to different spatial resolutions and data sources, ensuring flexible implementation in regional waterlogging management. In particular, the incorporation of landscape indices enables planners to evaluate the influence of land use patterns on waterlogging risk. This, in turn, provides generalizable insights for urban design and climate adaptation.

Furthermore, this integrated modeling framework can serve as a scientific tool for strategic interventions, such as Sponge City initiatives and resilient land use allocation in regions facing similar hydrological and urbanization challenges. By emphasizing methodological flexibility and scale independence, this approach advances the universality of waterlogging risk prediction, shifting the focus from empirical case descriptions to systematic spatial modeling.

5 | Conclusions

The present study developed a novel MaxEnt–PLUS model that incorporates landscape patterns to predict future urban waterlogging risk. The results demonstrate that considering landscape patterns enhances the reliability of waterlogging risk predictions. This approach contributes to understanding the causes of waterlogging and informing practical prevention strategies. The AUC values of the MaxEnt model increased after incorporating landscape indices (Cohesion, Division, and LPI), indicating that landscape patterns are informative for waterlogging risk assessment. Furthermore, landscape indices serve as quantitative descriptors of land use spatial features, enabling the identification of patterns that augment or mitigate waterlogging risk. This provides a scientific foundation for more informed decision-making in waterlogging control.

The prediction results demonstrate that emerging development areas and urban fringes are experiencing increasing impervious surfaces and decreasing ecological areas. These phenomena are associated with elevated waterlogging risks. To ensure the preservation and connectivity of ecological areas, future planning initiatives must prioritize avoiding the division of green-blue infrastructures by impervious development. In summary, the proposed method offers both data support and a practical framework for managing urban waterlogging risk and can be integrated into future sponge city planning.

Conventional GIS-based flood risk assessments generally treat land use as a static input and rely primarily on land cover proportions or topographic variables. These approaches usually overlook the spatiotemporal non-stationarity of urban environments and the complex spatial arrangement of landscape patches, both of which are critical for capturing urban spatial heterogeneity. Therefore, this study has addressed a fundamental GIScientific question: How can we formally integrate dynamic land-use simulation with spatial configuration metrics to enhance future flood risk prediction under data-scarce conditions? To this end, we proposed an integrated GIS framework that synergizes the PLUS model for spatially explicit land-use simulation, landscape indices for quantifying spatial configuration, and the MaxEnt model for presence-only probabilistic prediction. This framework can provide a robust, spatially interpretable mechanism for assessing flood risks amidst rapid urban changes. Specifically, the key innovation of this study lies in the synergistic integration of land use simulation, probabilistic risk modeling, and landscape pattern characterization. The proposed framework addresses the limitations of conventional waterlogging risk prediction by linking three distinct dimensions. First, the PLUS model captures the dynamic and scenario-based evolution of future land use. Second, landscape indices quantify the spatial configuration and fragmentation of land use. Third, the MaxEnt model establishes a robust probabilistic link between these environmental drivers and presence-only waterlogging events. Our controlled experiments provide empirical evidence for the innovation of this study. By comparing models with and without landscape indices, we demonstrate that land use spatial pattern provides unique explanatory power that is not captured by land use composition alone. The superior performance of the landscape-enhanced model indicates that waterlogging susceptibility is affected by both the quantity and the landscape pattern of land use. Thus, the PLUS-MaxEnt-landscape framework is a comprehensive tool that reconciles the temporal trajectory of urbanization with the spatial complexity of the urban landscape.

However, our method still has limitations. First, although the 1 km grid resolution is effective for capturing city-scale waterlogging patterns and supporting macro-level urban planning, its applicability to micro-scale analysis remains to be examined. As higher-resolution data may be available in future research, the proposed methodological framework can be further refined to enhance the accuracy of waterlogging risk prediction. Second, incorporating landscape patterns increases model complexity. This requires high-resolution, up-to-date data and may be constrained by data quality. Third, waterlogging is a complex process driven by multiple factors. For example, climate change and drainage systems can affect waterlogging risk. While this study focused primarily on land use and landscape patterns, future studies should consider integrating fine-scale meteorological data and drainage systems. Furthermore, multi-scenario analyses could be used to assess waterlogging risk under various planning conditions, offering broader guidance for waterlogging prevention.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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