

Article

Identification of Allergenic Plant Distribution and Pollen Exposure Risk Assessment in Beijing Based on the YOLO Model

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Abstract

With the continuous renewal of urban greening, pollen released by allergenic tree species has become a prominent environmental issue affecting residents' health. However, existing research still lacks city-wide, rapidly replicable methods for identifying allergenic tree species and assessing exposure risks. Taking Beijing's central urban districts as a case study, this research establishes a method for the automated identification of allergenic tree species and the assessment of pollen exposure risks based on high-resolution satellite imagery. This study coupled tree species distribution results derived from model inference with population density per unit area to delineate three tiers of exposure risk zones. Subsequently, these risk zones were overlaid with the road network within the study area to determine the distribution of roads with low, medium, and high exposure risk. Public transport stop locations were then introduced as a proxy variable for areas of high population mobility. Lorenz curves and Gini coefficients were calculated to quantify the spatial equity of pollen exposure risk. The results indicate that the model reliably identifies target tree species, with approximately 117,000 valid targets. Exposure risks exhibit significant clustering characteristics and can form continuous expansions along road networks. Incorporating population factors shows minimal change in risk concentration, suggesting pollen exposure risk is primarily driven by the spatial clustering of allergenic tree species and their accessibility within road networks. This risk is highly correlated with the spatial distribution patterns and accessibility characteristics of allergenic tree species, rather than being solely determined by population size. This study provides foundational data and methodological support for urban tree species identification, pollen exposure risk management, and optimised greening configurations.

Keywords: urban tree species identification; urban pollen sensitisation risk assessment; deep learning object detection; accessibility analysis; spatial distribution; Gini coefficient



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1. Introduction

Urban greenery plays a vital role in enhancing both the cityscape and the ecological environment [1]. It creates ecological value by enhancing biodiversity, improving air quality, and reducing noise pollution [2]. However, urban trees may also generate ecosystem disservices when highly allergenic species are extensively planted in public spaces, because pollen emissions can increase respiratory discomfort and allergic disease burdens among exposed populations [3,4]. As a seasonal and widely dispersed aeroallergen, pollen is

not only a botanical issue but also a spatial public health concern in densely populated cities, where exposure intensity may vary with urban morphology, human mobility, and atmospheric conditions. Air pollution has been reported to alter pollen grains and their allergenic properties, including changes in pollen structure, allergen content, and the release of sub-pollen particles, which may exacerbate allergic responses [5]. In densely trafficked and poorly ventilated street canyons, pollen may compound with pollutants like particulate matter and nitrogen oxides, amplifying discomfort and medical burdens among sensitive populations [6]. Therefore, urban greening should be understood not only in terms of ecological and aesthetic benefits, but also in relation to allergenic exposure risk and public health governance. From this perspective, achieving a measurable and actionable balance between ecosystem services and health-related disservices has become an important challenge for refined urban management [7].

With the advancement of urbanization and the increasing frequency of urban greening renewal [8], conducting precise distribution statistic measurements of allergenic tree species in urban environments and quantitatively assessing their pollen allergenicity and exposure risks holds significant importance for balancing urban ecology and the quality of the human living environment [9]. In recent urban forestry and aerobiology studies, allergenic pollen is no longer treated simply as a biological by-product of vegetation, but as a spatially uneven exposure factor that should be considered together with urban planning, species composition, and population vulnerability [5]. At the same time, the ecological benefits of urban trees may coexist with allergenic disservices, which means that urban planting strategies need to consider not only greening and aesthetic performance, but also the potential health burden associated with allergenic species distribution. The “yellow haze incident” in the Temple of Heaven area in March 2025 brought this contradiction into sharp focus: on the one hand, the city requires evergreen trees to form a structural framework supporting both landscape aesthetics and ecological services; on the other hand, the concentration of highly allergenic tree species in core public spaces could significantly increase exposure risks during commuting, recreation, and daily activities [10]. Management of urban allergenic tree species has largely relied on top-down principles and initiatives [11]; related studies have also proposed sensitization indicators or alternative strategies [12–14]. Nevertheless, two important gaps remain at the urban scale. First, rapidly updatable and spatially explicit inventories of allergenic tree species are still lacking, which limits the ability to identify where management is needed and how extensive interventions should be. Second, many assessments remain at the level of allergen presence and do not sufficiently incorporate the coupling of source distribution, human activity, road-corridor transmission, and high-frequency exposure locations, thereby constraining their direct use in traffic organization, green-space renewal, and health warning systems [15]. Moreover, the “riskscape” perspective highlights that pollen-exposure risk estimates can vary widely depending on the underlying allergenicity datasets, underscoring the need for reliable, spatially explicit source mapping [9].

The primary methods currently used to investigate the distribution of specific tree species include traditional manual surveys and remote sensing monitoring [16]. Manual survey methods typically involve fieldwork conducted by professionals to document tree species, quantities, and location information. For example, Chacalo et al. conducted field surveys in Mexico City to meticulously record the species composition, individual counts, and spatial distribution of roadside trees [17]. This method offers advantages such as high accuracy and clear classification criteria, making it suitable for small-scale, high-precision surveys [18]. However, it incurs relatively high labor and material costs and is not applicable to large-scale plots or complex environments [19]. In recent years, advances in computer deep learning technology have provided new technical support

for the intelligent allocation of urban ecological resources [20]. Unlike machine learning algorithms, deep learning employs neural network architectures to automatically learn the spatial characteristics of targets [21]. When combined with high-resolution remote sensing imagery, it enables the identification and classification of urban vegetation [22]. The YOLO (You Only Look Once) series of object detection algorithms are increasingly applied in urban tree species identification and localization [23]. Kilinc, et al. (2024) combined the YOLO model with drone-derived remote sensing imagery to achieve precise identification of plant species within images. They further integrated this into an urban heat island analysis model to obtain quantitative statistics, thereby evaluating the ecological benefits of green vegetation [24]. While this method exhibits high detection accuracy, false positives persist in areas of canopy overlap [25]. Current deep learning models for tree species distribution identification primarily rely on low-altitude remote sensing imagery and street-level images [26], which suffer from coverage limitations [27]. Meanwhile, the highly heterogeneous background of remote sensing images in urban areas, with dense buildings, severe shadow occlusion, and mixed ground textures, can interfere with the model's ability to distinguish target boundaries, thus affecting the stability of localization and classification. Therefore, to address these interference factors, it is necessary to specifically modify the structure of the model to improve robustness and detection performance. Furthermore, spatial distribution data of urban allergenic tree species alone remains insufficient for quantifying potential pollen exposure ranges and sensitization risks [28].

In urban environments, the risk level of pollen sensitization is determined not only by the spatial distribution patterns of sensitizing plants, but also jointly driven by the spatiotemporal distribution of exposed populations and the transmission pathways of risk sources [29,30]. On the one hand, the uneven spatial distribution of urban populations coupled with significant mobility during daily activities [31] results in pronounced regional variations in pollen sensitization [32]. Research indicates that in densely populated, highly mobile cities, pollen sensitization risks are amplified [33], underscoring the necessity of incorporating urban population size and distribution into pollen sensitization risk assessments [34]. On the other hand, dense urban road networks and the linear planting of certain sensitizing tree species (such as conifers) as street trees along roadways transform road spaces into potential corridors for pollen dispersion and exposure [35]. Furthermore, integrating the locations of allergenic plants with the road systems of the built urban environment into pollen dispersal models can generate pollen transport pathways and risk distribution maps. This demonstrates that combining pollen transmission corridors with urban road network morphology can be used for quantitative analysis of allergenic risk zoning [36]. Therefore, coupling the distribution of allergenic tree species with multi-source data—such as population density per unit area, road systems, and traffic node distributions—to construct a quantifiable influence factor system serves as a critical condition for quantitatively assessing pollen allergen exposure risks [37].

To address this ecological and public-health gap, this study focuses on the central urban districts of Beijing and uses *Juniperus chinensis* as the research subject. The climate of Beijing is well-suited to the growth of coniferous trees, and as these plants are evergreen, they are widely employed in urban greening initiatives. This study establishes an “identification–zoning–assessment” technical workflow. Specifically: 1. A high-resolution satellite remote sensing image-based *Juniperus chinensis* species dataset was constructed, combined with an enhanced YOLOv8s model, to achieve automatic identification and distribution mapping of the target species within the study area. 2. The species distribution results were overlaid with urban road network data for analysis, quantifying and delineating exposure ranges for allergenic pollen at different levels, and generating corresponding allergenic risk-graded street distribution maps. 3. Risk-tiered zones were coupled with urban bus stop

data and population density per unit area to calculate Lorenz curves and Gini coefficients, characterizing allergenic risk distribution patterns and revealing correlations with potential exposed populations. This study establishes a foundational, quantifiable, and reusable technical framework for urban allergenic tree species identification, allergenic risk zoning management, and balancing urban ecology with human living environments.

2. Materials

2.1. Study Area

The study area encompasses the central urban districts of Beijing, with geographical coordinates ranging from 116°10' E to 116°33' E and from 39°46' N to 40°03' N (Figure 1). The area has a temperate monsoon climate, flat terrain, and clear seasonal variation, which are favorable for the growth and stable landscape performance of evergreen coniferous species such as *Juniperus chinensis* [38]. The central urban area exhibits high population density and intense traffic activity. Residents frequently encounter roadside greenery and street tree canopies during commuting, recreation, and daily travel, making it the urban space type where pollen exposure risks are most amplified and require the most precise management. It possesses the typical characteristics of “high-frequency configuration and high-contact opportunity,” while also facilitating city-scale distribution mapping and risk zoning analysis. Second, the high complexity of the built environment in this area—characterized by high-rise buildings, dense street canyons, shadowing effects, and diverse ground features—poses significant challenges for tree species identification using high-resolution imagery. This makes it an ideal “challenging scenario” for testing the robustness of automated identification and risk assessment workflows. In summary, Beijing’s central urban area combines strong exposure demand, complex spatial structure, and representative tree species distribution. It therefore provides a representative and replicable test case for allergenic tree-species mapping and exposure-risk assessment in complex urban environments.

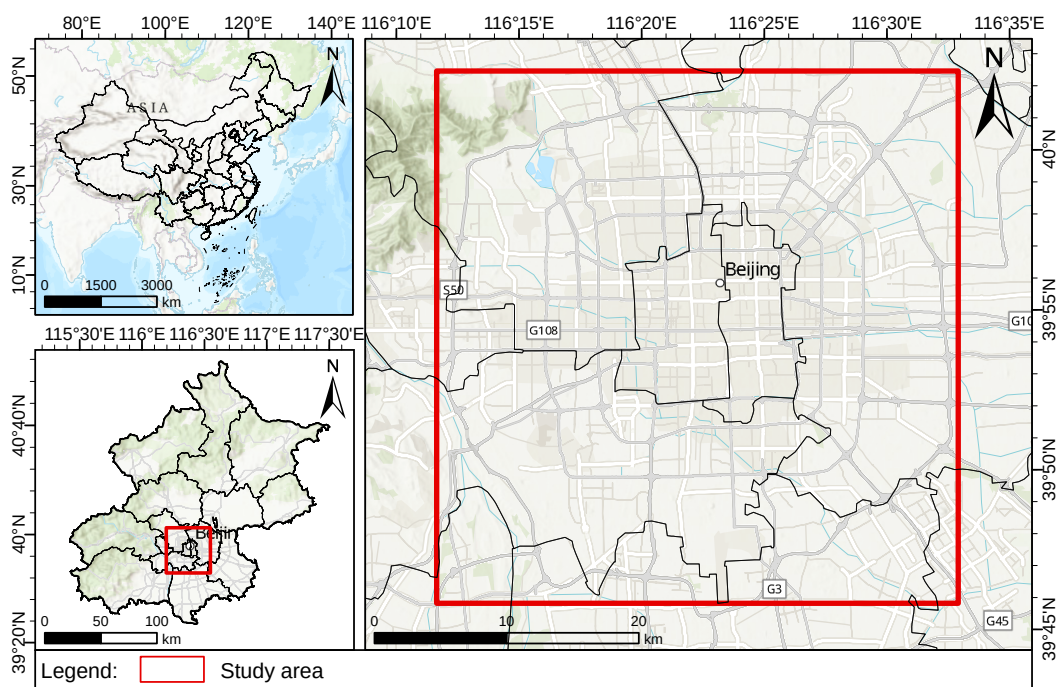


Figure 1. Scope of the research.

2.2. Data Sources

The high-resolution remote sensing imagery used in this study was acquired by the WorldView-3 commercial satellite operated by Maxar Technologies, Inc., Westminster, CO, USA. This satellite features a 0.3 m panchromatic spatial resolution and a 1.2 m multispectral resolution, characterized by high spatial resolution and a short revisit cycle [39]. To construct an image dataset capturing both seasonal variations and scene diversity, two sets of imagery covering the study area were collected: an autumn–winter dataset (October 2024 to February 2025) and a spring–summer dataset (April 2025 to August 2025). The data provider completed unified orthorectification, radiometric calibration, band registration, and color balance processing. The imagery is delivered in GeoTIFF format and employs a unified coordinate system (WGS84/UTM).

Road network data for the study area was sourced from OpenStreetMap Foundation, Cambridge, United Kingdom. Line data for Beijing’s road system (arterial roads, collector roads, and local roads) was extracted as required for the research, followed by topological checks and geometric cleanup (removing duplicate lines, repairing breaks, and handling dangling lines). Urban population data was obtained from the WorldPop project, University of Southampton, Southampton, United Kingdom, rasterized population product released by Google Earth Engine in 2022 (original spatial resolution approximately 100 m). Bus stop data was obtained through the POI retrieval interface of the AutoNavi Maps API service, AutoNavi Software Co., Ltd., Beijing, China. Using keywords such as “bus stop/bus station,” stop locations were batch-retrieved within the study area to generate a bus stop vector layer. This layer served as a proxy variable for high-mobility population activity nodes and was incorporated into subsequent Lorenz curve and Gini index calculations.

2.3. Data Processing

2.3.1. Remote Sensing Image Dataset Processing

To satisfy deep-learning input requirements, the spring–summer and autumn–winter satellite images were cropped into 512×512 non-overlapping tiles using a sliding-window strategy, producing 52,116 tiles per season (104,232 in total). The tile pool was then screened by computing the tile-level occlusion ratio (area blocked by buildings or objects) and shadow ratio (area under insufficient illumination); tiles with an occlusion ratio $> 50\%$ or a shadow ratio $> 40\%$ were removed, and remaining blur/defocus cases were further excluded by visual inspection, leaving 102,561 valid tiles for subsequent stratified sampling. Each tile was assigned a unique tile ID (season tag plus cropping row/column indices) for screening and scenario assignment, ensuring that every tile belonged to one and only one category. A 3×2 scenario design was adopted, with three spatial scenarios (built-up areas, streets, and parks) and two seasonal scenarios (spring/summer and autumn/winter); this stratification was used only for dataset construction and sampling control, and it was not used in subsequent model performance validation. Based on this design, 200 high-quality tiles were selected from each spatial scene, totalling 1200 tiles. Subsequently, 50 lower-quality tiles exhibiting shadowing or occlusion phenomena but where the target crown structure remained discernible were chosen, forming a dataset comprising 1250 selected tiles. This dataset was then partitioned into training and validation sets in an 8:2 ratio, with tile IDs used for deduplication to ensure no duplicate data. All selected tiles were manually annotated using the LabelImg tool. The annotations were saved as .txt files in YOLO format, in which each bounding box was represented by the normalized coordinates of its center point, width, and height relative to the corresponding image tile (Figure 2).

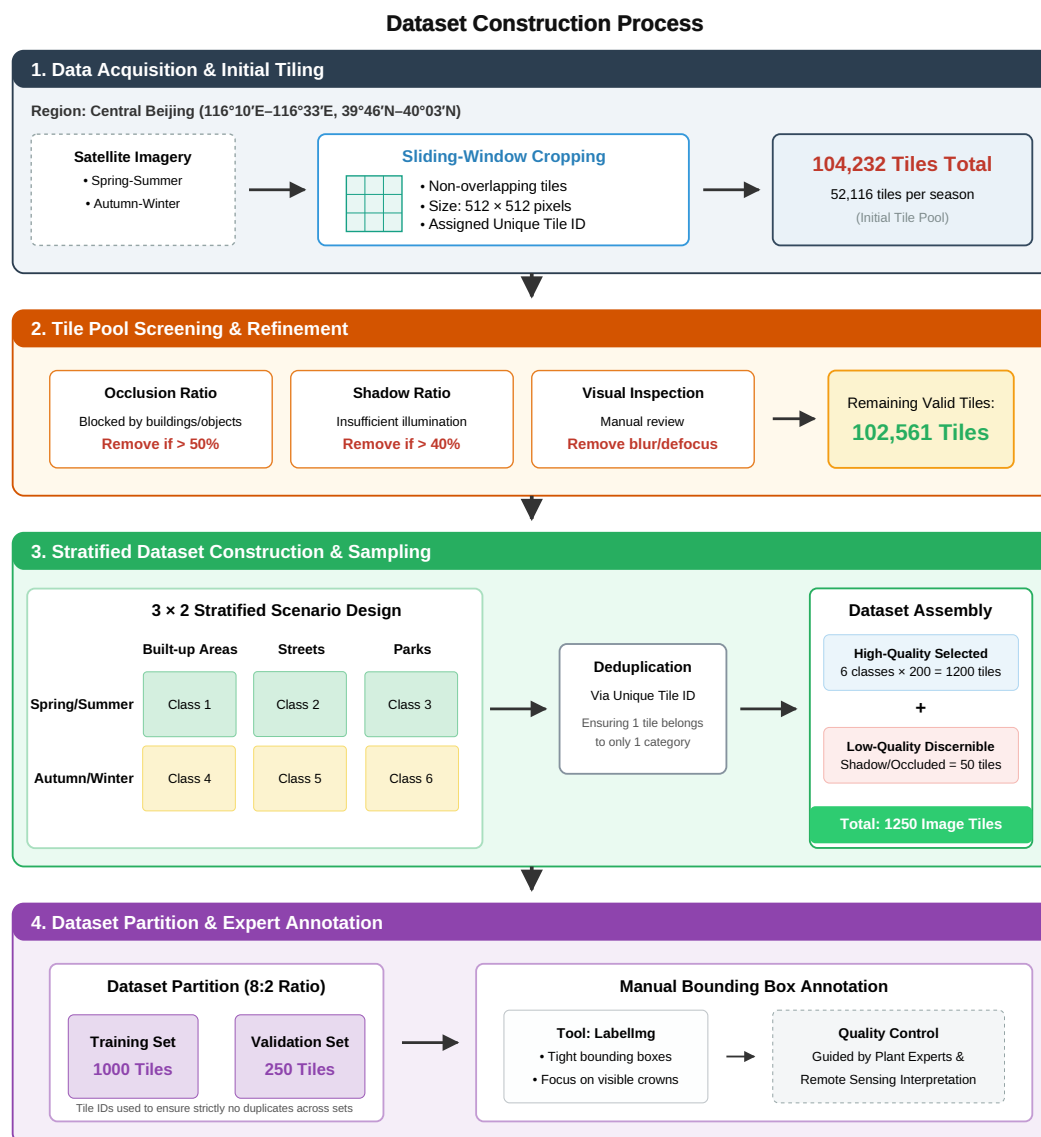


Figure 2. Dataset construction process.

2.3.2. Risk Analysis Data Preparation

After model inference, we used the detected *Juniperus chinensis* crown locations as allergenic-source proxies and conducted a city-scale allergenic exposure risk analysis by integrating multiple auxiliary datasets. First, a unified coordinate system was established for all supporting layers, including the road network, population distribution, and bus-stop points. A study-area mask derived from the remote sensing imagery was then used to clip these datasets, ensuring consistent spatial boundaries for subsequent spatial analysis. Next, a 200 m × 200 m fishnet grid was generated as the base analysis unit, enabling standardized aggregation and overlay operations across layers. To guarantee network-based computations and spatial overlays were reliable, geometric and topological cleaning was applied to the road network data, including removing duplicate segments, repairing broken and dangling lines, snapping endpoints when necessary, and splitting intersecting segments to ensure correct connectivity and stable topology. For population data, the acquired WorldPop raster was originally provided at a 100 m resolution; thus, it was resampled to the 200 m grid to match the analysis unit, and linear interpolation was applied to derive population projections for 2025 at the grid-cell level. In addition, the bus-stop dataset was processed through deduplication and merging of adjacent points to reduce positional redundancy and improve representativeness. With these pre-processed

layers aligned to the same grid framework, we subsequently overlaid allergenic-source density (derived from the model inference outputs) with population and mobility-related layers to quantify spatial exposure potential and identify high-risk hotspots and priority areas for management.

3. Methods

3.1. Model Selection and Optimization

3.1.1. Model Selection

As a widely adopted object detection model in industrial applications, the YOLOv8 architecture maintains structural stability, enabling high-speed inference with sustained accuracy on large-scale datasets [40]. This framework encompasses multiple variants (YOLOv8s, YOLOv8m, YOLOv8l, YOLOv8x), designed to adapt to diverse application scenarios. Among these, YOLOv8s (small) serves as a lightweight model suitable for edge device deployment or tasks demanding high real-time performance. Therefore, this study adopts YOLOv8s as the baseline model. In addition, YOLOv7 and RT-DETR are introduced as comparative models. YOLOv7 is incorporated primarily as an intra-family comparison within the YOLO series, since it represents a widely recognized real-time one-stage detector with strong efficiency–accuracy trade-offs and provides a useful reference for assessing whether the proposed improvements remain advantageous relative to another mature YOLO-based architecture [41]. RT-DETR, by contrast, is adopted as a transformer-based end-to-end real-time detector. It leverages a hybrid encoder to model global context while maintaining efficient multi-scale feature interaction, thereby improving the representation of complex scenes without sacrificing real-time capability [42]. This design aligns well with tree-crown species identification in high-resolution urban remote-sensing imagery, where targets are often small and the background is characterized by cluttered textures and highly heterogeneous spatial layouts.

All experiments were conducted on an Alienware M18 laptop equipped with 64 GB of RAM and an NVIDIA GeForce RTX 4080 laptop graphics card (12 GB VRAM). Parameters for each model and its version are shown in Table 1. Subsequently, we performed performance comparisons and generalization tests on baseline YOLOv8s, YOLOv7, enhanced YOLOv8s, and RT-DETR to evaluate their detection accuracy and robustness in different urban scenarios. All four models were trained for 300 epochs under the same training settings until the validation curve reached saturation.

Table 1. Complexity comparison of YOLOv8 variants and additional comparative models.

Model	Params (M)	FLOPs (G)	Speed (ms/Image)
YOLOv8n	3.2	8.7	2.5
YOLOv8s	11.2	28.6	3.0
YOLOv8m	25.9	78.9	4.7
YOLOv8l	43.7	165.2	6.4
YOLOv8x	68.2	257.8	8.0
YOLOv7	36.9	104.7	6.2
RT-DETR-L	32.0	110.0	8.8

3.1.2. Model Optimization

To address the challenges posed by small canopy scales of target tree species and complex surrounding backgrounds in remote sensing imagery, this study incorporates the SCAM (Spatial Context-Aware Module), FRM (Feature Reconstruction Module), and BiFPN (Bidirectional Feature Pyramid Network Module) into the neck segment of the baseline model (Figure 3).

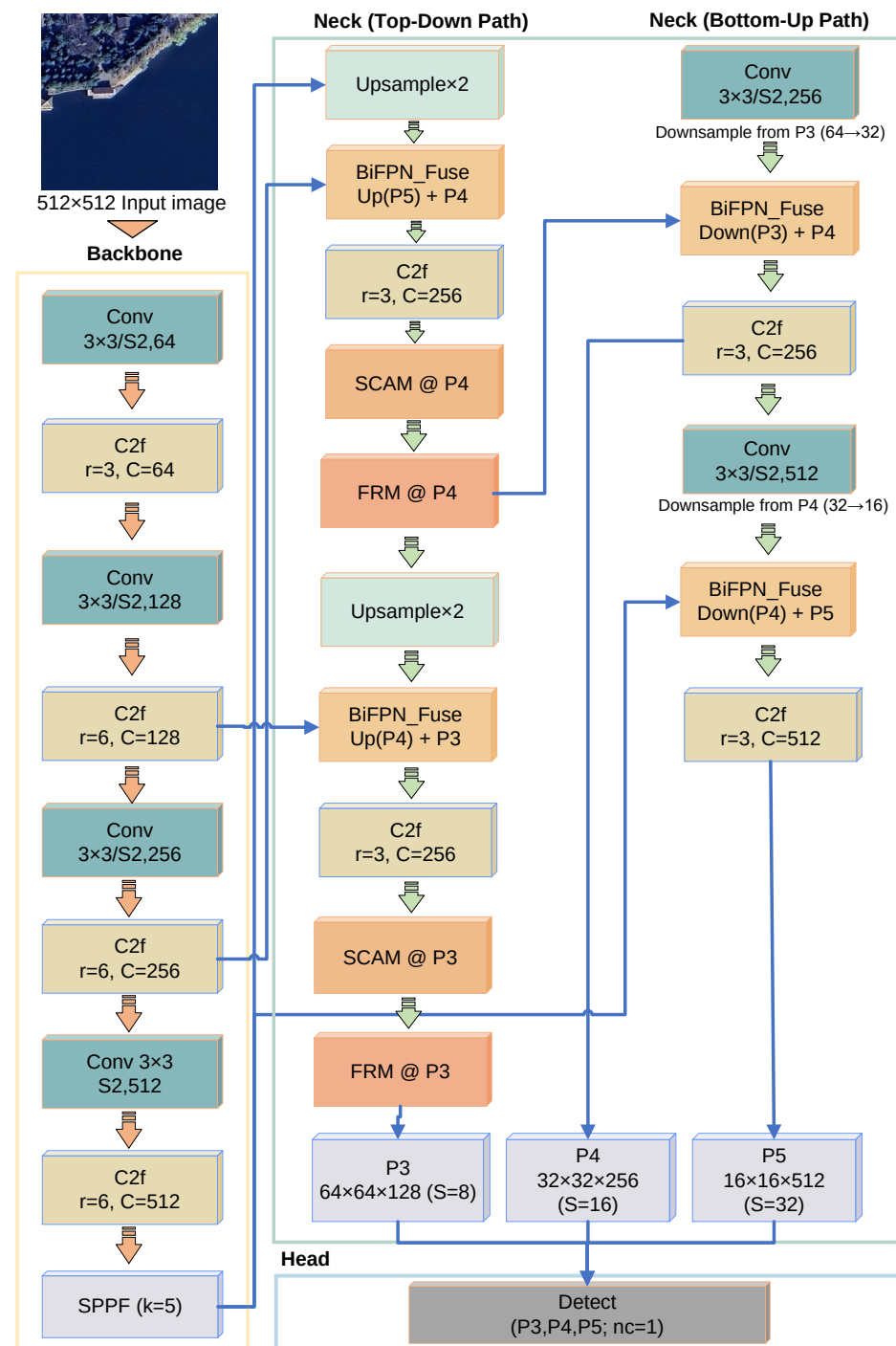


Figure 3. Model structure.

The SCAM is introduced to enhance the separation of *Juniperus chinensis* crowns from confusing urban textures in high-resolution remote-sensing imagery. It strengthens neighborhood-level spatial encoding to emphasize crown outlines and suppress layout-inconsistent background responses, thereby reducing false alarms and missed detections [43]. Unlike single-branch attention that re-weights either spatial or channel responses alone, SCAM forms a joint gate conditioned on both spatial and channel context, enforcing layout-consistent feature selection before neck fusion. The module inference formula is as follows:

$$X \in \mathbb{R}^{H \times W \times C} \quad (1)$$

Here, X denotes the input feature tensor (feature map) produced by the network, where H and W represent the spatial height and width of the feature map, respectively, and C indicates the number of channels encoding different semantic or texture responses at each spatial location.

$$Y_{\text{SCAM}} = X \odot \sigma(P_s(\phi(X)) \oplus P_c(\phi(X))), \quad (2)$$

In Equation (2), Y_{SCAM} denotes the SCAM-refined feature and $\phi(\cdot)$ is a lightweight projection. $P_s(\cdot)$ and $P_c(\cdot)$ aggregate the spatial and channel context, whose fusion ($\oplus$) is passed through a sigmoid gate $\sigma(\cdot)$ and applied to the input via element-wise multiplication ($\odot$). This structure-conditioned gating emphasizes crown-boundary cues while suppressing layout-inconsistent background responses.

The FRM addresses canopy-related challenges (blurred boundaries, fragmented patterns, and crown overlap) that can be weakened by pyramid aggregation. It integrates multi-scale cues and applies a reconstruction step to recover edge- and morphology-related details, improving robustness and reducing missed detections under disturbance conditions [44].

$$Y_{\text{FRM}} = \psi\left(\left[\mathcal{A}_{l_1}(X^{(l_1)}), \mathcal{A}_{l_2}(X^{(l_2)}), \dots\right]\right) + \eta(X^{(t)}), \quad (3)$$

In Equation (3), $X^{(l)}$ are multi-level features and $\mathcal{A}_l(\cdot)$ aligns them to a target resolution, after which they are fused $[\cdot]$ and reconstructed by $\psi(\cdot)$. A residual term $\eta(X^{(t)})$ preserves the target-level backbone cues, producing Y_{FRM} . Overall, the FRM combines aligned multi-level reconstruction with a residual path to recover edge/morphology details and improve separability under clutter and overlap.

To mitigate the loss of small-scale cues during deep convolution and multi-scale fusion, we introduce BiFPN, which performs bidirectional feature aggregation with adaptive, learnable weights to strengthen cross-scale information exchange and emphasize more discriminative feature maps [45]. To balance accuracy gains and computational overhead under a 12 GB GPU memory budget, we adopted the current backbone depth and a two-step BiFPN fusion design in the neck. This configuration provides a practical trade-off between localization quality (mAP@0.5:0.95) and efficiency (GFLOPs/FPS) for large-scale mapping and subsequent exposure-risk analysis. The fusion process can be formulated as follows:

$$\tilde{P}^{(l)} = \text{Conv}\left(\sum_{i \in \mathcal{N}(l)} \alpha_{l,i} \cdot \mathcal{R}_{l \leftarrow i}(P^{(i)})\right), \quad \alpha_{l,i} = \frac{\text{ReLU}(w_{l,i})}{\sum_{j \in \mathcal{N}(l)} \text{ReLU}(w_{l,j}) + \varepsilon}. \quad (4)$$

In Equation (4), $P^{(l)}$ denotes the input feature at pyramid level l , and $\tilde{P}^{(l)}$ is the fused output feature. $\mathcal{N}(l)$ is the set of adjacent levels connected to level l in the bidirectional pyramid (top-down and bottom-up). $\mathcal{R}_{l \leftarrow i}(\cdot)$ aligns the spatial resolution of $P^{(i)}$ to level l via up/down sampling. $w_{l,i}$ is a learnable fusion weight and $\alpha_{l,i}$ is its normalized coefficient after ReLU-based normalization. $\text{Conv}(\cdot)$ denotes a lightweight convolution for feature integration, and ε is a small constant for numerical stability.

3.2. Multi-Source Data Coupling and Road Exposure Risk Classification

3.2.1. Data Coupling

The target tree species locations obtained through model inference are output as a point layer for convenient import into ArcGIS Pro 3.5.0 for subsequent processing. As described in Section 2.3, this study generates a mask based on remote sensing imagery of the study area. Within the masked area, a 200 m $\times$ 200 m base grid is constructed to serve as the fundamental unit for subsequent statistical analysis and operations.

First, the WorldPop 2022 population raster data obtained for this study were resampled onto the study's 200 m grid cells. The process can be represented as follows:

$$\text{Pop}_{200,i} = \sum_{j \in \Omega_i} \text{Pop}_{\text{orig},j} \quad (5)$$

Here, $\text{Pop}_{200,i}$ denotes the population of the i th 200-m grid cell; Ω_i represents the set of original pixels falling within the boundaries of that grid cell.

Linear interpolation analysis was then conducted to obtain the population projections for 2025:

$$\text{Pop}_{2025,i} = \text{Pop}_{2022,i} + \frac{2025 - 2022}{t_2 - t_1} (\text{Pop}_{t_2,i} - \text{Pop}_{t_1,i}) \quad (6)$$

Among these, t_1, t_2 represent the two available reference years, while $\text{Pop}_{t_1,i}$ and $\text{Pop}_{t_2,i}$ denote the grid population for the corresponding years. The population data for each grid cell is then written into the grid attribute table field pop_{sum} for subsequent exposure risk analysis and calculation of exposure risk distribution characteristics.

First, this study establishes buffer zones of 100 m, 300 m, and 500 m centered on the distribution points of target tree species. These zones are then categorized into high, medium, and low exposure risk levels based on distance from the center, and overlaid onto the base grid. If a grid cell falls within multiple buffer zones, the higher risk level takes precedence. Based on this approach, the fundamental spatial risk level for each grid cell is defined as follows:

$$R_i^{(\text{zone})} = \max(3I_{100,i}, 2I_{300,i}, I_{500,i}) \quad (7)$$

Here, $R_i^{(\text{zone})}$ denotes the risk level of the i th grid; $\max(\cdot)$ indicates taking the maximum value within the brackets to implement the “high-risk priority” decision rule; and $I_{100,i}, I_{300,i}, I_{500,i}$ are indicator variables (taking values 0 or 1), indicating whether the grid intersects with the 100 m, 300 m, and 500 m buffer risk zones, respectively. A grid is assigned 1 if it spatially overlaps with the corresponding buffer zone, and 0 otherwise. The coefficients 3, 2, and 1 represent weightings for high, medium, and low risk, respectively, ensuring that when a grid falls within multiple buffer zones, the highest risk level is automatically assigned.

Considering that the mask range may cause variations in the area A_i of grid cells within the study area, this study converts the number N_i of sensitized tree species within each grid cell into a density indicator per unit area:

$$D_i = \frac{N_i}{A_i} \quad (8)$$

Here, D_i represents the tree species density in the i th grid, N_i denotes the number of tree species within the grid, and A_i indicates the actual area of the grid.

To further incorporate population exposure factors, this study represents the potential exposed population using the total grid population pop_{sum} . Tree density and total population are normalized to obtain $\tilde{D}_i$ and $\tilde{P}_i$, respectively:

$$\tilde{D}_i = \frac{D_i - \min(D)}{\max(D) - \min(D)} \quad (9)$$

$$\tilde{P}_i = \frac{\text{pop}_{\text{sum}} - \min(\text{pop}_{\text{sum}})}{\max(\text{pop}_{\text{sum}}) - \min(\text{pop}_{\text{sum}})} \quad (10)$$

Finally, by coupling the baseline spatial risk, tree species density indicators, and population exposure indicators, we construct a comprehensive exposure risk score for each grid cell:

$$S_i = R_i^{(\text{zone})} \cdot \tilde{D}_i \cdot \tilde{P}_i \quad (11)$$

Here, S_i represents the comprehensive exposure risk intensity index, indicating that within the same spatial risk zone, the greater the density of sensitized tree species and the larger the population scale within a grid, the higher the comprehensive risk. Based on the distribution of S_i , the comprehensive risk levels of each grid cell are reclassified into three tiers: high, medium, and low (1–3). These risk tiers (1–3) are then recorded in the grid attribute table to complete the risk level assignment and a spatial distribution map of allergenic pollen exposure risk in the study area was subsequently generated.

3.2.2. Road Exposure Risk Classification

Road networks serve as the primary spatial framework for residents' daily commutes and activities [46]. The “corridor” environment they create influences pollen dispersion concentrations and exposure levels. Consequently, the pollen sensitization risk depends not only on the presence of allergens but also on their diffusion within road spaces and the movement patterns of populations within sensitization risk zones [34]. Therefore, this study incorporates the road network system into a quantitative framework for assessing exposure risk levels.

This study first segments the road network into 100 m intervals, ensuring each road segment corresponds to a single risk background. Upon completion, the field length is recorded in the attribute table as the minimum unit for overlay operations. For assigning road risk levels, this study first overlays the three-tier exposure risk zones with road segments. It then counts whether each road segment intersects with a corresponding risk zone and determines the segment's composite risk level (risk_level) based on the “high-risk priority” principle. Specifically, let $I_{(j,k)}$ denote an indicator variable representing whether road segment k spatially intersects grid cell j (set to 1 if intersecting, 0 otherwise). The road segment's risk level can then be expressed as:

$$L_k = \max(3I_{(3,k)}, 2I_{(2,k)}, 1I_{(1,k)}) \quad (12)$$

Here, L_k denotes the risk level of the k th road segment (corresponding to the field risk_level); $I_{(3,k)}$, $I_{(2,k)}$, and $I_{(1,k)}$ indicate whether the road segment intersects with high-, medium-, or low-risk zones, respectively. This rule implies that when a road segment traverses multiple grids of differing risk levels, the higher risk level automatically takes precedence.

To further quantify road risk as impedance usable in path calculations, this study introduces a risk weighting coefficient cost based on individual road segments, serving as the comprehensive travel cost. The correspondence between risk levels and risk weight coefficients is as follows: low risk ($L_k = 0$) corresponds to 1, medium–low risk ($L_k = 1$) to 2, medium–high risk ($L_k = 2$) to 5, and high risk ($L_k = 3$) to 15. Thus, the cost of a road segment can be expressed as:

$$\text{cost}_k = \text{Len}_k \cdot w(L_k) \quad (13)$$

Here, cost_k denotes the comprehensive travel cost of the k th road segment, reflecting the potential sensitization risk incurred during travel on that segment; Len_k represents the geometric length of the road segment; and $w(L_k)$ is the exposure risk weighting coefficient. This formula implies that for road segments of equal length, those with higher risk levels carry larger risk weight coefficients, resulting in higher costs cost_k . This provides foundational data support for subsequent calculations of the Gini coefficient assessing the equilibrium distribution of sensitization exposure risks.

3.3. Calculation of Lorenz Curves and Gini Indices Revealing Risk Distribution Characteristics

To demonstrate the spatial distribution uniformity of sensitizer exposure risk within the study area, this research employs Lorenz curves and Gini indices to quantify its spatial distribution characteristics. First, the number of target tree species within a unit grid area is converted into the sensitizer source intensity per unit area (hectare), denoted as tree_per_ha_i ;

$$\text{tree_per_ha}_i = D_i \cdot 10000 \quad (14)$$

where D_i represents the density of sensitized tree species within a single base grid.

Simultaneously, bus stops distributed along roads serve as nodes representing high-frequency human activity. Combined with road network travel cost analysis, this yields the accessibility statistical value MEAN_i for each base grid:

$$d_{(b \rightarrow i)} = \min_{p \in P(b,i)} \sum_{k \in p} \text{cost}_k \quad (15)$$

$$\text{MEAN}_i = \frac{1}{|B|} \sum_{b \in B} d_{(b \rightarrow i)} \quad (16)$$

where b denotes the b th bus stop, B_i denotes the set of stops within grid i , and $|B|$ denotes the number of stops in this set. $d_{(b \rightarrow i)}$ denotes the minimum cumulative travel cost from stop b to grid i . $P(b, i)$ denotes the set of all feasible paths from station b to grid i , p is one such path, $\sum_{k \in p} \text{cost}_k$ represents the cumulative passage cost along path p , and $\min(\cdot)$ selects the path with the lowest cumulative cost among all feasible paths. Ultimately, MEAN_i represents the accessibility statistic for grid i , defined as the average of the minimum cumulative costs for all stations, thereby characterizing the accessibility conditions of that grid.

Building upon this, we construct the spatially based exposure risk indicator EB_i to express the combined effect of allergen intensity and transmission conditions within a unit grid. It is defined as:

$$\text{EB}_i = \text{tree_per_ha}_i \cdot \text{MEAN}_i \quad (17)$$

Here, i denotes the grid index, and tree_per_ha_i represents the allergen source intensity per unit grid area.

Furthermore, to maintain consistency with the comprehensive risk modeling described earlier, this study denotes the integrated exposure risk score derived from both population-based and spatially coupled approaches as S_i (i.e., the comprehensive exposure risk intensity indicator for each grid).

$$S_i = \text{EB}_i \cdot \tilde{P}_i \quad (18)$$

Subsequently, S_i is incorporated alongside MEAN_i , tree_per_ha_i , and EB_i into the Lorenz and Gini frameworks for comparative analysis. For any variable X_i to be evaluated (which could be tree_per_ha_i , MEAN_i , EB_i , or S_i), first sort all X_i values across all grid cells in ascending order to obtain a ranked sequence. Define the cumulative unit proportion as

$$p_k = \frac{k}{n} \quad (19)$$

The cumulative variable accounts for:

$$L_k = \frac{\sum_{j=1}^k x_{(j)}}{\sum_{j=1}^n x_{(j)}} \quad (20)$$

The Lorenz curve is constructed from points (p_k, L_k) . The Gini coefficient is defined as the proportion of area between the equality line and the Lorenz curve, which can be calculated using the trapezoidal rule in discrete cases:

$$G = 1 - \sum_{k=1}^n (L_k + L_{k-1})(p_k - p_{k-1}) \quad (21)$$

The values of L_0 and p_0 are 0. A G value closer to 0 indicates a more uniform distribution, while a value closer to 1 indicates stronger spatial clustering and distribution imbalance.

Considering that the spatial distribution equilibrium of exposure risks may differ from that of population-based distributions, this study further introduces the population value $\text{pop}_{\text{sum},i}$ within each grid unit area as the population weight w_i . For the sorted grid, the cumulative population proportion is defined as

$$P_k = \frac{\sum_{j=1}^k w(j)}{\sum_{j=1}^n w(j)} \quad (22)$$

The cumulative weighted variable proportion is

$$Q_k = \frac{\sum_{j=1}^k w(j) x(j)}{\sum_{j=1}^n w(j) x(j)} \quad (23)$$

The population-weighted Gini coefficient can similarly be expressed using the trapezoidal method as:

$$G_w = 1 - \sum_{k=1}^n (Q_k + Q_{k-1})(P_k - P_{k-1}) \quad (24)$$

By comparing the unweighted G with the population-weighted G_w , the correlation between the distribution characteristics of exposure risk and spatial location and population factors can be determined. Based on the Lorenz curve and plotted Gini coefficient, the spatial distribution characteristics of exposure risk within the study area and the degree of its inequality can be described.

4. Results

4.1. Model Comparison Experiment and Inference Results

4.1.1. Ablation Experiments

To quantify the individual and combined effects of the added modules, we conducted an ablation study comparing the baseline and enhanced *YOLOv8s* under identical training settings. The baseline *YOLOv8s* achieved a precision (P) of 78.69%, a recall (R) of 77.90%, an mAP@0.5 of 81.62%, an mAP@0.5:0.95 of 39.89%, and an F1-score of 78.29%, with an inference speed of 45.2 FPS (Figure 4). While the baseline can capture major canopy cues in complex urban imagery, its performance remains constrained under stricter IoU thresholds and challenging cases such as cast shadows, cluttered textures, and crown adhesion.

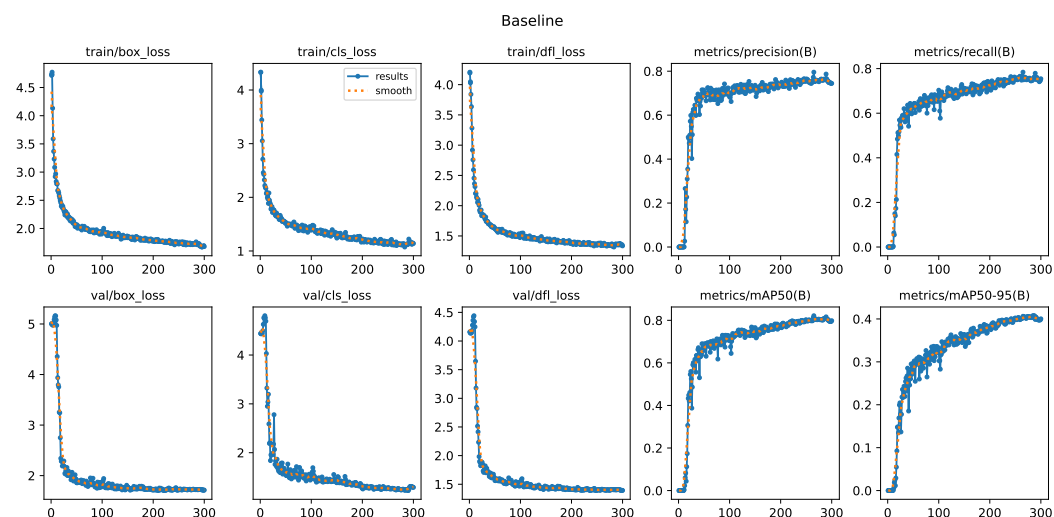


Figure 4. Baseline model results.

The SCAM ($P = 78.69\%$, $R = 77.45\%$, $mAP@0.5 = 82.53\%$, $mAP@0.5:0.95 = 40.07\%$, and $F1 = 78.07\%$) increases $mAP@0.5$ while keeping precision close to the baseline (Figure 5a), suggesting improved separation of target crowns from confusing textures, especially where edges are mixed with shadows or fine background patterns. The FRM ($P = 80.12\%$, $R = 78.40\%$, $mAP@0.5 = 82.00\%$, $mAP@0.5:0.95 = 40.03\%$, and $F1 = 79.25\%$) corresponds to higher recall and F1 (Figure 5b), indicating fewer missed crowns under occlusion and overlap in green-space scenes. The BiFPN module ($P = 79.10\%$, $R = 77.76\%$, $mAP@0.5 = 82.36\%$, $mAP@0.5:0.95 = 41.37\%$, and $F1 = 78.42\%$) improves $mAP@0.5:0.95$ (Figure 5c), consistent with better localization under stricter IoU thresholds when crown scales vary and background textures resemble the target. Overall, SCAM supports cleaner discrimination, FRM reduces omissions in dense/occluded canopies, and BiFPN stabilizes cross-scale localization in mixed urban–green environments.

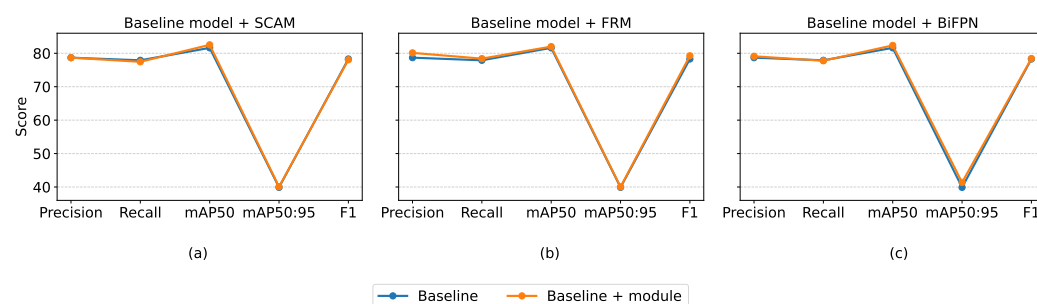


Figure 5. Performance profiles of module-wise ablation results: (a) Baseline model with SCAM; (b) Baseline model with FRM; (c) Baseline model with BiFPN.

Ultimately, this study integrates SCAM, FRM, and BiFPN modules into the neck region of the baseline model to construct an enhanced architecture. The enhanced YOLOv8s achieves $P = 80.69\%$, $R = 78.70\%$, $mAP@0.5 = 83.42\%$, $mAP@0.5:0.95 = 41.69\%$, and $F1 = 79.68\%$ (Figure 6). These gains suggest that stacking the three modules cooperatively refines multi-scale features, improving localization and classification reliability in complex urban scenes.

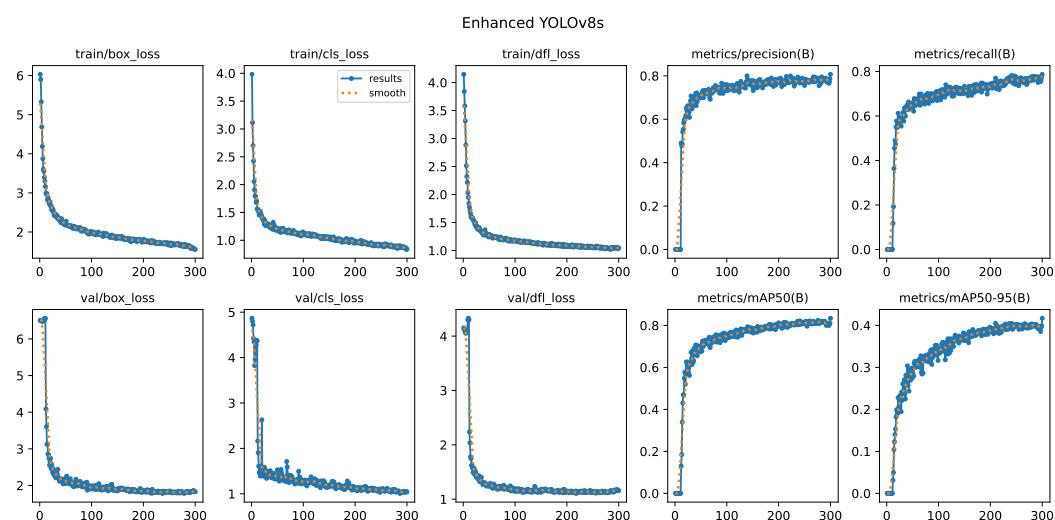


Figure 6. Enhanced YOLOv8s model results.

4.1.2. Comparative Analysis of Multi-Model Performance and Multi-Scenario Generalization Capabilities

This study addresses the challenges posed by target tree-species characteristics and complex urban backgrounds through structural optimization of the baseline model. Compared with the baseline model, the enhanced YOLOv8s improves precision, recall, $mAP@0.5$,

mAP@0.5:0.95, and F1 score by approximately 2.00, 0.80, 1.80, 1.80, and 1.39 percentage points, respectively. Although the inference speed decreases slightly from 45.2 FPS to 44.2 FPS, the model still maintains good real-time performance and deployment efficiency. In addition, the optimized model shows faster convergence during training. For comparison, YOLOv7 achieved $P = 78.21\%$, $R = 77.32\%$, $mAP@0.5 = 79.64\%$, $mAP@0.5:0.95 = 39.72\%$, $F1 = 77.76\%$, and an inference speed of 42.7 FPS, indicating strong runtime efficiency but relatively lower detection accuracy than the enhanced YOLOv8s. RT-DETR achieved $P = 74.23\%$, $R = 76.80\%$, $mAP@0.5 = 72.67\%$, $mAP@0.5:0.95 = 38.42\%$, $F1 = 75.49\%$, and an inference speed of 38.1 FPS, suggesting that although it provides a recent transformer-based baseline, its performance on this task remains lower than that of the YOLO-based models under the current experimental setting (Figure 7).

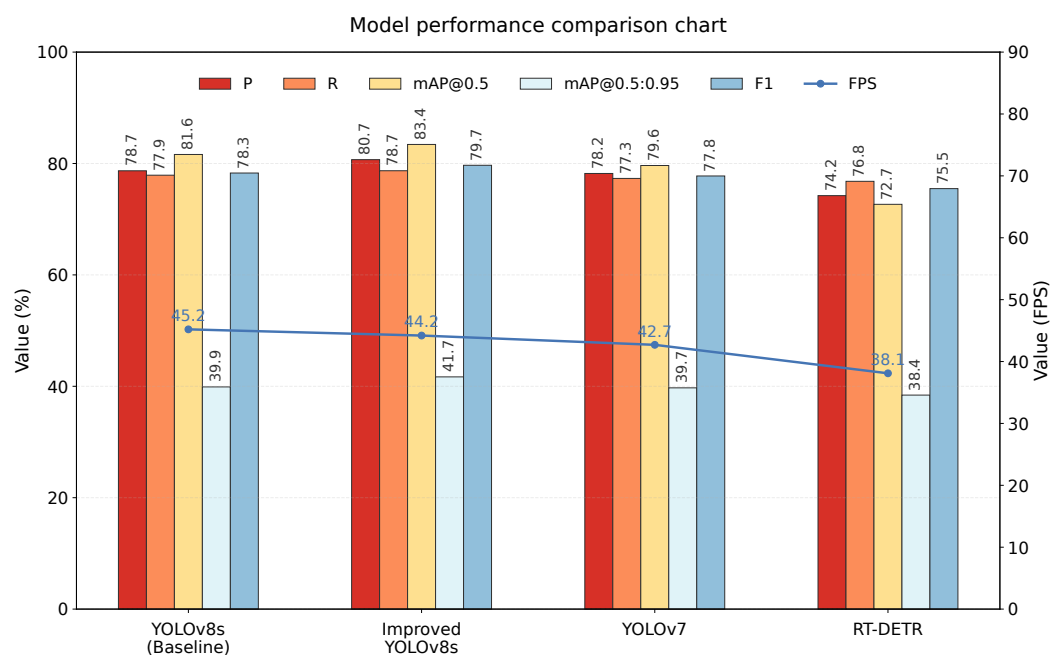


Figure 7. Model performance comparison chart.

To evaluate the stability and robustness of the improved model under different land-cover types and seasonal background conditions, we manually selected 50 images from each of the five scene categories—urban built-up areas, parks, streets, spring/summer, and autumn/winter—to construct a new validation set. Tile IDs were then checked to remove any duplicate samples and to ensure that this validation set was independent from the previous dataset.

In urban built-up areas, the detection performance of all four models declined because of dense buildings, complex impervious surfaces, and cluttered backgrounds. Nevertheless, the enhanced YOLOv8s still achieved the best overall recognition performance, with a precision of 42.9%, a recall of 35.7%, an mAP@0.5 of 31.6%, an mAP@0.5:0.95 of 17.8%, and an F1-score of 38.9%. YOLOv7 showed comparable precision and F1 performance in this scene, reaching $P = 43.7\%$, $R = 35.1\%$, $mAP@0.5 = 32.6\%$, $mAP@0.5:0.95 = 15.4\%$, and $F1 = 38.9\%$, but its overall localization quality under complex urban interference remained slightly weaker. In park settings, where *Juniperus chinensis* trees often appear as relatively regular clusters or columnar forms with clearer structural features, all four models performed well overall. The enhanced YOLOv8s obtained the best results, with $P = 84.2\%$, $R = 82.9\%$, $mAP@0.5 = 89.2\%$, $mAP@0.5:0.95 = 50.2\%$, and $F1 = 83.5\%$. YOLOv7 also showed strong generalization in park scenes, achieving $P = 83.2\%$, $R = 80.6\%$, $mAP@0.5 = 82.7\%$, $mAP@0.5:0.95 = 40.5\%$, and $F1 = 81.9\%$. In street scenes, where occlusion, roadside facilities, and mixed urban elements further deteriorated recognition

conditions, the enhanced YOLOv8s continued to show clear advantages in precision, mAP@0.5, and F1-score. RT-DETR showed relatively limited adaptability in street scenes, where complex roadside objects and frequent occlusion reduced its discrimination ability for small and densely distributed canopies. Its performance remained lower than that of the enhanced YOLOv8s in terms of precision, mAP@0.5, and overall F1-score, indicating that the transformer-based architecture did not provide a clear advantage under such highly cluttered urban conditions.

In autumn and winter imagery, sparse deciduous canopies made evergreen crowns more visually prominent, thus creating relatively favorable detection conditions. Under this setting, the enhanced YOLOv8s achieved $P = 71.3\%$, $R = 61.4\%$, $mAP@0.5 = 61.5\%$, $mAP@0.5:0.95 = 30.8\%$, and $F1 = 65.9\%$, outperforming the baseline YOLOv8s ($P = 70.2\%$, $R = 55.0\%$, $mAP@0.5 = 60.6\%$, $mAP@0.5:0.95 = 28.7\%$, and $F1 = 61.7\%$), YOLOv7 ($P = 69.7\%$, $R = 55.4\%$, $mAP@0.5 = 59.8\%$, $mAP@0.5:0.95 = 30.7\%$, and $F1 = 61.7\%$), and RT-DETR ($P = 67.8\%$, $R = 63.4\%$, $mAP@0.5 = 60.1\%$, $mAP@0.5:0.95 = 27.2\%$, and $F1 = 65.5\%$). In spring and summer imagery, dense foliage and increasingly similar canopy textures among tree species substantially increased the difficulty of detection. All models exhibited performance degradation under these conditions. Even so, the enhanced YOLOv8s still produced the best overall performance, with $P = 41.7\%$, $R = 38.4\%$, $mAP@0.5 = 31.4\%$, $mAP@0.5:0.95 = 16.1\%$, and $F1 = 40.0\%$. By comparison, YOLOv7 achieved $P = 37.4\%$, $R = 38.1\%$, $mAP@0.5 = 30.1\%$, $mAP@0.5:0.95 = 15.3\%$, and $F1 = 37.7\%$, indicating slightly weaker generalization under dense canopy interference. RT-DETR also exhibited noticeable performance degradation in spring and summer scenes. Although its recall remained relatively competitive in some cases, its overall detection accuracy and stability were still inferior to those of the enhanced YOLOv8s, suggesting weaker robustness when target crowns were embedded in visually complex vegetation backgrounds.

4.1.3. Inference of Target Tree Species Distribution

Comparative experiments indicated that the enhanced YOLOv8s achieved the most balanced performance; therefore, the complete dataset was processed by this model for large-scale inference of the target tree species. All predicted locations were exported as a .gpkg point layer and imported into ArcGIS Pro for spatial overlay and visualization, where detections are marked as orange dots on the map. Manual quality checks were performed in high-density target areas, and remote sensing and botanical experts were consulted for ambiguous cases. After removing erroneous points, 117,391 valid canopy targets were retained, and the mapped outputs reveal the spatial distribution pattern of juniper trees within the study area, providing an allergenic-source proxy for subsequent exposure-risk analysis (Figure 8). Typical errors observed during verification included occasional false positives in shaded/occluded or densely vegetated regions where overlapping crowns and cluttered textures reduce separability (sometimes confusing *Pinus tabulaeformis* and *Sabina chinensis* with the target), as well as missed detections when strong shadows fragmented crown appearance or when connected canopy patches lacked clear boundary cues.

The survey results indicate that juniper exhibits distinct clustering patterns within the study area. It is primarily distributed in large parks, historical and cultural sites, as well as courtyards of government agencies and universities. Simultaneously, it displays noticeable linear or block-like distribution patterns in residential areas and street green belts, confirming its role as a key backbone species within the urban–green space system. Two key findings emerge from the distribution map: First, it clearly delineates the primary distribution zones of *Juniperus chinensis*, providing a spatial basis for future vegetation renewal and intervention measures in high-allergen-risk areas. Second, the main distribution zones overlap with Beijing’s densely populated areas, indicating a significant increase in

the potential number of people affected during pollen seasons. This exposure may interact with air pollution, further exacerbating the risk of respiratory diseases.

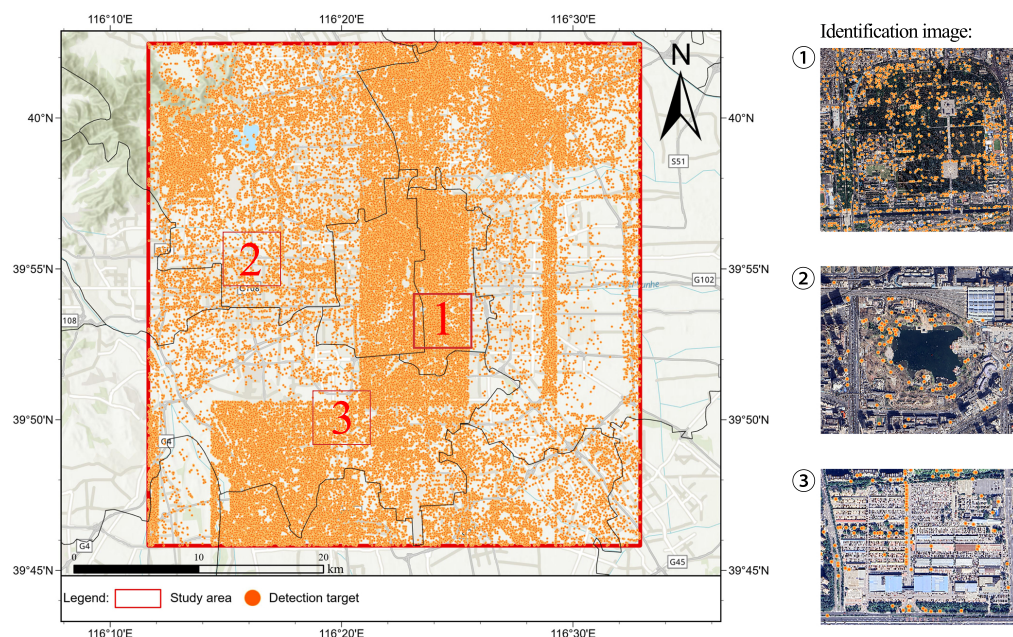


Figure 8. Target tree species distribution map.

4.2. Exposure Risk Level Zoning and Road Exposure Risk Level Distribution

4.2.1. Exposure Risk Level Classification

This study identifies the distribution points of allergenic tree species derived from model inference as risk sources. Buffer zones with three distance thresholds—100 m, 300 m, and 500 m—were constructed and overlaid with a 200 m × 200 m baseline grid to form a foundational spatial risk area. Subsequently, this area was coupled with allergenic tree species density indicators and population density indicators to generate an exposure risk level distribution map (Figure 9).

Overall, exposure risk exhibits a spatial pattern of “gradual expansion from points to areas”: high-risk zones primarily consist of discrete patches, forming multiple hotspots concentrated around areas with dense risk sources; medium-risk zones form distinct expansion belts around the periphery of high-risk patches, with increased patch size and continuous distribution; and low-risk zones cover the largest area, forming extensive continuous distributions within the study area, exhibiting spatial characteristics closer to contiguous areas.

Spatial distribution characteristics reveal that high-risk zones predominantly exhibit concentrated clusters, with scattered point distributions along the study area’s periphery and in localized areas (Figure 10a), demonstrating distinct “hotspot” features. This indicates that high-density aggregations of sensitizing tree species are more likely to form high-exposure risk zones. Medium-risk zones exhibit greater connectivity, with smoother patch boundaries and higher contiguity (Figure 10b). This reflects the risk impact beginning to diffuse from localized concentrations to surrounding areas, establishing a more stable pattern within the urban environment. Low-risk zones further expanded, forming extensive contiguous coverage in multiple directions (Figure 10c). This revealed a distinct areal coverage pattern within the study area, indicating that potential exposure risks persist over a certain range even far from the core risk source areas.



Figure 9. Exposure risk distribution chart.

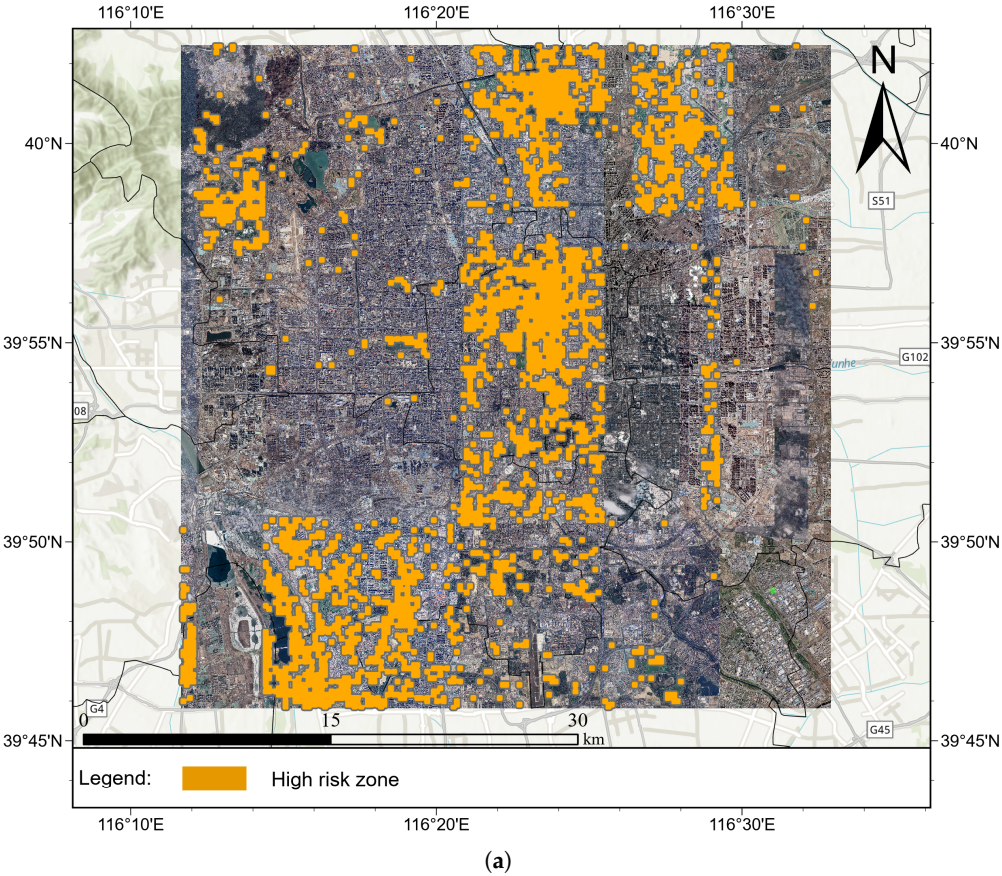


Figure 10. Cont.

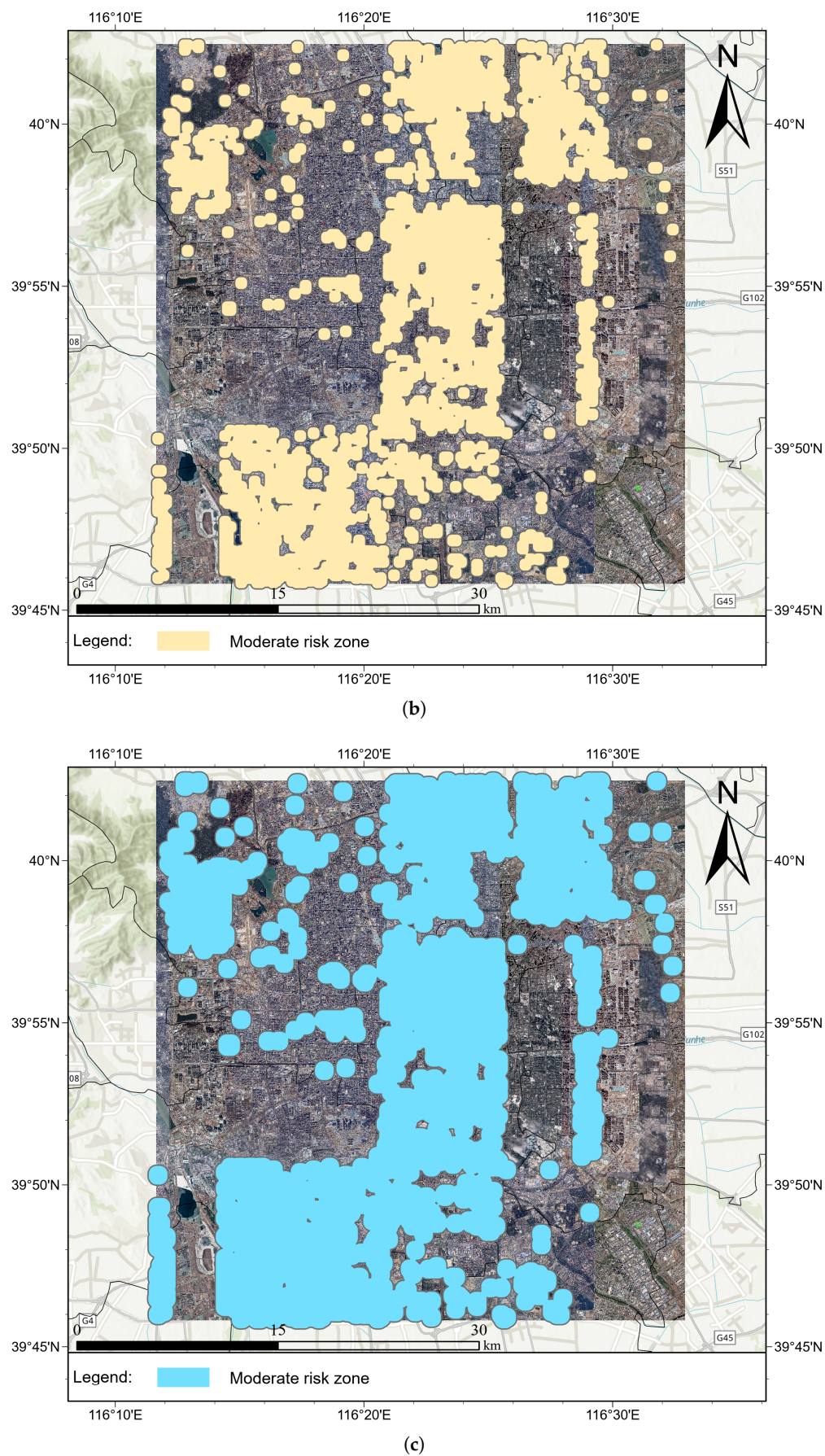


Figure 10. Exposure risk grading distribution chart: (a) Spatial distribution of high-risk zones; (b) Spatial distribution of moderate-risk zones; (c) Spatial distribution of low-risk zones.

4.2.2. Road Exposure Risk Level Distribution

To quantify the exposure risk levels of urban roads, this study spatially overlays the aforementioned three-tier risk zones with the road network system. By determining the intersection relationships between road segments and risk zones of varying grades, corresponding exposure risk levels are assigned to roads, yielding a road exposure risk level distribution map (Figure 11).

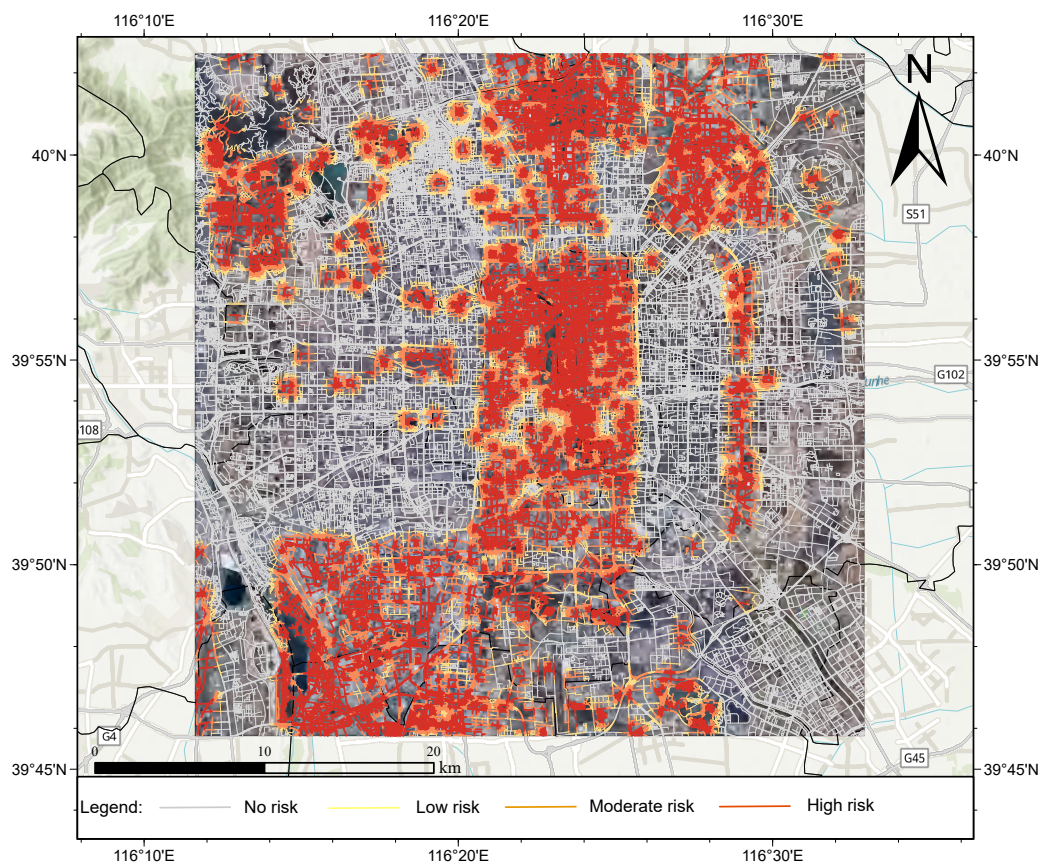


Figure 11. Road exposure risk level distribution map.

The results indicate that high-exposure-risk roads primarily exhibit localized characteristics; medium-risk roads function as transitional zones connecting high-risk areas within the study area, extending outward along internal urban road networks; and low-risk roads cover the widest area, forming extensive distributions throughout the study region. Overall, the exposure risk within the road network exhibits a stronger linear and networked pattern. High-risk roads frequently appear along major thoroughfares and in densely populated road areas, demonstrating that the road system not only facilitates resident mobility but may also serve as a transmission channel for allergenic pollen. This enables risks to more readily evolve from “point-like hotspots” into “linear expansions” and “areal clusters” along transportation networks.

Comparing spatial risk patterns with road-based risk reveals that exposure risk is not uniformly distributed but exhibits distinct clustering structures. High-risk areas predominantly correspond to localized hotspots of tree species density, while road-based risk further highlights the continuity and connectivity of risk within urban road networks. This provides spatial evidence for analyzing exposure risk distribution characteristics and informing future urban greening strategies to manage allergenic pollen exposure risk.

4.3. Distribution Characteristics of Exposure Risks and Population Disturbance

4.3.1. Spatial Distribution Characteristics of Exposure Risk

The Lorenz curves derived from the above Section 3.3: $MEAN_i$ (grid accessibility index), $tree_per_ha_i$ (tree density per unit area), and the composite exposure load indicator EB_i , all deviate significantly from the line of equal risk (Figure 12), indicating pronounced spatial unevenness in the relevant risk factors across the study area.

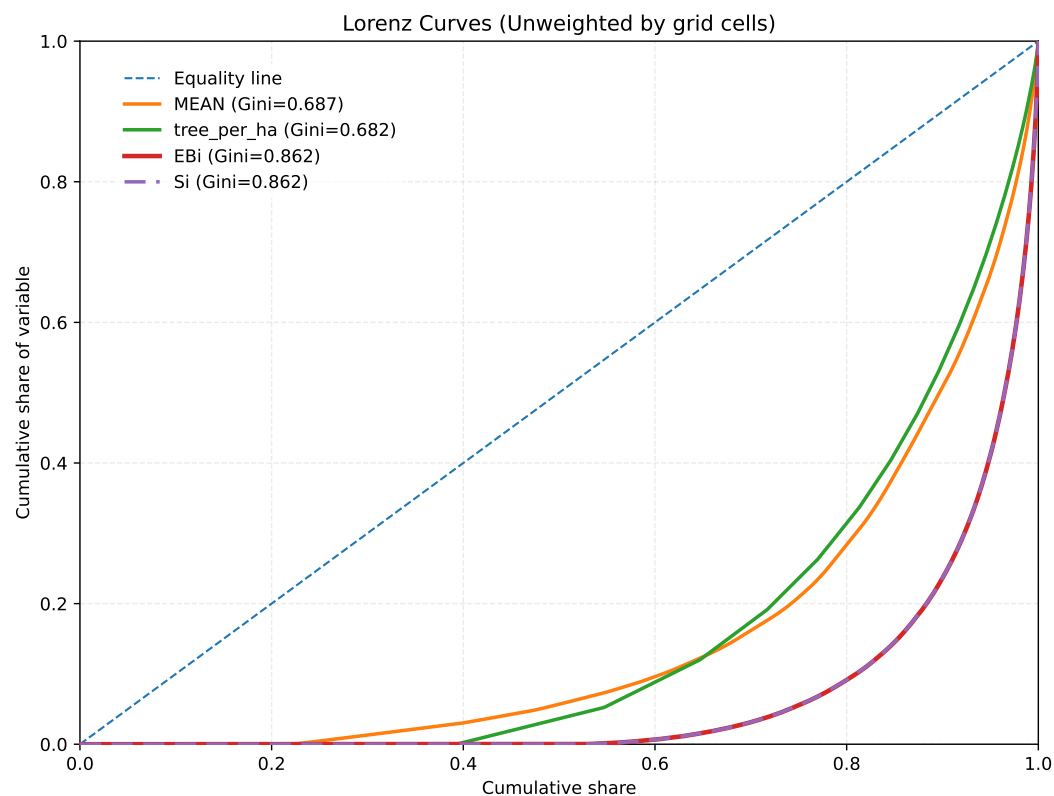


Figure 12. Lorenz curve based on spatial unit sensitization exposure risk index.

The Gini coefficient for $MEAN_i$ is 0.687, while that for $tree_per_ha_i$ is 0.682, both indicating relatively high levels. This suggests that both accessibility conditions and hazard source intensity exhibit a spatial pattern characterized by “concentration in a few grid cells and clustering of high values.” Furthermore, the Gini coefficient for the composite indicator EB_i reached 0.862, with its Lorenz curve exhibiting significantly greater curvature than individual variables. This indicates that when “tree density” and “accessibility conditions” are combined, the concentration of potential exposure risk within spatial units markedly increases, becoming more concentrated in hotspot units. The Gini coefficient for the composite risk score S_i is also 0.862, consistent with EB_i . This indicates that the spatial variation in composite risk captured by S_i is primarily driven by the “high-value clustering” characteristic of EB_i .

From a cumulative contribution perspective, the inequality between EB_i and S_i is particularly pronounced: the top 10% of grid cells contribute approximately 76%, while the top 20% contribute about 91%, revealing a strong “head-heavy” pattern. In contrast, $MEAN_i$ and $tree_per_ha_i$ exhibit a weaker but still noticeable concentration (the top 10% of grid cells contribute approximately 49% and 46%, respectively). This indicates that sensitizing exposure risk in the study area is not determined by a single factor—trees or accessibility—but is jointly driven by the combined effects of both within a small number of spatial units. Specifically, a few grid cells simultaneously exhibit high risk source intensity and stronger transmission conditions, leading to the clustering of exposure risk.

4.3.2. Distributional Equity of Exposure Risk Under Population Disturbance

To examine the impact of population distribution on the unevenness of pollen exposure risk, this study further employed the grid population field pop_{sum} as a weighting factor. Population-weighted Lorenz curves were plotted for variables MEAN_i , tree_per_ha_i , EB_i , and S_i , and weighted Gini indices were calculated (Figure 13).

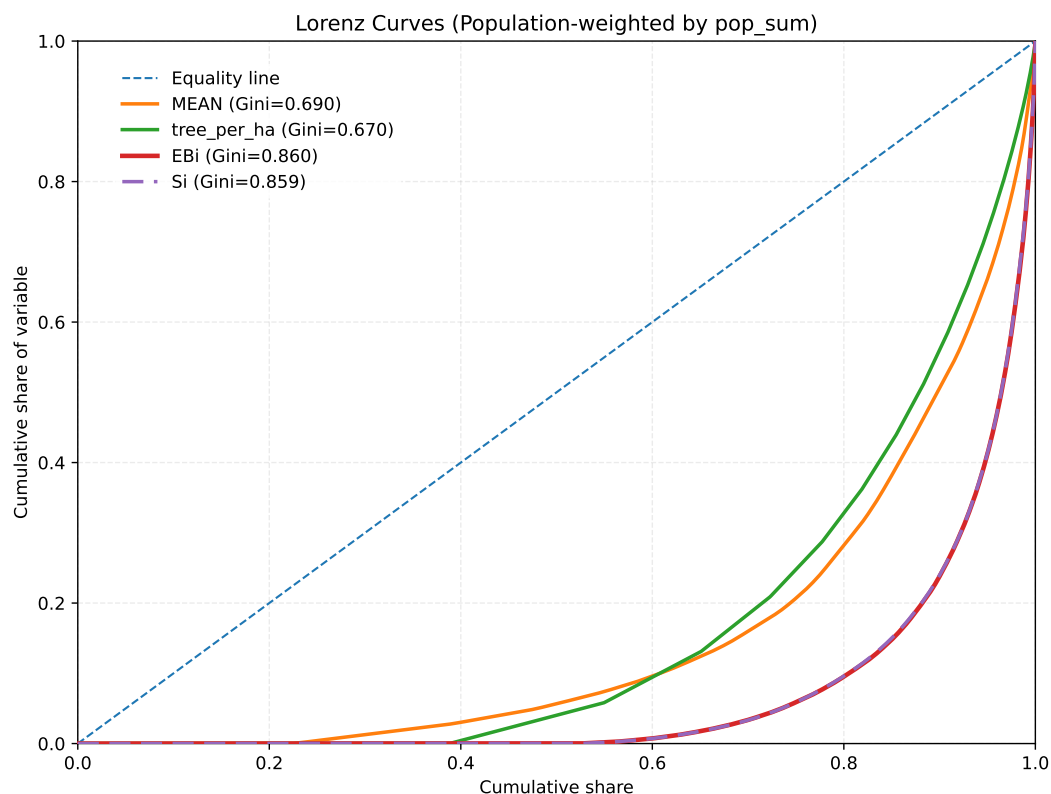


Figure 13. Lorenz curve of the risk indicator for sensitization exposure following the introduction of population disturbance.

The population-weighted Gini coefficient for MEAN_i is 0.69, nearly identical to the unweighted value, indicating that high-accessibility grids exhibit significant concentration even under population interference. The weighted Gini coefficient for tree_per_ha_i is 0.670, slightly lower than the unweighted value of 0.682, indicating relatively limited spatial overlap between high-tree-density grids and high-population-value grids. The weighted Gini coefficients for the composite indicators EB_i and S_i are 0.860 and 0.859, respectively, both at extremely high levels. Their Lorenz curves exhibit significantly greater curvature than those of single variables, reflecting equally pronounced head-heavy concentration in the “population-weighted unequal distribution of exposure vulnerability” characteristic.

These results indicate that population distribution exerts a certain moderating effect on inequality, though its impact is limited: After introducing the pop_{sum} weighting, the inequality of MEAN_i remains virtually unchanged, while that of tree_per_ha_i decreases slightly. This indicates that populations are more concentrated in areas with stronger transmission conditions, yet spatial overlap with high-risk source intensity remains insufficient. Meanwhile, the weighted Gini coefficient for EB_i and S_i remains close to 0.86, suggesting that the dominant factor driving uneven exposure risk distribution in the study area is not the spatial unevenness of population, but more likely the spatial overlay structure between transmission conditions MEAN_i and risk source intensity tree_per_ha_i ; even under the “population-weighted” evaluation metric, the potential exposure burden remains concentrated in a small number of high-risk units.

This finding indicates that subsequent exposure risk intervention strategies should prioritize targeted management in comprehensive high-risk hotspot grids (e.g., tree species optimization and traffic exposure management in areas where key transmission corridors overlap with high allergen sources), rather than relying solely on balanced allocation based on population size.

5. Discussion

5.1. Interpretation of Model Performance and Analysis of Current Limitations

5.1.1. Interpretation of Model Performance

The superior performance of the enhanced YOLOv8s can first be explained by the structural differences within the YOLO family. Compared with YOLOv7, the enhanced YOLOv8s provided stronger feature extraction and multi-scale representation ability, which are particularly important for detecting *Juniperus chinensis* crowns in high-resolution urban remote sensing imagery. In practical scenes, target crowns are frequently disturbed by building shadows, road surfaces, adjacent vegetation, and partial occlusion, while their size is often relatively small and their boundaries are not always clear. Under such conditions, a detector must preserve fine local details while maintaining stable localization across different scales. The enhanced YOLOv8s was better able to adapt to these scene characteristics, which explains its more consistent performance across built-up areas, streets, parks, and seasonal backgrounds.

The performance difference between the enhanced YOLOv8s and RT-DETR is mainly related to the distinction between convolution-based and transformer-based detection mechanisms. RT-DETR has advantages in modeling global contextual relationships, but the target species in this study usually appeared as dense, small, and visually similar crowns embedded in complex urban backgrounds. In this task, accurate local discrimination and robust multi-scale localization were more critical than global dependency modeling alone. Therefore, the enhanced YOLOv8s was better suited to capturing subtle crown features and separating target trees from surrounding interference. By contrast, the transformer-based framework did not show a clear advantage under the combined influence of dense background clutter, high inter-class similarity, and limited spectral separability.

Overall, the results indicate that the enhanced YOLOv8s was more compatible with the detection requirements of this study. Its improved performance was not only a consequence of architectural optimization, but also reflected its stronger adaptability to the actual disturbance conditions commonly encountered in urban high-resolution remote sensing imagery.

5.1.2. Model Limitations and Future Improvement Directions

Although the enhanced YOLOv8s achieved the best overall performance in this study, its results also indicate that the proposed framework already has practical potential for *Juniperus chinensis* identification in urban high-resolution remote sensing imagery. In addition to the quantitative evaluation, field investigation and manual verification further confirmed that most detected targets were consistent with the actual spatial distribution of the species, suggesting that the model can provide reliable support for subsequent distribution mapping and allergenic risk analysis.

However, several limitations remain. First, the model still shows reduced detection capability in some complex scenes, particularly where target crowns are small, densely distributed, partially occluded, or highly similar to surrounding vegetation. Second, the current framework relies primarily on optical satellite imagery, and its performance is therefore sensitive to image quality and acquisition conditions, including cloud cover, shadows, illumination differences, and seasonal variation. These factors may reduce the

separability of the target species from background objects or morphologically similar evergreen trees.

Future work should therefore focus on both data expansion and information enhancement. A larger and more diverse dataset covering more cities, seasons, and complex urban scenes would help improve model robustness and generalization. In addition, multimodal data fusion may further enhance species-level discrimination by integrating optical imagery with near-infrared, hyperspectral, or other auxiliary data sources, thereby improving the accuracy of *Juniperus chinensis* detection in visually complex urban environments.

5.2. Target Tree Species Distribution Analysis

The target tree species distribution map reveals that *Juniperus chinensis* within the study area exhibit a distribution pattern featuring hotspot clusters with linear corridors. Major aggregation zones include large urban parks, historical and cultural spaces, government building complexes, and university campuses. Green belts along primary and secondary streets interconnect, forming continuous linear strip distributions. Within residential areas, this species predominantly exhibits a patchy distribution. This pattern can be attributed to three key factors: First, as an evergreen species, *Juniperus chinensis* offers stable landscape performance and strong adaptability in northern cities, making it a frequent choice for roadside planting, campus landscaping, and institutional courtyards. Second, in historical and cultural sites, *Juniperus chinensis* is often used to shape symbolic landscape features, leading to repeated planting within fixed spaces. Third, standardized greening regulations and nursery supply chains may drive repeated selection of the same tree species across different regions, thereby forming stable ecological corridors connecting urban roads and green spaces.

Furthermore, this distribution map overlaps significantly with major human activity zones. Consequently, residents are more likely to repeatedly encounter allergenic pollen during commutes and daily life, substantially increasing the probability of allergic symptoms among susceptible individuals during pollen seasons.

5.3. Analysis of the Impact of Exposure to Allergenic Pollen

In urban environments, the impact of highly allergenic pollen is not isolated. It interacts synergistically with human activities, urban spatial patterns, and air pollution. Particularly when allergenic plants are located near major thoroughfares and corridor-like streets, pollen released during the pollen season is more likely to coexist with traffic-related pollutants in the same area. Pollen may also disperse along corridor environments formed by roadways, increasing exposure risks during commutes and exacerbating allergic respiratory diseases and related health hazards [47].

From a health mechanism perspective, air pollutants may compromise the airway mucosal barrier and amplify inflammatory responses, heightening human sensitivity to allergens and thereby magnifying pollen's health risks [48]. Consequently, in heavily polluted, traffic-dense areas, pollen often acts not as a sole sensitizing agent but synergistically with pollutants within complex urban environments—both triggering allergic symptoms and exacerbating pre-existing respiratory conditions. Some epidemiological studies have identified interactions between pollen and air pollutants, with such interactions closely associated with acute asthma attacks.

Urban spatial configurations further influence the dispersion and retention patterns of pollen and pollutants. In poorly ventilated, densely built-up areas, restricted airflow causes pollen and pollutants to accumulate near ground level, elevating local exposure levels. Such spaces often include vulnerable populations and areas with insufficient green space renewal, such as older residential communities and zones surrounding schools and hospitals. Planting highly allergenic species near high-traffic roadways further creates

localized high-risk exposure points. Therefore, optimization efforts in road- and building-dense areas should prioritize source control. Specific measures include: adjusting the planting density and layout of highly allergenic plants and optimizing regional biodiversity and green space structure to reduce allergenic risks at the source, while also laying the groundwork for subsequent early warning systems and refined management.

5.4. Urban Greening Renewal Strategies to Mitigate Exposure Risks from Allergenic Pollen

In future urban greening renewal research, the technical workflow proposed in this study can be used to identify the spatial distribution of allergenic tree species. By integrating key information such as population density, road systems, and public transit nodes, high-risk areas for pollen season allergies can be determined. With the rapid advancement of digital media and big data analytics, location data for primary allergen distribution zones can be integrated with multi-source data. This includes meteorological factors, topography and street ventilation conditions, air pollution levels, and vegetation change information updated via remote sensing. Such integration further enhances the predictive accuracy of pollen exposure levels and allergen risk across different areas. Building on these findings, location-based services within social or transportation apps can push real-time risk level alerts to residents. This enables timely countermeasures—such as reducing outdoor exposure during high-risk periods, adjusting commuting routes, using protective gear, or preemptively taking medication—shifting from reactive responses to proactive prevention [49].

Additionally, policies and urban ecological optimization strategies should be implemented to mitigate the negative impacts of allergenic plants. Allergenicity indicators should serve as key references for landscape design and species selection, balancing ecological benefits with “green health” objectives. On the one hand, interdepartmental coordination should be strengthened through establishing low-allergenicity planting guidelines and zoning control rules. In densely populated areas and sensitive zones like schools, hospitals, and nursing homes, stricter controls on species selection and planting layouts are needed to prevent high-risk plants from overlapping in high-exposure units. On the other hand, allergenic species distribution data should be further integrated with multi-source information to precisely identify high-risk areas. Public health risks can be further mitigated by guiding residents to adopt reasonable avoidance and protective measures through public early warning and information services. Given the potential interactions between allergens and air pollutants, relevant policies should also synergistically advance traffic emission reductions and improvements in street microenvironment ventilation to achieve more stable and sustainable risk management.

6. Conclusions

This study aims to establish a rapidly replicable process for identifying allergenic tree species and assessing pollen exposure risks in built-up areas of megacities. It tests a core hypothesis: in high-density urban spaces, the spatial clustering of exposure risks is primarily driven by the distribution patterns of allergenic tree species and their accessibility/dispersal conditions within road networks, rather than solely by population size. To achieve this objective, we combined high-resolution satellite imagery with an improved object detection model to automate the identification and mapping of allergenic coniferous species like *Juniperus chinensis*. We further coupled tree locations with grid, road, and public transit station data to generate hierarchical exposure risk zones and road risk level maps. Statistical indicators measuring imbalance were employed to characterize the spatial concentration of risk.

The results demonstrate that the improved model reliably extracts small-scale canopy features within complex built environments, enabling rapid city-scale surveys and map-

ping. Risk zoning based on these identifications reveals that potential exposure does not diffuse uniformly but exhibits a complex “hotspot clustering–corridor connectivity” pattern. High-risk areas tend to form in regions of high tree density and show continuous expansion along road networks. Further analysis of the exposure risk distribution equilibrium reveals significant spatial concentration in comprehensive exposure load. Comparisons between population-weighted and unweighted data show limited variation in imbalance, suggesting risk clustering is jointly determined by source intensity and transmission/contact opportunities shaped by road networks. Population size exhibits relatively weaker explanatory power than spatial structural factors in the overall pattern. These findings provide actionable spatial evidence for explaining urban pollen exposure mechanisms through the “source–channel–contact” logic chain. Theoretically and practically, this study contributes by proposing an integrated framework (“satellite image auto-identification–multi-source data coupling–risk zoning and inequality diagnosis”) that shifts allergenic tree management from empirical judgment to quantifiable, updatable spatial decision-making. Conceptually, it highlights the “corridor effect” of road networks in exposure formation, offering an interdisciplinary perspective on understanding the coexistence of urban ecological services and ecological negative effects. Practically, it directly supports prioritization for greening renewal and species replacement, avoids travel routes during pollen seasons, enables refined early warnings, and facilitates zoned management around sensitive facilities like schools and hospitals, thereby supporting trade-offs between “ecological benefits and health risks.”

In summary, the proposed technical framework—“high-resolution satellite imagery + enhanced YOLOv8s + multi-source data coupling assessment”—enables rapid identification, distribution mapping, and sensitization risk zoning of specific tree species at the urban scale. Furthermore, by utilizing the Lorenz–Gini index, it reveals risk clustering and its underlying mechanisms, providing replicable methodological support for optimizing urban greening configurations, pollen sensitization risk management, and improvement of urban human habitats and ecological environments. This study provides a replicable technical pathway and decision-making basis for rapid surveys of sensitizing tree species and spatialized governance of pollen exposure risks in megacities, facilitating more refined and quantifiable synergistic optimization of urban greening and public health.

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