

Article

Improving Vegetation Mapping from LiDAR Point Clouds Using a Transmissivity-Based Feature

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Highlights

What are the main findings?

- A transmissivity feature improves urban vegetation classification from LiDAR point clouds.
- Transmissivity is highly informative across multiple spatial scales and enhances model interpretability.

What are the implications of the main findings?

- Transmissivity can be computed efficiently from standard multi-return LiDAR data without additional inputs.
- Echo-enriched point clouds support scalable and interpretable urban vegetation monitoring.

Abstract

Urban vegetation provides essential ecosystem services, including temperature regulation, air purification, noise reduction, and carbon storage. However, urban densification and climate-induced stresses increasingly threaten these ecosystems. Accurate classification of urban vegetation is critical for sustainable urban planning, yet remains challenging due to the structural complexity and high data density of urban LiDAR (Light Detection and Ranging) point clouds. To address current research gaps, including insufficient model interpretability, high computational demands, and limited generalization capabilities, we introduce transmissivity, a novel feature that combines echo-based LiDAR properties with spatial context to more effectively characterize urban vegetation structures. This feature enhances vegetation classification by estimating whether laser beams tend to traverse or terminate within a local neighborhood, independent of the specific return order of individual beams, thereby characterizing vegetation's volumetric permeability. This makes transmissivity highly interpretable, unlike other echo-based statistical features. Transmissivity was evaluated alongside 52 conventional features using three different feature-importance measures across two distinct urban LiDAR datasets from Berlin and Hessigheim 3D (both datasets are from Germany). Transmissivity consistently ranked among the most influential features in both datasets across multiple scales and achieved the highest average gain (Berlin: 0.465; Hessigheim: 0.286) and the second highest mean absolute Shapley value (Berlin: 2.066; Hessigheim: 0.824). Permutation importance confirmed that transmissivity has the strongest impact on the mean decrease in F1-score (Berlin: 0.53; Hessigheim: 0.34) if used in uncorrelated feature subsets. Our findings support that echo-enriched point clouds allow efficient and accurate monitoring of urban vegetation. The feature is simple to compute and does not require additional data beyond standard multi-return LiDAR attributes.



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conditions of the [Creative Commons](#)[Attribution \(CC BY\)](#) license.**Keywords:** LiDAR; echo-information; feature importance; vegetation; urban; classification

1. Introduction

Vegetation is an essential part of our urban environment, providing important ecosystem services such as temperature regulation, air purification, and noise reduction, which all directly impact our well-being (e.g., [1–3]). Other important services include water flow regulation and runoff mitigation, waste treatment, and carbon storage [4]. This sensitive ecosystem is threatened by increasing urban densification and climate-induced drought stresses, which are expected to intensify in the future [5,6].

Monitoring urban vegetation structure enables the quantification, modeling, and optimization of ecosystem services for a wide range of environmental conditions. Such information supports evidence-based decision-making for urban green-space management and the development of climate adaptation and mitigation strategies. However, accurately characterizing vegetation structure across large urban areas remains challenging due to the high spatial heterogeneity and structural complexity of urban environments.

Urban vegetation is strongly influenced by human activities and management practices. Unlike natural ecosystems, trees and shrubs in urban settings are frequently pruned, shaped, or otherwise modified to satisfy functional, aesthetic, or safety requirements, resulting in highly variable and often artificial geometries. In addition, species composition and spatial distribution are typically heterogeneous, reflecting the diverse objectives of vegetation planting and management in parks, streetscapes, residential areas, and other urban land-use types. Consequently, urban landscapes contain a complex mixture of vegetation forms and structures within relatively small areas. Furthermore, numerous anthropogenic objects, such as light poles, fences, or wire-based constructions, exhibit geometric characteristics that can resemble those of vegetation in point cloud data, thereby increasing the likelihood of misclassification.

Urban vegetation mapping has been addressed using a wide range of sensors and methodological approaches (e.g., [7,8]). Optical and aerial imagery-based methods are widely used for urban vegetation mapping due to their rich spectral information, which enables detailed discrimination of vegetation types and species. However, their performance is strongly influenced by trade-offs between spatial and spectral resolution, sensitivity to shadow effects, and high within-class spectral variability in complex urban environments. Recent advances increasingly rely on hyperspectral data and data fusion approaches to improve robustness, particularly by integrating multi-temporal observations or complementary information sources, yet challenges remain in achieving consistent accuracy across heterogeneous urban landscapes (e.g., [7,9]).

LiDAR (Light Detection and Ranging) is an active remote sensing technique that provides detailed 3D point cloud representations of the environment over large areas. With its ability to record multiple backscatter signals (returns) from a single laser pulse, it can penetrate canopies and capture the full structure of vegetation, which makes it a valuable mapping method for urban areas [7,8]. The precise classification of vegetation points is a fundamental step towards an accurate assessment.

Improving point cloud classification can be approached by refining neighborhood construction (e.g., [10–12]), optimizing feature extraction and selection (e.g., [13–15]), or enhancing model architectures and learning strategies (e.g., [16–18]). Many recent studies have focused on the latter, including deep learning approaches that achieve strong results but are computationally expensive (e.g., [19–21]). With the increasing availability of data and denser point clouds, the need for efficient classification strategies is increasing in importance.

In our study, we investigate ways to improve the feature extraction process. Feature extraction is the process of calculating meaningful characteristics of a single point that can be used to predict its class. Commonly used features can be categorized into the

following groups: *Echo*-based features contain direct return properties, and echo-based statistical features summarize the distribution of return properties within a defined local neighborhood. *Height*-based features quantify the vertical structure of the surrounding area in relation to a point. *Geometric* features are derived from the eigenvalue decomposition of the covariance matrix computed from a point's neighborhood, providing measures of local shape and spatial arrangement.

Constructed features are examined to determine their importance in relation to predicting a certain class. Multiple promising features have been presented to characterize the vegetation class, which we describe in more detail in the following Section Comparison of Previously Described Echo-Based Features [22–25].

We identified three main gaps in large-scale urban vegetation mapping from airborne laser scans: (i) the insufficient interpretability of machine-learning models, which makes it difficult to understand which structural characteristics drive classification decisions; (ii) high computational demands that make it difficult to classify large datasets; and (iii) limited model generalization capabilities, which prevent the transfer of a trained model to other sites. To address these challenges, we introduce transmissivity, a feature designed to describe the local permeability of vegetation structures in LiDAR point clouds. By combining echo-based information with neighborhood context, transmissivity captures whether laser beams tend to pass through or terminate within a local region. We evaluate the feature against 52 commonly used descriptors using three feature-importance measures across two urban datasets, Berlin and Hessigheim 3D, to investigate feature relevance for different point cloud characteristics and locations. Furthermore, we assessed the contribution of transmissivity to classification performance, especially in reducing model complexity and cross-site transferability. Our results demonstrate that transmissivity provides an interpretable structural descriptor that consistently ranks among the most informative features while requiring relatively low computational effort and maintaining robust performance across datasets.

Comparison of Previously Described Echo-Based Features

This section reviews existing features that use the spatial distribution of echo-based information to characterize vegetation structures. Figure 1 shows the six metrics most similar to transmissivity based on mutual information for visual comparison. A concluding discussion of the conceptual difference is given in Section 4.1.

The ratio between first and intermediate returns relative to single returns within a spherical neighborhood has been used to detect trees and shrubs in urban environments [24]. In the absence of single returns, the ratio is not defined, and the sum of the first and intermediate returns was implemented instead. Although this approach is capable of separating most of the vegetation from other classes, the values within the vegetation exhibit substantial variation, which is undesirable for accurate classification (cf. Figure 1E).

The ratio of multiple returns to the total number of points has been used to classify segmented point clouds [25]. The return ratio was computed for all points within each segment, which had been generated using a surface-growing algorithm. Their results showed vegetation-point recall values ranging from 72.99% to 98.82% across multiple scenes. We implemented this feature using a spherical neighborhood. The ratio shows a clear difference between vegetation and most non-vegetation points (cf. Figure 1D). However, points located on facades or on the ground beneath trees also exhibit a large number of multiple returns, similar to those observed in vegetation, which diminishes the separability between these areas.

Counts of single, first, intermediate, and last returns within a neighborhood have been used to describe different urban classes such as ground, power lines, vegetation,

and buildings [26]. This approach was further extended by [23], who calculated the variance of the four return types within a point's neighborhood to capture a local return type dispersion. This feature shows high dispersion where single and multi-return points are close, which is mostly on the ground below the trees. Vegetation and buildings show similar low dispersion values, which reduces separability (cf. Figure 1F).

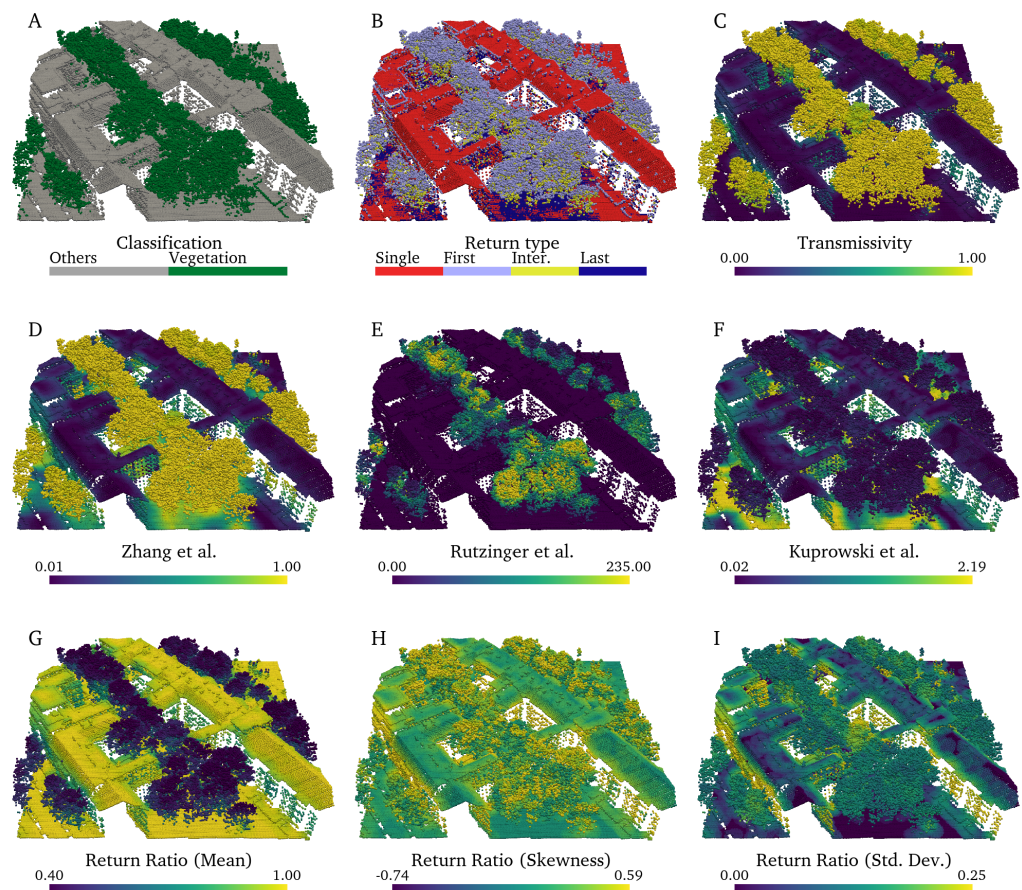


Figure 1. Examples of features that capture the spatial distribution of echo-based information within a spherical neighborhood ($r = 3.25$ m): (A,B) Classification labels and four return types. (C) Sum of first and intermediate returns divided by all returns (transmissivity). (D) Sum of multiple returns divided by all returns [25]. (E) Sum of first and intermediate returns divided by sum of single returns [24]. (F) Variance of the four return types [23]. (G–I) Mean, skewness, and standard deviation of the return ratio [14].

The mean number of returns has been identified as one of the most important echo-based features for vegetation classification based on Shapley value analysis [14]. The statistical operators, including mean, median, mode, skewness, and standard deviation of the echo attributes, were highly relevant among the features tested. This importance was attributed to their ability to capture spatial consistency within the scattered data. Figure 1G,H shows the mean, skewness, and standard deviation of the return ratio, which shares the most information with transmissivity. The mean return ratio effectively separates vegetation points from non-vegetation points, since early returns from multi-return beams yield low values. The values increase with decreasing height because the return number increases along the beam directions. This results in a blurred separation of lower-vegetation and non-vegetation points. The skewness and standard deviation of the return ratio exhibit lower visual separability, despite their relatively high information content with respect to transmissivity.

2. Materials and Methods

This section outlines the datasets and methodology for evaluating the importance of the proposed transmissivity feature for mapping vegetation against established alternatives. The transmissivity feature is first introduced, followed by a summary of existing features. Afterwards, the feature importance metrics, including average gain, Shapley values, and permutation importance, are described. Finally, the experimental setup used to evaluate classification performance and model robustness is presented.

2.1. Datasets

We selected two distinct urban LiDAR datasets for our experiments: An airborne dataset from Berlin [11] and a benchmark dataset from Hessigheim [27] (cf. Figure 2). They differ in their acquisition platforms (airborne laser scan (ALS) vs. Unmanned Aerial Vehicle (UAV)), their point density (13 pts/m^2 vs. 939 pts/m^2), and their structural characteristics (metropolitan vs. suburban environment). The key characteristics are summarized in Table 1. This allows us to compare the relevance of the features for vegetation mapping in different scenarios.

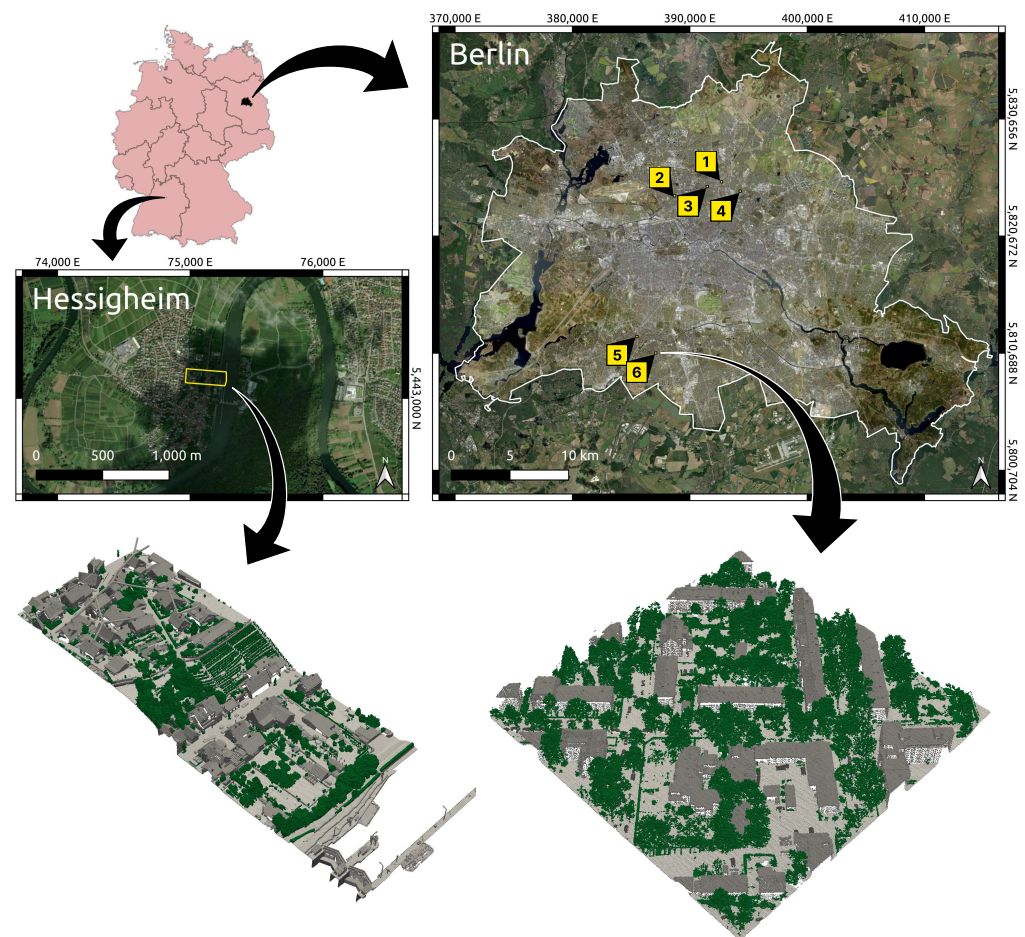


Figure 2. Geographic overview of the two datasets from Berlin [28] and Hessigheim [27] in Germany. Data characteristics are given in Table 1. The numbers in the Berlin view show the location of the six tiles used in this study. The spatial extents of the LiDAR clips at the bottom of the figure are $100 \times 300 \text{ m}$ for Hessigheim and $200 \times 200 \text{ m}$ for Berlin. For improved visibility, the vegetation class is shown in green, contrasted with the other classes. Projection is in UTM Zone 33N for both datasets. Background basemap: Esri, World Imagery, scale not provided, (accessed on 1 July 2026). Sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

Table 1. Dataset characteristics used in this study.

Name	Berlin	Hessigheim (Validation Set)
Reference	[28]	[27]
Platform	Airborne	UAV
Median point density	13 pts/m ²	939 pts/m ²
Total Points	3,819,608	31,190,362
Vegetation points	1,200,975 (31.44%)	5,075,428 (16.27%)
Non-Vegetation points	2,618,633 (68.56%)	26,114,934 (83.73%)

The Berlin dataset was recorded in 2021 and annotated into the four classes of ground, buildings, vegetation, and others by [11]. The labeled tiles are available in [28]. The dataset covers six 200 by 200 m areas with high vegetation density. Data preparation included binarizing the class labels by joining all non-vegetation classes together. Feature calculation was performed for the entire point cloud, which resulted in a matrix with dimensions $3,819,608 \times 53$.

The Hessigheim dataset includes 11 classes, of which shrubs and trees were grouped into vegetation and the remaining classes into non-vegetation points. The features were computed for the entire point cloud, yielding a feature matrix with dimensions $31,190,362 \times 53$.

2.2. Transmissivity Feature

Transmissivity describes how well a laser beam can penetrate the neighborhood of a point. Points were grouped into first and intermediate, or last returns, with single returns treated as last returns. This was achieved by generating a binary mask, where values were set to true when the return number equaled the number of returns and to false otherwise. For a point p_i , we calculate the transmissivity t_i from the fraction of first and intermediate returns $n_{first+inter}$ relative to all returns n_{all} within its neighborhood, following Equation (1) and described in Algorithm 1.

$$t_i = \frac{n_{first+inter}}{n_{all}} \quad (1)$$

Algorithm 1 Computation of point-wise transmissivity

Require: Point cloud P with attributes return_number, number_of_returns and radius r

Ensure: Transmissivity values for all points

```

1: for each point  $p_i \in P$  do
2:   Determine neighborhood:

$$N_i = \{p_j \in P \mid d(p_i, p_j) \leq r\}$$

3:    $n_{all} \leftarrow |N_i|$ 
4:    $n_{first+inter} \leftarrow 0$ 
5:   for each point  $p_j \in N_i$  do
6:     if return_number $j$  < number_of_returns $j$  then
7:        $n_{first+inter} \leftarrow n_{first+inter} + 1$ 
8:     end if
9:   end for
10:   $t_i \leftarrow \frac{n_{first+inter}}{n_{all}}$ 
11: end for
12: return  $\{t_i\}_{i=1}^{|P|}$ 

```

A value of one indicates that all neighbors are first- or intermediate returns, and all laser beams must have passed through the neighborhood. In contrast, a value of zero indicates that all neighbors are last returns and all beams ended in that neighborhood.

The range between 0 and 1 represents the different permeability, or transmissivity, of the defined neighborhood. This feature is intended to emphasize volumetric objects, such as vegetation, in contrast to solid objects, such as facades, roofs, or ground. Figure 3 shows a sketch with 3 different example points and their Neighborhood: Point A belongs to a solid object, and its neighbors are only last returns (red dots). Its transmissivity value is 0. Point B belongs to a tree crown, and its neighbors are only intermediate returns (blue dots). Its transmissivity value is 1. Point C belongs to the tree trunk, which is a solid object in a permeable neighborhood and has a transmissivity value of 0.5.

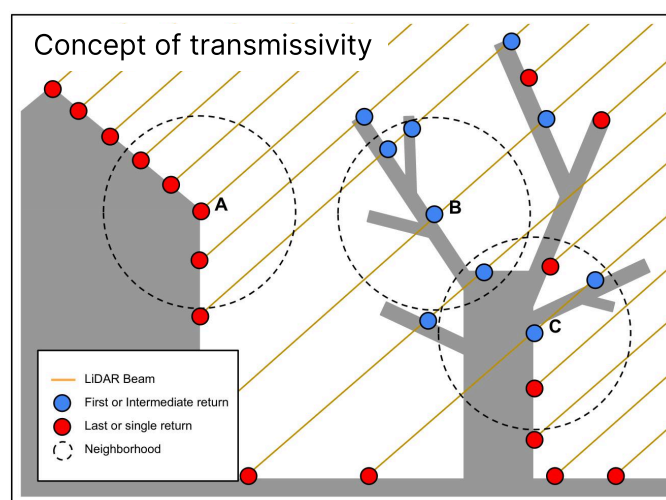


Figure 3. Concept of transmissivity with (A) a point on a solid surface surrounded by only last returns (transmissivity = 0.0), (B) a point in vegetation surrounded by only intermediate returns (transmissivity = 1.0), and (C) a point on a solid surface but surrounded by a penetrable neighborhood with both return types (transmissivity = 0.5). Transmissivity, therefore, responds to space-filling vegetation rather than solid surface roughness.

Transmissivity, therefore, describes the aggregated structural behavior of a local neighborhood rather than the properties of individual laser beams. Unlike return-ratio features that depend on the exact return order within a beam, transmissivity characterizes whether beams tend to traverse or terminate within a neighborhood. This makes the feature less sensitive to beam direction, penetration depth, and scan geometry.

2.3. Other Features

Echo-based features included intensity and reflectance values for the Berlin and Hessigheim datasets, respectively, along with the return number, the total number of returns, and their ratio [22]. For all four echo-based features, six statistical measures, including mean, median, standard deviation, mode, skewness, and range, were computed within a spherical neighborhood [14]. The minimum scales were selected so that each point has a minimum of one neighbor.

For geometric features, we calculated the centered covariance matrix $\mathcal{C}(p)$ of a point p and its neighborhood $\mathcal{N}$ as:

$$\mathcal{C}(p) = \frac{1}{|\mathcal{N}|} \sum_{p \in \mathcal{N}} (p - \bar{p})(p - \bar{p})^T, \quad (2)$$

where $\bar{p}$ is the centroid of the neighborhood $\mathcal{N}$. Through the eigenvalue decomposition of $\mathcal{C}$, we derived the eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \in \mathbb{R}^3$ and the respective eigenvectors $e_1, e_2, e_3 \in \mathbb{R}^3$. Following the equations in Table 2, we compute the geometric features according to [11,15,29].

Table 2. List of features used in this study. Echo-based features marked with a star are also calculated with statistical operators, including mean, median, standard deviation, mode, skewness, and range within a spherical neighborhood.

Feature Name	Definitions	Reference
Echo-based and echo-based statistical features		
Intensity/Reflection *		-
Return number *		[22]
Number of returns *		[22]
Return ratio *	$\frac{RN}{NoR}$	[22]
Rutzinger2008	$\frac{n_{first+inter}}{n_{single}}$	[24]
Zhang2013	$\frac{n_{multi}}{n}$	[25]
Kuprowski2023	$Var(echo\ types)$	[23]
Geometric features		
Sum of eigenvalues	$\sum \lambda_i$	[29]
Omnivariance	$\sqrt[3]{\lambda_1 \lambda_2 \lambda_3}$	[29]
Eigenentropy	$-\sum_{i=1}^3 \lambda_i \ln(\lambda_i)$	[29]
Anisotropy	$\frac{\lambda_1 - \lambda_3}{\lambda_2}$	[14]
Surface curvature	$\frac{\lambda_1}{SE_\lambda}$	[14]
Sphericity	$\frac{\lambda_3}{\lambda_1}$	[15]
Linearity	$\frac{\lambda_1 - \lambda_2}{\lambda_1}$	[15]
Planarity	$\frac{\lambda_2 - \lambda_3}{\lambda_1}$	[15]
Principal component 1	$\frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3}$	[15]
Principal component 2	$\frac{\lambda_2}{\lambda_1 + \lambda_2 + \lambda_3}$	[15]
Principal component 3	$\frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}$	[15]
1st order 1st axis		[13]
2nd order 1st axis		[13]
1st order 2nd axis		[13]
2nd order 2nd axis		[13]
Height features		
Local height	$p_z - \min(\mathcal{N}_z)$	[14]
Local depth	$p_z - \max(\mathcal{N}_z)$	[14]
Height range	$\max(\mathcal{N}_z) - \min(\mathcal{N}_z)$	[14]
Height Std. Deviation	$\sigma_{\mathcal{N}_z}$	[14]
Height rank	$\frac{CF - (0.5 \cdot F)}{N} \times 100$	-
Orientation feature		
Zenith angle	$angle(v_3, v_z)$	[13]

Additional features include four features describing the first- and second-order moments for the first and second axes, which were calculated following [13], four height-based features described by [14], which were extended by the height rank of a point within its neighborhood and an orientational feature, and the zenith angle, which describes the orientation of the point normal vector [13].

2.4. Feature Importance Measurements

For all of our experiments, we used the XGBoost classifier [30], version 3.0.2 with 1000 trees, a learning rate of 0.1, and a maximal depth of 10 splits. These hyperparameters were selected based on commonly adopted settings for gradient boosting models and were further validated through preliminary experiments to ensure stable and consistent performance. To assess the robustness of the feature importance and classification results,

we performed cross-validation and repeated the experiments using the numbers 0 to 4 as seeds for the XGBoost classifier.

For the Berlin dataset, the six available tiles were evaluated using leave-one-out cross-validation. In each fold, the classifier was trained on five tiles and evaluated on the remaining held-out tile. For the Hessigheim dataset, the data were spatially divided into four quadrants based on the x- and y-coordinates, which were used in the same way as the tiles in the Berlin dataset.

To capture various aspects of importance, we used three different feature-importance measures: the average gain reflects the degree to which the XGBoost classifier relies on a feature during training [30], Shapley values explain each feature's contribution to individual predictions [31], and permutation importance—applied to a subset of uncorrelated features—quantifies the impact of each feature on overall model performance [32]. Each metric is explained in the following section.

2.4.1. Average Gain Calculations

The first metric of feature importance employed in this study is average gain, a measure directly derived from the training process of the XGBoost model. XGBoost is a gradient-boosted decision tree algorithm that builds an ensemble of trees in an additive fashion. During training, the model sequentially adds trees to minimize a predefined objective function. In binary classification, the log loss is used for the loss term of the objective function. Each new tree is constructed using a greedy algorithm that iteratively selects the best split at each node based on the gain metric.

The gain quantifies the improvement in the model's objective function from a potential split and is calculated as follows:

$$\text{Gain} = \frac{1}{2} \left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma \quad (3)$$

where I denotes the set of instances at a given node before the split, while I_L and I_R represent the sets of instances assigned to the left and right child nodes, respectively. The terms g_i and h_i correspond to the first- and second-order gradients of the loss function for the prediction of the i -th instance. The parameter λ is an L2 regularization term applied to leaf weights, and γ is a pruning parameter that represents the minimum gain required to justify further splitting.

The average gain for each feature is computed by averaging the gain across all splits in the model where the feature is used. This metric provides a quantitative measure of the contribution of a feature to improving the predictive performance of the model.

2.4.2. Shapley Values Calculations

As a second measure of feature importance, we used Shapley values [33]. Shapley values derived from cooperative game theory provide a principal measure of each feature's contribution to a model's prediction. They quantify the average marginal effect of a feature across all possible feature combinations, accounting for feature interactions. In practice, we computed Shapley values using a GPU-accelerated implementation for tree-based models [34], which efficiently calculates Shapley values for tree-based models. Since Shapley values are calculated for each instance, we computed the mean absolute Shapley value for each feature to serve as a measurement of importance.

2.4.3. Permutation Importance Calculations

As a third measure of feature importance, we used permutation importance, a model-agnostic method. It evaluates how a single feature affects the classification score (F1-score)

by randomly shuffling its values and breaking its connection to the target. The model's score after permutation is compared to the original score. The drop in score indicates the importance of the feature.

Permutation importance has known limitations when applied to features that are highly correlated. If one important feature is permuted, other correlated features may still carry similar information. As a result, the classification score may not decrease, even if an important feature is shuffled. This can bias the results in favor of uncorrelated features.

To address this issue, we select a subset of uncorrelated features and apply permutation importance only to that subset. At the same time, we compare how our transmissivity feature compares to the features with high correlation. To do so, we applied the following 4 steps (a summary of the method is shown in Figure 4):

1. **Correlation:** We calculated the Spearman correlation coefficient between all pairs of features.
2. **Clustering:** Hierarchical clustering was applied to all features using a distance metric defined as the reversed absolute Spearman correlation coefficient, $d = 1 - |r|$, where r denotes the pairwise Spearman correlation between features. The distance between any two clusters was defined as the minimum distance between their features. By adjusting the distance threshold, features can be clustered based on their pairwise correlations: a small threshold groups only highly correlated features, while a larger threshold allows more loosely correlated features to be clustered together. The threshold can be determined analytically, for example, by identifying natural separation levels in the dendrogram, or it can be chosen to correspond to meaningful correlation strengths, thereby reflecting the desired degree of similarity between clustered features. We selected a distance threshold of 0.25, which corresponds to a maximum Spearman correlation coefficient below 0.75 between features belonging to different clusters.
3. **Feature Selection:** To obtain a subset of uncorrelated features, we selected one feature from each cluster. We selected Transmissivity from its cluster and the most promising feature from the remaining clusters. The most promising feature was the one with the highest Spearman correlation coefficient to the target class. This ensured a reasonable selection of features for the final subsets, where inter-feature correlation is minimized while maintaining a high degree of relevance to the target.
4. **Permutation Importance:** For each feature, we calculated the decrease in classification score relative to a baseline by shuffling the feature values. In our experiments, the F1-score served as the evaluation metric, and the permutation procedure was repeated 10 times for each fold and seed, with the mean and standard deviation recorded.

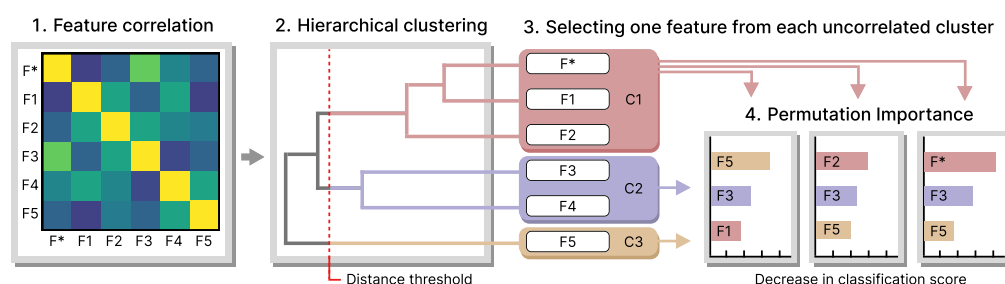


Figure 4. Conceptual workflow for estimating permutation importance of uncorrelated feature sets: (1) Compute the Spearman correlation coefficient (r) between all features; (2) Perform hierarchical clustering using single linkage and a distance metric defined as $1 - |r|$ to group correlated features; (3) Select the feature with the highest correlation to the target class from each cluster to form a subset of uncorrelated features; and (4) compare the permutation importance of our feature F^* against other features from the same cluster ($C1$).

2.5. Classification and Model Performance

Finally, we quantify the improvement of our classification model obtained by incorporating transmissivity as a feature. We evaluate the combination of transmissivity and related metrics both as individual features and in combination with height and geometric features.

Additionally, we tested the capability of the transmissivity feature to separate a multi-class environment. Therefore, we used the Hessigheim dataset with its 11 original classes and performed a classification using the XGBoost classifier and the standard cross-validation schema. The held-out results were joined together and used to compute a confusion matrix, which was normalized using the total number of true instances for each class.

Besides our main results, we investigated the impact of transmissivity on model performance. The use of a more informative feature is expected to reduce the total number of features required to achieve strong performance, thereby decreasing model complexity. Reduced model complexity leads to lower computational cost and improved model interpretability. To evaluate this effect, we employ the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to assess the performance of models with feature sets of varying sizes.

The AIC balances a model's goodness of fit and complexity [35]. Goodness of fit is measured by the log-likelihood $\log(L)$, while complexity is represented by the number of model parameters k (Equation (4)). Lower AIC values indicate better trade-offs between fit and model complexity.

$$AIC = -2\log(L) + 2k \quad (4)$$

Similarly, the BIC penalizes model complexity more strongly by incorporating the sample size n (Equation (5)). In BIC, the penalty term increases with $\log(n)$, which leads to stronger penalization of complex models as the dataset size grows. As with AIC, lower BIC values indicate a better balance between goodness of fit and model complexity [36].

$$BIC = -2\log(L) + k\log(n) \quad (5)$$

Because XGBoost is an ensemble-based method, the standard AIC and BIC cannot be applied directly, since the effective number of model parameters is not well-defined. We therefore adapted the AIC and BIC by approximating the model complexity as the total number of leaf nodes across all trees. While this measure is related to the regularization term used to penalize tree complexity, it should be interpreted only as a proxy for relative model complexity rather than an exact parameter count [30]. For comparison, we repeated this analysis using Gaussian mixture models with two and five components. The results are reported in Section 4.3 and Appendix A Figures A4 and A5.

To evaluate different feature combinations, we constructed an ensemble of feature sets by iteratively excluding one feature at a time. This ensemble was duplicated by systematically excluding transmissivity from all feature sets and, in a parallel ensemble, including transmissivity in all feature sets. This procedure resulted in two ensembles, each comprising 52 feature sets. Within each ensemble, feature sets were ordered by iteratively computing the mean absolute Shapley values of all unselected features and adding the feature with the highest value at each step. This approach corresponds to a greedy search strategy in which the most informative feature of the remaining pool is selected at each iteration.

To keep the workload of this additional analysis manageable, we decided on a different experimental setup: For each dataset, an equal number of non-vegetation points were randomly selected to match the number of vegetation points. The features of selected points were those computed on the full point cloud.

3. Results

This section describes the experiments conducted to assess the feature importance for vegetation classification for both datasets. To guide interpretation, we first analyze how scale affects overall performance, then ask which features matter most at those scales, and finally test whether transmissivity reduces model complexity.

3.1. Scale Dependency

Transmissivity, like most features used in this study, is scale-dependent. It is therefore necessary to consider how its importance changes across scales. Small scales are computationally efficient, but the limited neighborhood may fail to capture the surrounding point cloud. We set the smallest scale to 0.25 m to ensure a minimum of 1 neighbor per point. Larger scales are more expensive to compute and, if too large, may blur specific local characteristics. The effect of scale is visible in the F1-score when all features are used for classification (cf. Figure 5). The F1-scores show an increase for small radii and a decline after reaching a maximum towards larger scales. Comparing the two datasets shows that the maximum for the Hessigheim dataset occurs at a smaller radius (0.75 m) than the corresponding point for the Berlin dataset (3.00 m). This can be explained by the higher point density in the Hessigheim dataset, which captures more characteristics in small neighborhoods. We further computed the mean number of neighbors contained within each scale for both datasets, confirming substantially higher neighbor counts for the Hessigheim dataset (cf. Figure A1). Since classification performance depends on both point density and the scale at which features are computed, we selected the ranges of scales for each dataset according to these findings. The selected scales range from 0.25 to 3.00 m for the Hessigheim dataset and from 0.25 to 5.00 m for the Berlin dataset.

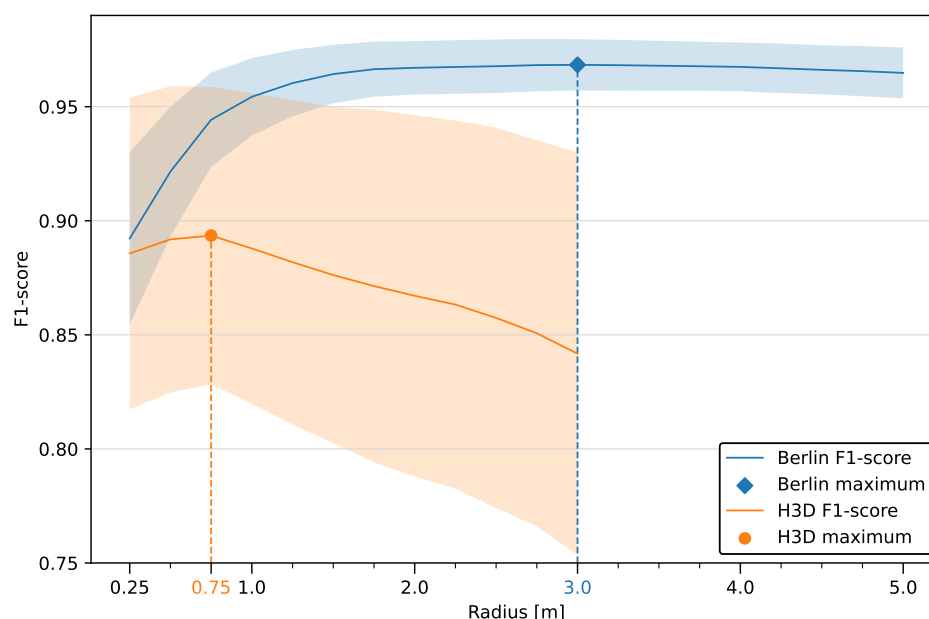


Figure 5. F1-score of the full feature set over different radii for Hessigheim (orange) and Berlin (blue) with selected radii based on maximum F1-score. Shading includes the standard deviation of cross-validation and seed permutation. The optimal radius is substantially smaller for the denser Hessigheim dataset than for Berlin.

3.2. Feature Importance

Since the classification score changes across scales, we performed the feature importance calculation for each scale to estimate the contribution of each feature.

3.2.1. Average Gain

The average gain varies significantly across scales in both datasets (Figure 6). Only a small subset of features accounts for most of the average gain, while the remaining features contribute little to no explanatory power. For both datasets, four of the five main contributing features depend on echo-based information (cf. Table 3). Transmissivity and Rutzinger2008 are the only features present in the top five features of both datasets. Transmissivity shows a high average gain contribution across multiple scales, especially in smaller ranges between 0.5 and 2.5 m.

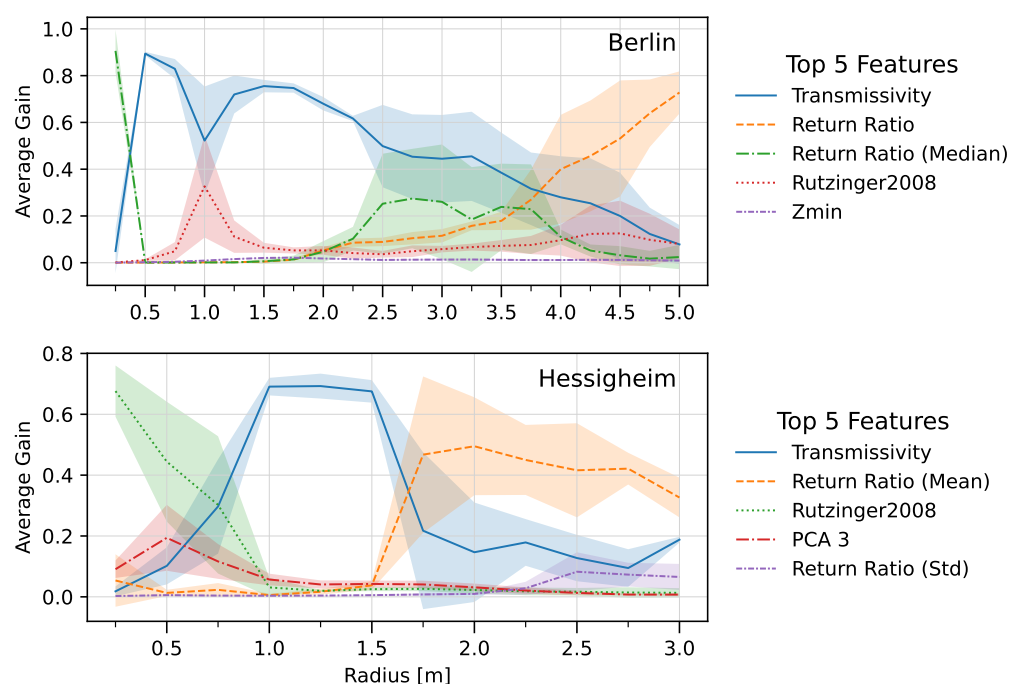


Figure 6. Average gain for the top 5 features from Berlin (**top**) and Hessigheim (**bottom**) for different scales. Subplots are shown with suitable scales. Shading includes the standard deviation of cross-validation and seed permutation. Transmissivity remains among the dominant gain-based features across a broad range of scales in both datasets.

Table 3. Top five ranked features for the Berlin and Hessigheim datasets based on average gain. Values are reported as mean $\pm$ standard deviation for the selected scale at the maximum F1-score (cf. Figure 5) and the mean across all scales.

Dataset	Feature	Average Gain at 3 m	Mean Across Scales
Berlin	Transmissivity	0.445 ± 0.187	0.465 ± 0.249
	Return Ratio	0.115 ± 0.029	0.192 ± 0.227
	Return Ratio (Median)	0.260 ± 0.245	0.138 ± 0.203
	Rutzinger2008	0.058 ± 0.014	0.080 ± 0.065
	Zmin	0.013 ± 0.004	0.012 ± 0.005
Hessigheim	Transmissivity	0.297 ± 0.155	0.286 ± 0.240
	Return Ratio (Mean)	0.023 ± 0.022	0.227 ± 0.206
	Rutzinger2008	0.302 ± 0.226	0.134 ± 0.211
	PCA 3	0.116 ± 0.057	0.055 ± 0.052
	Return Ratio (Std)	0.004 ± 0.001	0.024 ± 0.029

3.2.2. Shapley Values

The mean absolute Shapley values exhibit patterns similar to the average gain, varying across scales for both datasets, and most of the contribution is explained by only a few features (Figure 7). However, the main contributing features differ: for Berlin, the key features originate from the echo-based statistics category (Transmissivity, Return Ratio, Return Ratio (Median), and Rutzinger2008) and the height-based category (Zmin), whereas for Hessigheim, the important features include echo-based (Transmissivity, Rutzinger2008), height-based (Zscore, Zmin), and a geometric feature (PCA3). Notably, transmissivity shows high values across most scales in the Berlin dataset. For scales larger than 2 m, Zmin is the dominant feature (cf. Table 4). In the Hessigheim dataset, transmissivity shows high values in the mid-range between 1.00 and 1.75 m, and PCA 3 is dominant below 1 m.

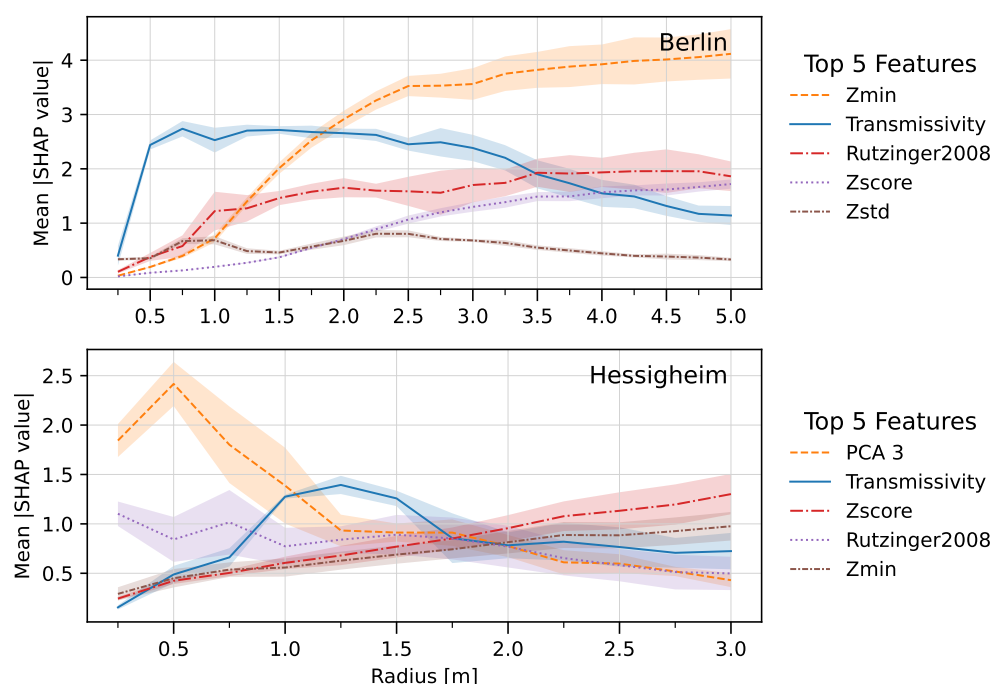


Figure 7. Mean absolute Shapley values for the top 5 features from Berlin (**top**) and Hessigheim (**bottom**) for different scales. Subplots are shown with suitable scales. Shading includes the standard deviation of cross-validation and seed permutation. Transmissivity shows consistently high mean absolute SHAP values, although the dominant competing features differ between datasets.

Table 4. Top five ranked features for the Berlin and Hessigheim datasets based on mean absolute Shapley values. Values are reported as mean $\pm$ standard deviation for the selected scale at the maximum F1-score (cf. Figure 5) and the mean across all scales.

Dataset	Feature	Average Gain at 0.75 m	Mean Across Scales
Berlin	Zmin	3.561 ± 0.292	2.781 ± 1.408
	Transmissivity	2.384 ± 0.242	2.066 ± 0.665
	Rutzinger2008	1.702 ± 0.319	1.497 ± 0.531
	Zscore	1.299 ± 0.090	0.966 ± 0.600
	Zstd	0.682 ± 0.026	0.541 ± 0.153
Hessigheim	PCA 3	1.801 ± 0.388	1.095 ± 0.601
	Transmissivity	0.661 ± 0.093	0.824 ± 0.333
	Zscore	0.504 ± 0.032	0.812 ± 0.318
	Rutzinger2008	1.016 ± 0.327	0.778 ± 0.180
	Zmin	0.537 ± 0.074	0.699 ± 0.203

3.2.3. Permutation Importance

We selected the features calculated using the radius corresponding to the respective F1-score maximum for each dataset to ensure a meaningful choice of scale. Following the process described in Section 2.4.3, we constructed a feature subset with a maximum pairwise Spearman correlation coefficient below 0.75. The subset containing transmissivity is shown in Figure 8.

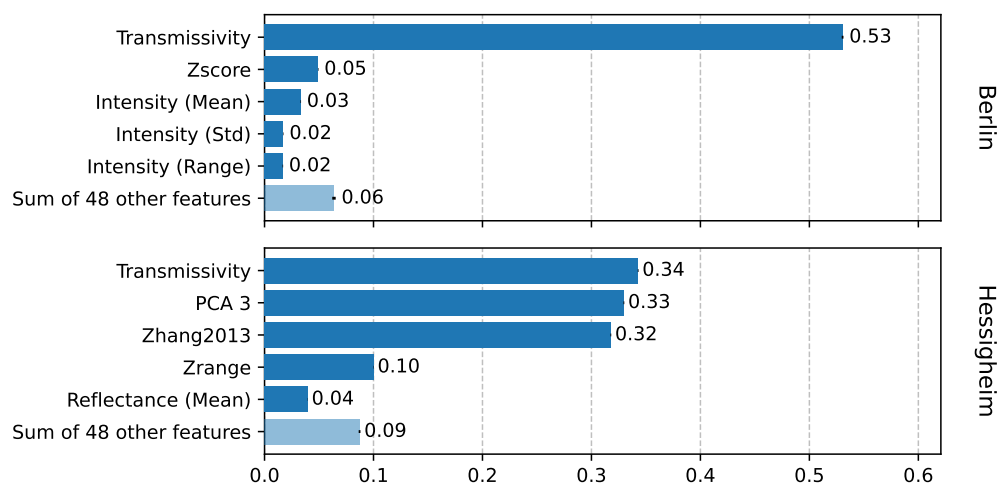


Figure 8. Permutation importance of the uncorrelated feature set for Berlin (**top**) and Hessigheim (**bottom**). Radii for feature calculation correspond to the F1-score maxima (3.00 for Berlin and 0.75 for Hessigheim). Hierarchical clustering was applied using a distance threshold of 0.25, consistent with the procedure described in Figure 4. This threshold corresponds to a maximum Spearman correlation coefficient below 0.75 between features belonging to different clusters. The light-blue bar summarizes the cumulative permutation importance of the remaining 48 features. Among the decorrelated feature subsets, permuting transmissivity causes the largest decrease in F1-score in both datasets.

Transmissivity shows the largest impact among the evaluated features on the classification score when permuted with other uncorrelated features for both datasets (cf. Figure 8). While this effect is prominent in the Berlin dataset, it is slightly visible in the Hessigheim dataset.

Across all three importance measures, transmissivity is consistently among the top-ranked features and is the only feature that remains highly informative across datasets, scales, and correlation-aware evaluations.

3.3. Classification Scores

Transmissivity achieved F1-scores comparable to the related feature and in combination with height and geometric features (cf. Figure 9). This demonstrates that it provides a competitive representation despite its simplicity. Similar results are achieved for the Hessigheim dataset (cf. Figure A2).

Classifying the 11 classes of the Hessigheim dataset using transmissivity alone resulted in a high recall of 0.91 for the tree class (Figure 10). The tree class was most frequently confused with urban furniture and shrubs, with 27% and 39% of the samples from these classes being misclassified as trees, respectively. Similarly, 37% of shrub samples were misclassified as roofs. Most of the remaining misclassifications involved the low vegetation class, corresponding to grass-covered ground surfaces, or the roof class, as shown in the first and fifth columns of the confusion matrix (Figure 10).

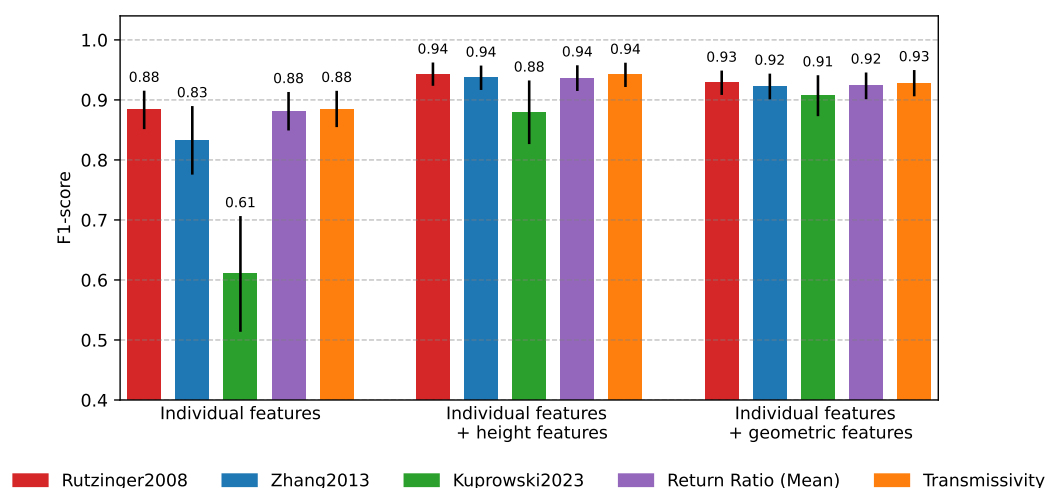


Figure 9. Comparison of F1-score results for transmissivity and related metrics for the Berlin dataset at a 3.00 m neighborhood scale. Values next to bars report the mean value, while the black error bars reflect the standard deviation from cross-validation. Transmissivity performs competitively both alone and when combined with geometric or height features.

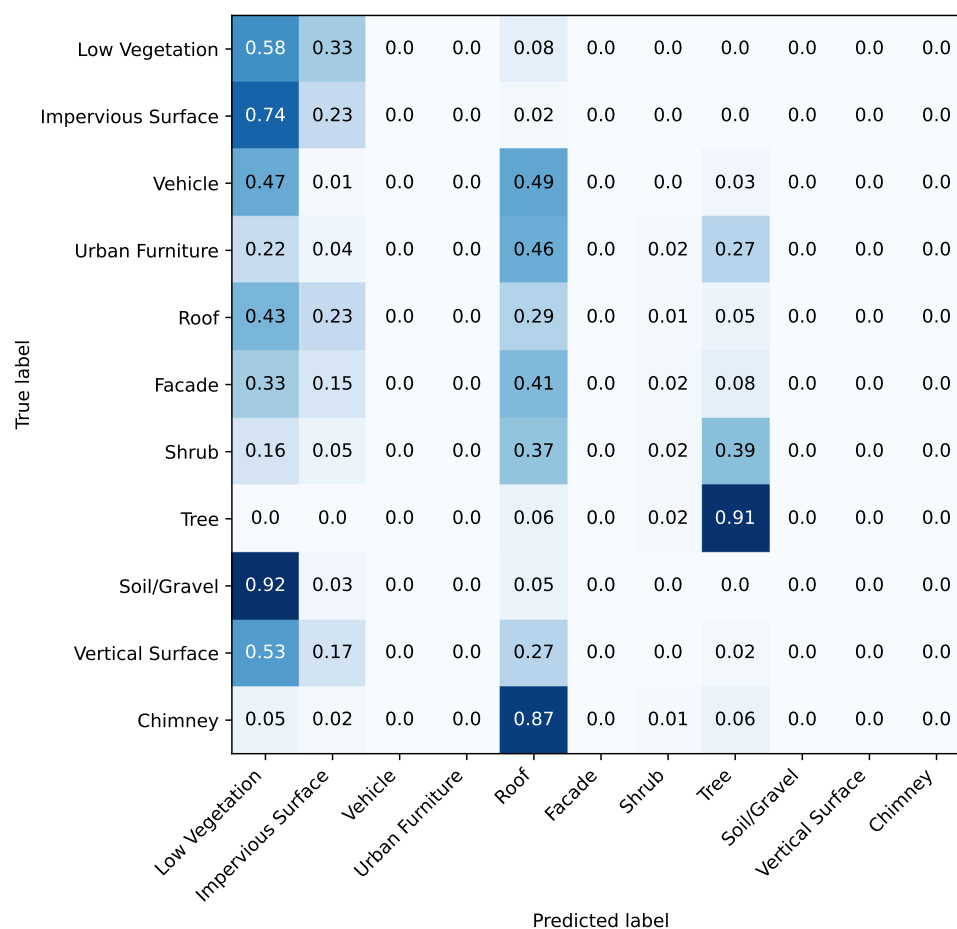


Figure 10. Normalized confusion matrix obtained from cross-validation on the Hessigheim dataset using only transmissivity as a feature. Rows correspond to the ground-truth classes and columns to the predicted classes. Each row is normalized to sum to one; consequently, the diagonal entries indicate the per-class recall, while off-diagonal entries represent the proportion of samples misclassified as other classes. Larger values are represented in darker blue for better readability. Transmissivity alone identifies trees reliably but cannot distinguish many non-vegetation classes and shows substantial ambiguity between shrubs, trees, and roofs.

4. Discussion

Our experiments demonstrated that transmissivity provides competitive classification performance compared to other features, including closely related approaches, while consistently achieving higher feature importance across datasets and scales. We next discuss the conceptual novelty, limitations of our experimental setup, the relevance of informative features on model complexity, and feature categories in the following sections.

4.1. Conceptual Novelty

Information about multiple returns is a valuable attribute of LiDAR data, and its spatial distribution has been used to describe vegetation in different variations before [14,22–25]. The limitations of the existing features are described in Section Comparison of Previously Described Echo-Based Features and are visually compared in Figure 1.

Some conceptual assumptions differentiate the transmissivity feature from existing features: First, multiple returns are not only specific to the vegetation class. In particular, the last returns are often found beneath vegetation on the ground or on facades and roof features (cf. Figure 1B). To account for this, transmissivity focuses on first and intermediate returns in contrast to the features described by [23,25], which include last returns. This solves issues of beam-shadow effects visible in Figure 1D,F.

Second, vegetation is described through the absence of single and last returns, which both determine the endpoints of traveled laser beams. Rutzinger et al. [24] uses the ratio of multiple to single returns to distinguish between penetrability and solidity of structures. Although this feature does not use last returns, its outcomes are highly impacted by the number of single returns, which drastically decrease the resulting value. This results in a stronger emphasis on solid structures. Besides this bias, it relies on the presence of single returns within the vegetation, which may not be the case. Adapting it to use the sum of multiple returns in the absence of single returns results in high variation of values within the vegetation and thus an unclear definition of the class in the feature space.

Lastly, transmissivity does not rely on the exact return order within individual laser beams. Instead, it characterizes the aggregate tendency of beams to traverse or terminate within a local neighborhood. This reduces sensitivity to beam direction, penetration depth, and scan angle, allowing transmissivity to describe vegetation as a volumetric and penetrable structure rather than as a sequence of ordered returns (cf. Figure 1G).

4.2. Caveats

Transmissivity's capability to separate vegetation and non-vegetation has been shown both visually and experimentally (cf. Figures 1C and 10, as well as Sections 3.2.1–3.2.3). The conceptual design of the feature does not uniquely distinguish vegetation from all other structures in the urban environment. Urban furniture is the most likely to be misclassified as vegetation, followed by facades and chimneys (cf. Figure 10). These objects also generate first and intermediate returns in the absence of last returns when hit by the LiDAR laser. Since these structures mostly differ in shape or size, e.g., due to a smaller footprint, additional shape-defining features may improve a transmissivity-based vegetation classification. The results also reveal that trees are easier to classify when considered separately from smaller vegetation classes, such as shrubs. This suggests that shrubs share a similar transmissivity signature with grass or the roof classes, leading to increased confusion in the classification (cf. Figure 10). As a neighborhood-based feature, transmissivity is limited in describing vegetation near class boundaries because neighboring non-vegetation points contribute to the feature computation, thereby reducing class separability. This effect is expected to become more pronounced near the ground and when larger neighborhood sizes are used.

Feature importance was assessed only for feature sets computed at a single scale, not for mixed-scale sets. This approach allows exploration of a wide range of radii without generating very large feature sets that might include highly correlated features across scales [14]. We tested multiscale feature sets for both datasets using the maxima points shown in Figure 5 as scales. Combining features from both scales led to no significant increase in the F1-score for both datasets (cf. Appendix A Figure A3).

Another limitation of this study is that we considered only spherical neighborhoods for features relying on spatial context. Spherical neighborhoods are commonly used for geometric, momentum, and echo-based statistical features (e.g., [13–15]). In contrast, height-based features may benefit more from cylindrical neighborhoods, as suggested by [37]. While this is appropriate for height-related metrics, it reduces the separability between vegetation and underlying ground points, as both would share the same cylindrical neighborhood. Adaptive neighborhoods show improved classifications and could also be beneficial for the transmissivity feature (e.g., [11,38,39]).

The study focuses on variations in point density, acquisition platform, and degree of urbanization of two datasets from Germany. Our experiments showed that the Hesse dataset with its high point density of 939 pts/m² achieves good classification performance already on smaller scales compared to the Berlin dataset with 13 pts/m² (cf. Figure 5). Our results show promising classification abilities for the transmissivity feature (cf. Figures 1 and A2). The applicability of transmissivity for vegetation classification in other regions with different vegetation structures or urbanization patterns remains unclear and needs to be studied further. Future investigations across diverse vegetation types and remote sites are required to assess the generalizability of the transmissivity feature to other countries and applications.

4.3. Model Complexity and Performance

Our experiments focused on the XGBoost classifier due to its strong performance in airborne lidar classification in an urban context (e.g., [23,40]). We assessed the influence of transmissivity on model complexity and predictive performance by computing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for the XGBoost model and AIC for a simple Gaussian mixture model across an assembly of 52 feature sets, each varying in size between 1 and 15 features (cf. Figure 11 and Appendix A Figures A4 and A5). Smaller sets of 1 to 6 features that included transmissivity yielded lower AIC values. For feature sets comprising more than seven variables, the differences in AIC became negligible. These results indicate that highly informative features can improve classification performance while keeping model complexity low. We are aware that the total number of leaves is only a proxy measure of the complexity of the XGBoost model. For the BIC analysis, the effect of transmissivity depends on the number of included features (cf. Appendix A Figure A4). For small feature sets, models including transmissivity do not consistently achieve lower BIC values than feature sets without transmissivity, indicating that the stronger BIC penalty for model complexity can offset the gain in predictive performance. However, from feature sets of eight variables onward, transmissivity-containing models yield lower BIC values, suggesting a more favorable accuracy–complexity trade-off once a sufficient number of complementary features is included. We therefore interpret the BIC results as partial support for the added value of transmissivity, while acknowledging that this effect is not uniform across all feature-set sizes. Taken together, the AIC and BIC results indicate that transmissivity provides greater flexibility in defining decision boundaries (i.e., tree leaves), achieving a favorable trade-off between model fit and complexity across different feature-set sizes.

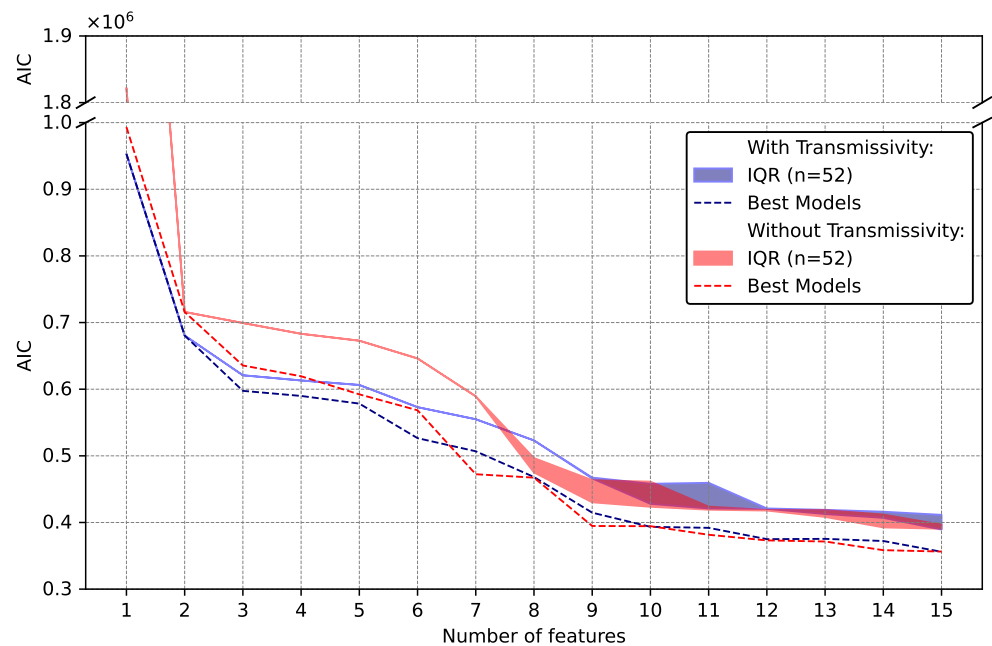


Figure 11. Akaike Information Criterion (AIC) values for the XGBoost classifier trained and tested on the Berlin dataset using different feature set sizes. A total of 52 sets were constructed using leave-one-out rules. Lower AIC values indicate a better trade-off between model accuracy and complexity. Feature sets are ordered by their mean absolute Shapley values. For clarity, the interquartile range (IQR) and the best-performing models are highlighted. BIC values are shown in Appendix A Figure A4.

The Gaussian mixture model exhibits the most favorable trade-off between model complexity and performance when using four features that include transmissivity, whereas the optimal feature set excluding transmissivity requires five features and yields a higher AIC (see Appendix A Figure A5). This indicates that incorporating transmissivity improves model efficiency beyond what is achieved with conventional feature sets. These results suggest that transmissivity improves the predictive performance of models for vegetation classification, regardless of the model architecture. This reduction is particularly relevant for large-area urban mapping, where feature computation and model inference dominate runtime.

4.4. Feature Categories

This study includes features from different categories, namely, echo-based, echo-based statistics, geometric, and height-based. Our results from three different feature importance metrics show that echo-based statistics are among the most important features for vegetation classification (cf. Figures 6–8). This result is consistent with the results of [14]. Using each feature category independently for classification shows that echo-based statistics achieve the highest F1-score across all scales (cf. Figure 12). Furthermore, adding transmissivity to geometric features significantly improves model performance, particularly at smaller radii. These findings demonstrate that echo information provides crucial enrichment for point clouds in classification tasks.

We additionally test the transmissivity feature against related echo-based statistical features on their own and in combination with features from other categories to quantify their impact on F1-scores. Transmissivity achieved F1-scores comparable to the related feature, demonstrating that it provides a competitive representation despite its simplicity (cf. Figures 9 and A2).

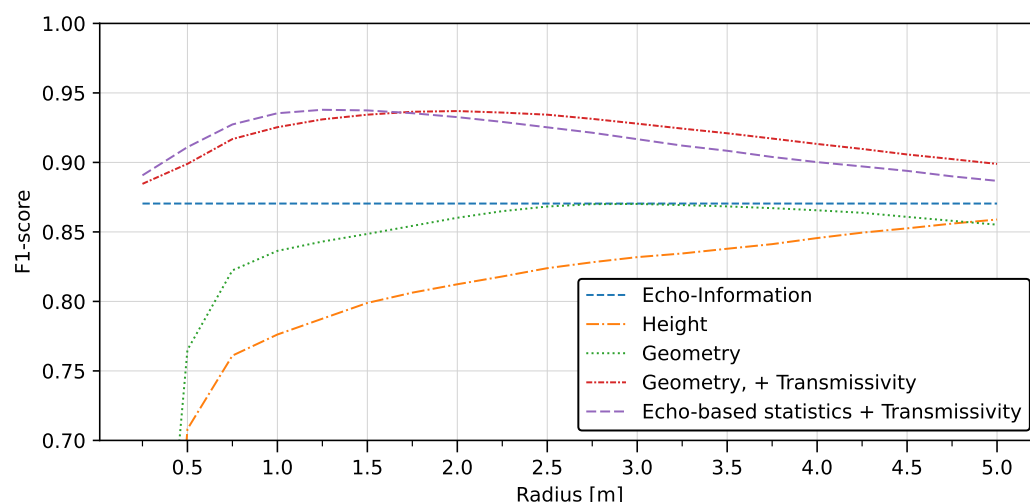


Figure 12. F1-scores for independent feature categories across different radii for the Berlin dataset. Table 2 lists all features in each category.

5. Conclusions

This study introduced an interpretable echo-based feature formulation, namely transmissivity, to improve vegetation classification in urban LiDAR point clouds. Its relevance is evaluated against 52 commonly used features in two distinct datasets from Germany. We specifically compare LiDAR echo-based features, which exploit multiple-return characteristics and can be aggregated into statistical descriptors, with geometric features that rely solely on the spatial distribution of points and their local neighborhoods.

Feature importance analyses revealed that only a subset of 5 features contributes substantially to model performance. Echo-based statistical features were the most useful feature category.

Transmissivity consistently ranked among the most influential features in both datasets and achieved the highest average gain across scales (Berlin: 0.465; Hessigheim: 0.286) and the second highest mean absolute Shapley value across scales (Berlin: 2.066; Hessigheim: 0.824). While other features showed higher values at individual scales, transmissivity exhibited the most consistent importance across the evaluated scale range. Permutation importance analysis further confirmed that transmissivity has the strongest impact on classification performance, with a mean decrease in F1-score of 0.53 and 0.34 for the Berlin and Hessigheim datasets, respectively. Additional analysis indicates that transmissivity improves model efficiency, making it a useful feature for large-area point cloud classification tasks.

This study highlights the importance of echo information in point cloud data for vegetation classification. Conceptually, transmissivity reframes vegetation detection as a problem of local LiDAR penetrability, aligning signal behavior with ecological structure.

Author Contributions: Conceptualization, M.H., A.R. and B.B.; methodology, M.H.; software, M.H.; validation, M.H., A.R. and B.B.; formal analysis, M.H.; investigation, M.H.; resources, B.B.; data curation, M.H.; writing—original draft preparation, M.H.; writing—review and editing, A.R. and B.B.; visualization, M.H.; supervision, A.R. and B.B.; project administration, B.B. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Code for the feature calculation: <https://github.com/UP-RS-ESP/Transmissivity-Feature> (accessed on 15 July 2026).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

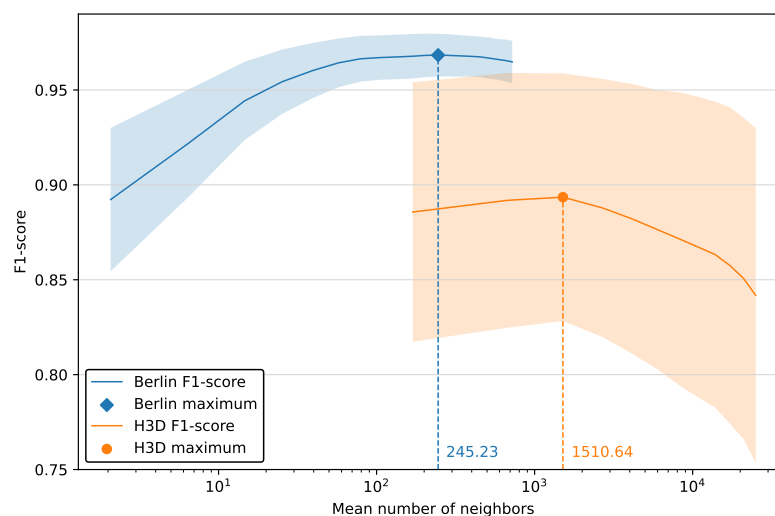


Figure A1. Replication of Figure 5 with a modified x-axis showing the F1-score versus mean number of neighbors per scale for the Berlin (blue) and Hessigheim (orange) datasets. Shading includes the standard deviation of cross-validation and seed permutation. Scales range from 0.5–5.0 m and 0.5–3.0 m (0.25 m step), respectively. Maximum points follow Figure 5.

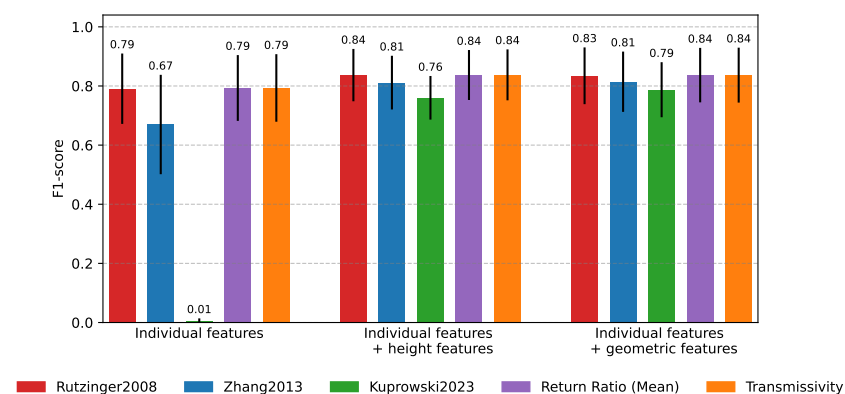


Figure A2. Comparison of F1-score results for transmissivity and related metrics for the Hessigheim dataset at a 0.75 m neighborhood scale (F1-score maximum).

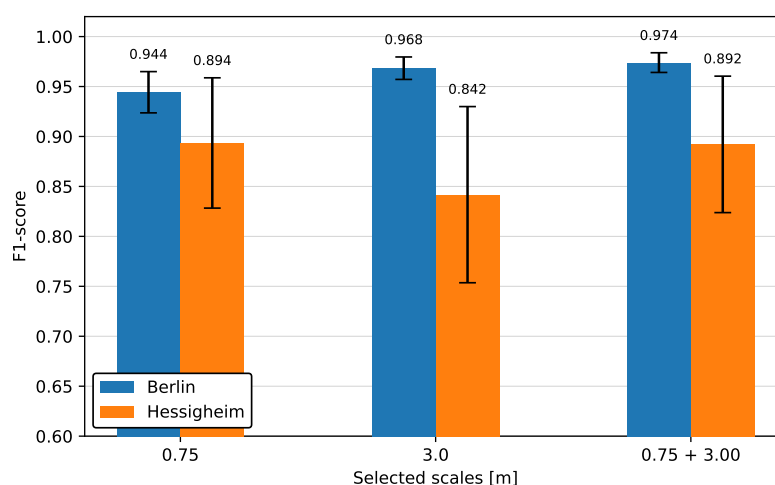


Figure A3. F1-score of all 53 features computed at different scales for the Berlin dataset (blue) and Hessigheim dataset (orange): 0.75 m (F1-score maximum of Hessigheim), 3.00 m (F1-score maximum of Berlin), and the aggregate features from both scales (0.75 m + 3.00 m).

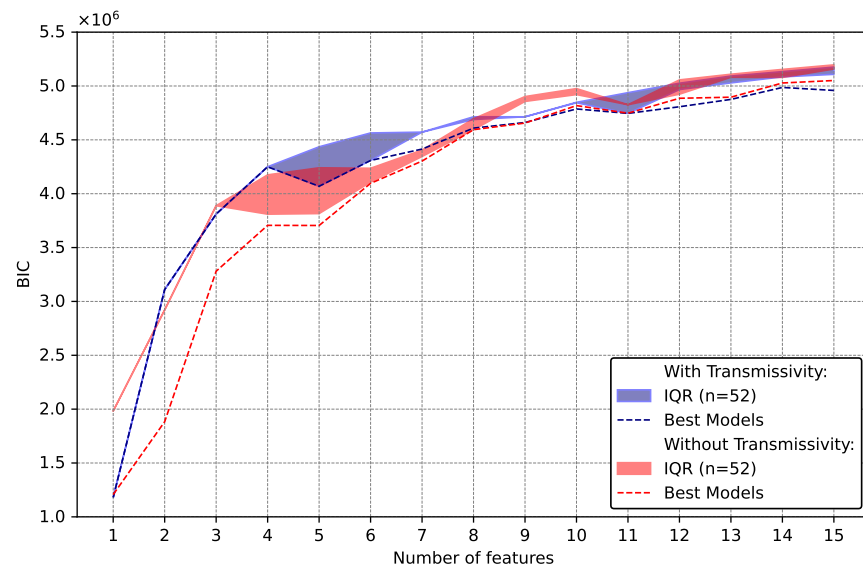


Figure A4. Bayesian Information Criterion (BIC) for the XGBoost model classifier trained and tested on the Berlin dataset across different feature set sizes. A total of 52 feature sets were constructed using leave-one-out rules. Lower BIC values indicate a better trade-off between model fit and complexity. Feature sets are ordered by mean absolute Shapley values. The interquartile range (IQR) and best-performing models are highlighted for clarity.

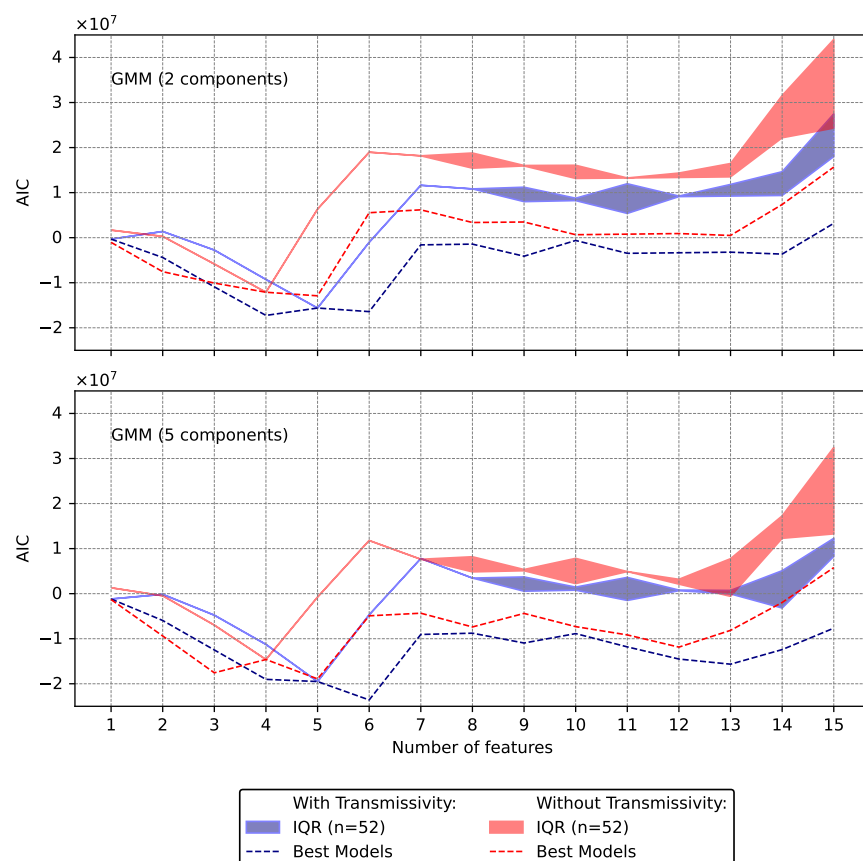


Figure A5. Akaike Information Criterion (AIC) values for the Gaussian mixture model classifier trained and tested on the Berlin dataset using different feature set sizes. A total of 52 sets were constructed using leave-one-out rules. Lower AIC values indicate a better trade-off between model accuracy and complexity. Feature sets are ordered by their mean absolute Shapley values. For clarity, the interquartile range (IQR) and the best-performing models are highlighted.

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