Response to Reviewer 1's Comments

Dear reviewer,

We sincerely thank you for your careful reading of our manuscript and for the constructive and insightful comments. We greatly appreciate your recognition of the importance of quantifying vegetation structural complexity in coastal ecosystems, as well as the concerns raised regarding the conceptual basis of VSRE, the fairness of metric comparisons, and the manuscript's overall focus and presentation.

In response to these comments, we have carefully revised the manuscript at both the conceptual and structural levels. First, we have clarified that VSRE is not intended to represent all dimensions of vegetation structural complexity, but rather to quantify a specific, ecologically meaningful dimension: spatial configurational heterogeneity. Second, we have substantially strengthened the description of the experimental basis for the low-, medium-, and high-VSC groups, and further clarified the role of the biomass-based Shannon index as an independent ecological proxy rather than a direct ground truth of VSC. Third, we have reorganized the manuscript to emphasize better the main storyline of this study: the development of VSRE, its validation using fixed plots and field LiDAR samples, and its first wall-to-wall application along the coast of China. In addition, we have revised the title, improved the structure of the Introduction and Methods, clarified the distinction between fixed-plot validation and nationwide field sampling, strengthened the presentation of classification and mapping results, and added or redesigned key figures to improve clarity and transparency.

We believe that these revisions have substantially improved the manuscript and have made our study more focused, rigorous, and accessible. Below, we provide a detailed, point-by-point response to each comment. Once again, we sincerely thank you for your valuable comments.

(*Black Italic*: *reviewer comments*; Blue: our responses; Purple: revised text).

Comment 1: *Vegetation structural complexity (VSC) is increasingly recognized as a key attribute influencing ecosystem processes and functions. The quantification of VSC from 3D LiDAR data has therefore become an important area of research to support such studies. In this work, the authors investigate methodologies for quantifying VSC specifically in coastal ecosystems, propose a new index, namely VSRE, and demonstrate that this metric outperforms existing approaches. They further combine this metric with the latest Google AEF dataset to produce a nationwide VSC product. Overall, this is a timely study for advancing VSC research in coastal ecosystems, and the resulting dataset is valuable. However, I have several major concerns that prevent me from recommending its publication in its current form.*

Response: We are very grateful for your recognition of the value of our research. Your encouraging comments on the clarity, organization, and contribution of our study are highly appreciated, and they motivate us to refine our work further.

Comment 2: *First, I have difficulty understanding the rationale for using relative entropy to quantify VSC. Fundamentally, relative entropy measures the dissimilarity of LiDAR point distributions between different voxels. It is unclear how this directly reflects vegetation structural complexity. By definition, structural complexity relates to both the randomness of canopy element distribution and the extent of space occupation. In this sense, VSC should capture at least two components: the abundance of structural elements and the variability in their spatial arrangement. However, strong dissimilarity between layers does not necessarily indicate high structural complexity. For instance, in tropical forests, the canopy is often densely filled due to complementary layering, resulting in relatively similar element distributions across layers. Despite this similarity, such forests exhibit high structural complexity. Therefore, I remain fundamentally uncertain about the appropriateness of using relative entropy as a metric for quantifying VSC.*

Response: We appreciate you raising this fundamental question. We agree that VSC is a multidimensional concept for which no single, universally accepted definition currently exists. Consequently, no individual metric can fully represent all aspects of VSC. Previous studies have characterized VSC from different structural perspectives and have adopted diverse metric systems for its quantification. In a broad sense, VSC is commonly understood as the three-dimensional organization of vegetation elements, including leaf area and density, canopy height, canopy arrangement, canopy openness, and spatial variability (Coverdale and Davies, 2023). This concept can also be summarized, as you noted, as the spatial occupancy of structural elements and the variability or randomness of their arrangement.

Based on this understanding, we wish to clarify that VSRE was not designed to serve as a unified metric covering all dimensions of VSC. Instead, it focuses on a specific but ecologically meaningful dimension: the relative configurational differences and local heterogeneity of vegetation structural elements in three-dimensional space. In other words, VSRE primarily targets spatial configurational heterogeneity rather than structural occupancy itself. This focus on a particular structural dimension is not unique to VSRE. Many widely used VSC metrics also emphasize specific aspects of structural complexity rather than its full multidimensional meaning. For example, FHD mainly reflects the vertical distribution of vegetation elements among height layers, rugosity emphasizes variation in canopy surface height, and canopy entropy focuses on the uncertainty of spatial point distributions. These metrics infer the broader concept of structural complexity by quantifying explicit features of vegetation organization in point clouds.

Therefore, the central question is not whether VSRE explicitly encodes every component of VSC, but whether the structural dimension quantified by VSRE has a clear ecological meaning and is appropriate for the target ecosystem.

We acknowledge that the mentioned example of tropical forests provides an important reminder. In tropical forests with strong vertical infilling and complementary canopy layers, spatial occupancy and multilayer filling are indeed important components of structural complexity. However, the present study focuses on coastal wetlands rather than mature tropical forests. Compared with those of forest ecosystems, coastal wetland vegetation is generally lower in height, more open in canopy structure, and more spatially patchy, often consisting of mixed herbaceous (saltmarshes) and woody vegetation (mangroves), interspersed with bare tidal flats and water surfaces. In such ecological settings, local differences in spatial arrangement and configurational heterogeneity may better reflect structural differences among communities than simple measures of space occupation. Spatial occupancy can often be described by cumulative metrics such as canopy cover or biomass, but these metrics may become relatively homogeneous in communities dominated by dense herbaceous vegetation with sparse woody components. This consideration motivated our development of VSRE at the very first. Our results (**Figs. 3, 4, and 5**) further showed that conventional metrics more closely related to structural occupancy, such as canopy cover and mean vegetation height, did not consistently reflect the expected complexity gradient in coastal wetland fixed plots. By contrast, VSRE demonstrated greater stability in discrimination across different point cloud densities and more effectively captured continuous gradients of structural variation.

We also recognize the more fundamental concern you raised: relative entropy measures differences in LiDAR point-cloud distributions across voxels or windows, but why should these differences reflect vegetation structural complexity? In our view, this link is not arbitrary. LiDAR point clouds capture the discrete spatial distribution of vegetation structural elements in three dimensions. When a local point cloud is voxelized and normalized within a sliding window, the resulting voxel histogram represents the spatial distribution function of the local vegetation structure. Differences in such distribution functions across windows therefore do not merely reflect differences in point counts. Instead, they indicate whether local structural configurations are repeated in similar ways or vary across space. If voxel distributions are highly similar among windows, the community structure is spatially repetitive and homogeneous. Conversely, large differences among window-level distributions indicate stronger local heterogeneity and greater variation in spatial configuration. We therefore regard local configurational difference as an important dimension of VSC, especially in relation to structural heterogeneity rather than structural occupancy.

Accordingly, in the revised manuscript, we will clarify the conceptual boundary of VSRE. VSRE should be understood as a structural metric designed to quantify spatial configurational heterogeneity. It is intended to complement existing VSC metrics, rather than to replace all other definitions or dimensions of vegetation structural complexity.

Revised text:

Main text: Line 585-593

Second, VSRE should be interpreted as an index that primarily captures spatial configurational heterogeneity rather than the total area of occupied vegetation. In a broad ecological sense, vegetation structural complexity may include both spatial occupancy and spatial heterogeneity (Coverdale and Davies, 2023). VSRE is more closely aligned with the latter because it compares differences among local voxel-based structural distributions. Therefore, in structurally more complex ecosystems or in mature ecosystems where vegetation space is nearly saturated, VSRE alone may not fully capture all dimensions of structural complexity. In such cases, combining VSRE with complementary metrics such as canopy cover, vegetation height, or a spatial occupancy index (Zhao et al., 2026) would provide a more complete characterization of VSC.

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Comment 3: *Second, the comparison among metrics appears methodologically unclear and potentially unfair. The authors used three groups of plots—categorized as low, medium, and high VSC—to evaluate the performance of the proposed metric against existing ones. However, it is not clear how these groups were defined in the field. Were they based on visual assessment or some quantitative criteria? Given that VSC is inherently difficult to measure directly, establishing reliable ground-truth data is challenging without the use of simulation or well-defined structural proxies.*

Response: Thank you for this important comment. We apologize for the lack of clarity in this section. We agree that, because VSC is difficult to measure directly, any plot grouping used to compare the performance of different structural metrics must be clearly defined, repeatable, and as independent as possible from the metrics being evaluated. We want to clarify that the low-, medium-, and high-VSC groups in this study were not defined solely by subjective human-visual assessment. Instead, they were derived from three representative coastal wetland community structure scenarios formed within a controlled near-natural experimental fixed plot and were further supported by independent field survey data.

Specifically, the experimental fixed plots used in this study were not natural plots selected at random, but were designed to represent three typical coastal wetland community-structure scenarios (**Fig. 1, 2**). The first scenario was a monodominant herbaceous community commonly associated with high salinity and high tide-level conditions, represented by the globally widespread *Phragmites australis* community. The second scenario was a mixed herbaceous community under medium-salinity and low-tide-level conditions. The third scenario was a mixed herbaceous--woody community under low-salinity and high-land with drier habitat conditions, which is more commonly observed in mangrove--saltmarsh ecotones.

In terms of ecological and structural characteristics, these three scenarios broadly correspond to an increasing complexity gradient under nearly-natural conditions, from monodominant saltmarsh vegetation to mixed herbaceous communities and then to herbaceous--woody assemblages. More importantly, these communities were not artificially planted or assembled. Instead, they developed through near-natural succession after ground-water levels above the water table (to simulate tide level) were regulated in this experimental platform, which has been operating since 2018. Besides, six replicate plots were established for each scenario to improve sample representativeness and reproducibility. Therefore, the structural gradient represented by these three plot groups was primarily defined by the experimental design and community formation processes, rather than by post hoc subjective visual assessment.

To further verify the objectivity of this structural gradient, we conducted herbaceous vegetation surveys and individual-tree segmentation during the same period as the LiDAR data collection (**Fig. S3,** 2025), and we quantified biomass and diversity across all sub-plots. Using these data, we constructed a biomass-weighted Shannon index based on each species' biomass proportion. This index served as an independent, continuous ecological proxy to examine whether the three subplot groups exhibited a significant structural complexity gradient. Rather than using individual abundances, as is common in many diversity calculations, we used each species' total biomass. This choice was necessary because herbaceous plants and woody trees often differ greatly in individual abundance, yet such numerical differences do not imply proportional differences in their contributions to spatial structural complexity. By contrast, biomass provides a common currency across growth forms and better reflects the relative contribution of different species to community structure, making it more appropriate for coastal wetland communities with large trait contrasts among plant growth forms. We further clarify that the Shannon index was not introduced here as a direct ground truth of VSC. Rather, in this experimental system, it provides a relatively bottom-up and objective structural reference at the level of community composition. As community biomass composition shifts from dominance by a single species to a more diverse assemblage, and from purely herbaceous vegetation to herbaceous--woody communities, the types and relative configurations of structural elements within the community generally increase in parallel. This pattern is consistent with our field observations of vegetation complexity in the sample plots (**Fig. 2**). Therefore, we consider this index an independent external proxy supporting the existence of a structural gradient, rather than a repeated expression of the metric being tested.

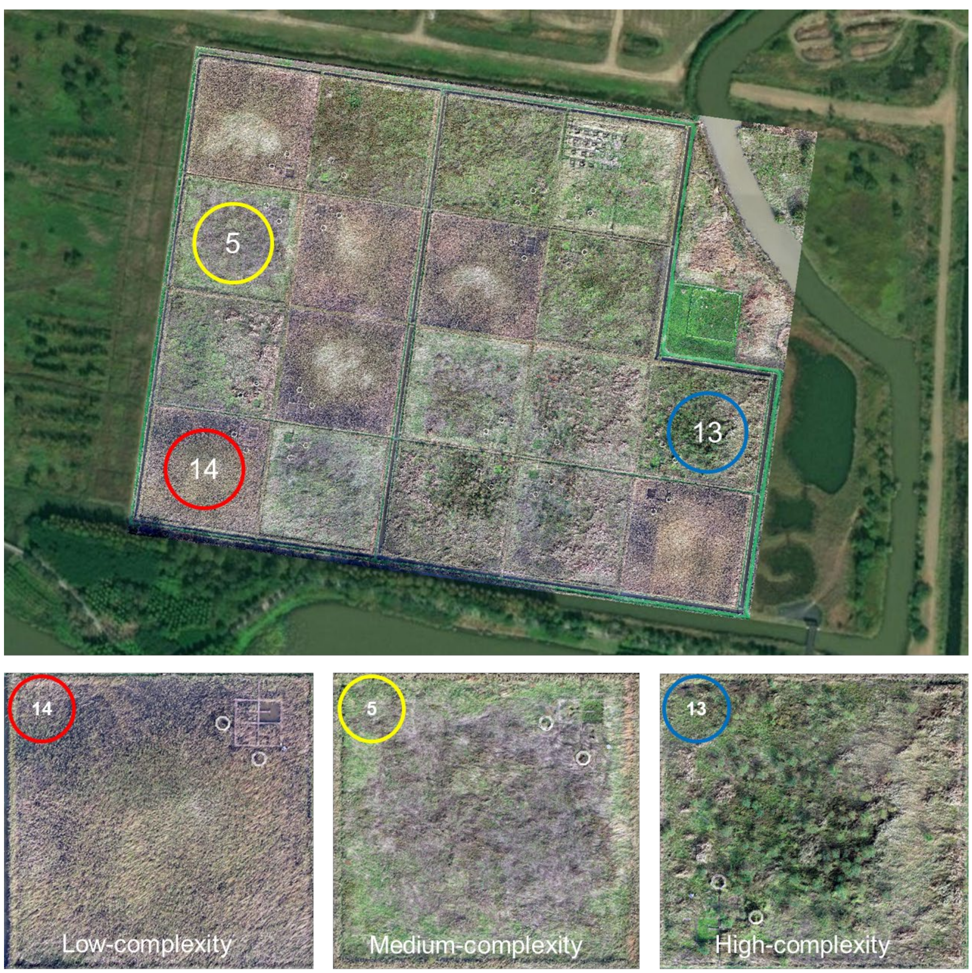


Fig 2. A high-resolution optical image of the fixed plot acquired in March 2025, with a spatial resolution of 0.5 cm pixel^{-1}.

The relevant results are shown in Fig. S3, which indicates a clear, consistent relationship between the human-observed and quantified gradients across the three subplot groups. We acknowledge that this supplementary figure was not explicitly cross-referenced in the main text, which made the basis of the grouping insufficiently clear. In the revised manuscript, we will add this explanation and explicitly state that Fig. S3 does not use the Shannon index as a direct ground truth of VSC. Instead, it uses an independent external proxy to support the rationale for the structural gradient represented by the three plot groups.

We also fully recognize that VSC in natural ecosystems does not always occur as discrete groups. More commonly, it varies continuously and may involve subtle structural differences. Therefore, we further introduced a continuous-gradient test in **Section 1.3.3**. In this analysis, the biomass-weighted Shannon index was used as a continuous external reference to test whether VSRE could respond to subplots without obvious categorical groupings but with gradual differences in VSC. The results showed that VSRE not only distinguished the three predefined structural scenarios but also maintained high sensitivity and stability along a continuous complexity gradient. This analysis complements the discrete-group comparison: the group-based test evaluates the discriminatory ability of the metrics in representative structural scenarios, whereas the continuous-gradient test further shows that VSRE is not effective only for strongly differentiated groups but can also detect more subtle structural variation that commonly occurs in natural ecosystems.

Based on these considerations, we believe that the three subplot groups used in this study have clear ecological representativeness, experimental reproducibility, and independent external support. They therefore provide a reasonable gradient system for evaluating the discriminatory ability of VSRE and other structural metrics in coastal wetland settings. In addition, the continuous-gradient analysis in **Section 1.3.3** further supports the effectiveness of VSRE in detecting more subtle structural variation closer to real ecological conditions.

Revised text and figures:

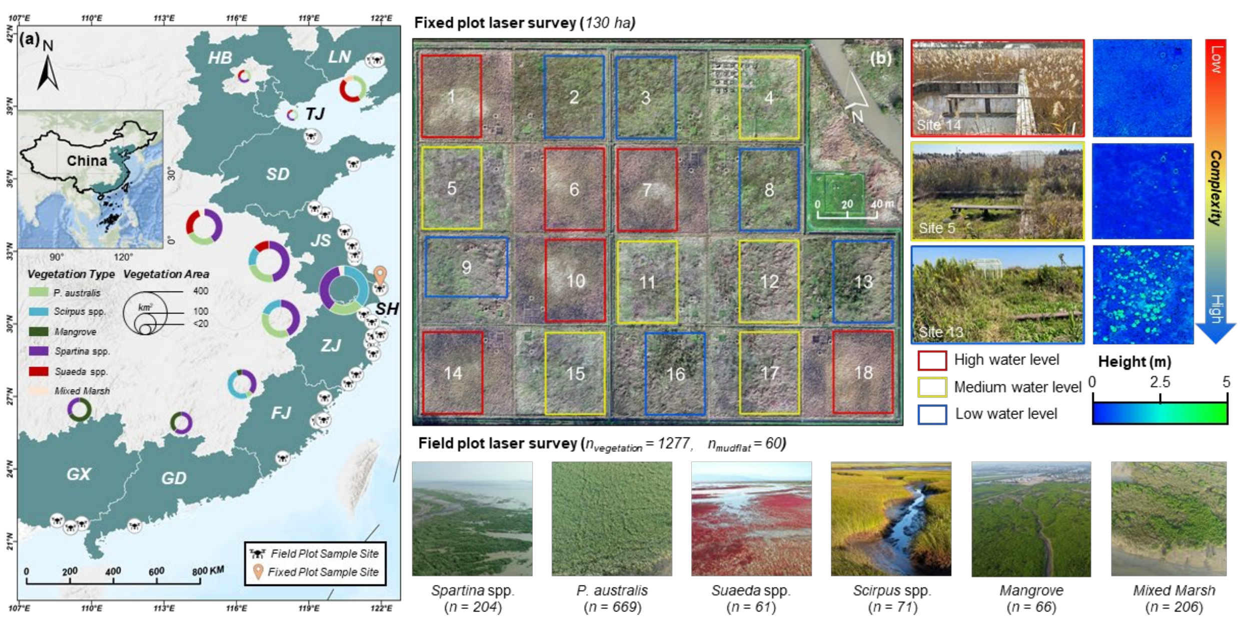


Fig. 1 | Overview of fixed plots and spatial layout of field drone sampling sites. a, Spatial distribution of all LiDAR sampling locations. Blue-green shading indicates sampled provinces, abbreviated with two-letter codes; drone icons represent the field LiDAR sampling sites, and the orange icon indicates the location of the fixed sampling site. **b**, LiDAR sampling conditions within fixed plots and primary vegetation communities surveyed. The LiDAR acquisition ranges under varying water levels are illustrated using three-color boxes, indicating that VSC decreases significantly as tidal levels rise. Representative field photos and digital surface elevation profiles from three sampling points are displayed on the right. Field-collected LiDAR data encompass six typical coastal wetland vegetation types, including succulent herbs (*Suaeda* spp., *Scirpus* spp.), graminoid vegetation (*Phragmites australis*, *Spartina* spp.), mixed marsh communities, and tree-dominated communities (mangroves).

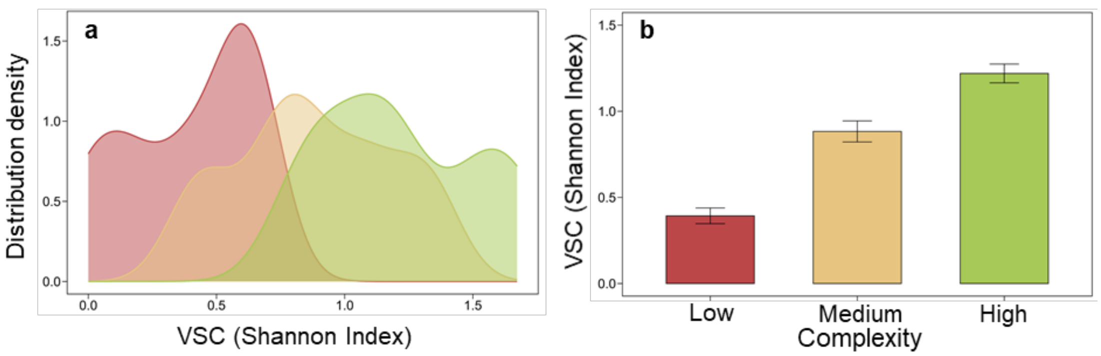


Fig. S3 | VSC index distribution characteristics constructed based on the Shannon index. a, the VSC distribution curve was fitted using kernel density estimation. **b,** Mean values of VSC in groups with different human-defined complexity. Error bars indicate standard deviation.

Comment 4: *Furthermore, I do not consider the comparison between VSC and species richness to be a robust or appropriate way to demonstrate the superiority of the proposed metric. The relationship between VSC and species richness remains debated in the literature and is not necessarily positive or consistent. For example, in northern temperate forests, single-layer, monocultural stands can still exhibit relatively high VSC due to selection effects and high space occupation.*

Response: We appreciate your important comment. We agree that there is no universal or necessary positive relationship between species richness, biodiversity, and vegetation structural complexity. As you noted, in some forest ecosystems, even stands with relatively homogeneous species composition, such as single-layer plantations or communities dominated by a single species, may exhibit high values for certain structural complexity metrics (canopy cover or density) due to high spatial occupancy, canopy density, or selection effects. We therefore agree that species richness alone cannot serve as a universal standard for validating VSC metrics.

We want to clarify that this study did not use species richness to directly evaluate VSC, nor did it treat biodiversity as the definition or absolute ground truth of VSC. Instead, we used a biomass-weighted Shannon index. The purpose of this index was not to argue that higher biodiversity necessarily leads to higher VSC, but rather to construct an independent, continuous gradient of community composition and structural material distribution within our fixed plots.

This gradient was used as a supplementary reference to examine whether different structural metrics could capture continuous structural variation among the plots.

This approach was motivated by the specific characteristics of our study system. The fixed plots contained both herbaceous and woody plants, which differed greatly in individual abundance, body size, and contribution to spatial structure. If conventional diversity metrics were calculated directly using species richness or individual abundance, the extremely large number of herbaceous individuals could mask the contribution of woody plants to three-dimensional structure and introduce substantial bias. We therefore used biomass, rather than individual abundance, to calculate the Shannon index. Although biomass is not equivalent to structural complexity itself, it represents an important material basis for the formation of three-dimensional vegetation structure. A more even distribution of biomass among species or growth forms usually indicates that structural material is not dominated by a single morphological unit, but is more likely composed of vegetation elements differing in height, form, and spatial configuration.

In our experimental plots, this biomass-weighted gradient was consistent with multiple independent observations. The water-level gradient drove a transition from a monodominant herbaceous community to a multispecies herbaceous community and then to a mixed herbaceous-woody community. This process was accompanied by consistent structural changes in field observations, plot photographs, digital surface profiles, and the predefined low-, medium-, and high-VSC groups. Therefore, within the specific experimental system of this study, the biomass-weighted Shannon index provides a reasonable external ecological reference for evaluating the sensitivity of different structural metrics to continuous changes in community structure.

Importantly, the evaluation of VSRE in this study does not rely solely on this correlation analysis. We first compared structural metrics across low-, medium-, and high-complexity communities formed in the water-level-controlled experiment at different point cloud densities. The results showed that conventional metrics were prone to misclassifying medium-complexity communities in coastal wetlands, whereas VSRE distinguished different VSC gradients more consistently. We then used the biomass-weighted Shannon index as an independent continuous gradient to further test each metric's responsiveness to continuous variation in community structure. In the revised manuscript, we will more clearly distinguish these two components of the validation framework: the former assesses each metric's ability to discriminate discrete structural gradients, whereas the latter provides a supplementary test of sensitivity to continuous ecological gradients.

We also agree with you that this analysis should not be presented as the sole or decisive evidence for the superiority of VSRE. Therefore, in the revised manuscript, we will further soften the relevant wording and avoid referring to the Shannon index as an objective VSC measure or a direct measure of VSC. Instead, we will describe it as biomass-weighted community heterogeneity or as an independent continuous ecological gradient associated with structural differentiation in this experimental system. We will also clearly state that this analysis provides only supplementary evidence for the ecological relevance and continuous-gradient sensitivity of VSRE, rather than using biodiversity as a universal validation criterion for VSC.

Revised text and figures:

Main text: Line 719-727

Because the initial VSC grouping of the secondary plots was based primarily on predefined vegetation community composition, structural characteristics, and expert field assessment, we further calculated a biomass-weighted Shannon diversity index as an independent and continuous reference for the degree of structural differentiation in each secondary plot. Biomass, rather than individual abundance, was used for weighting because the plots contained both herbaceous and woody plants, which differed markedly in individual abundance, body size, and contribution to three-dimensional spatial structure. Compared with diversity indices based on individual abundance, the biomass-weighted approach better reflects the relative contributions of different species and growth forms to the material basis of vegetation structure, thereby reducing bias introduced by the extremely high abundance of herbaceous individuals when characterizing community structure (Cousins, 1991).

Comment 5: *Third, the overall writing of the manuscript requires improvement. The current version attempts to integrate a wide range of content, which reduces its focus, while several important components lack sufficient detail. For instance, the classification of coastal vegetation types is itself a substantial task, yet it is only briefly described. A similar issue arises with the nationwide VSC mapping, where methodological and implementation details are limited. I therefore suggest that the authors consider dividing the work into two separate papers: one focusing on the technical development and validation of the proposed VSC metric, and another dedicated to its application in national-scale mapping.*

Response: We are very grateful for your important suggestion. We agree that integrating several components, including metric development, vegetation classification, and national-scale mapping, may have reduced the focus of the current manuscript. We also agree that the methodological details of vegetation classification and national-scale VSC mapping were not sufficiently presented in the main text. We fully understand the suggestion that the manuscript could be divided into two separate papers, as this was also an option that we carefully considered during the early stage of the study design.

At the same time, we would like to clarify the role of vegetation classification and national-scale mapping in this work. Vegetation classification is not an independent research objective in this study. Instead, it serves as an intermediate layer that links structural metrics with ecological interpretation, allowing us to examine whether VSRE can distinguish structural differences associated with different vegetation types at the species or community level. In this sense, the main role of this component is to support functional validation and ecological interpretation of VSRE, rather than to constitute the core technical contribution of the manuscript.

We acknowledge that the original description of the vegetation classification method was relatively brief, which may have contributed to misunderstanding regarding its role. The full workflow of this method has been systematically described in a recently published independent study. Because that study had not been formally published at the time of initial submission, we retained several classification steps in the Methods section to provide necessary information for interested readers. Since the independent study was published with this classification dataset, which is publicly accessible, on February 20, 2026 (Qi et al., 2026), we will remove the original **Section 1.2.5** and retain only the necessary brief description in the revised manuscript and refer readers to that publication for details, thereby reducing interference with the main storyline and more clearly emphasizing the auxiliary role of the classification component.

After further consideration, we still believe the national-scale mapping component should be retained for two main reasons. First, from a conceptual perspective, this study develops and validates a structural metric tailored to coastal vegetation. After plot-level validation, presenting national-scale mapping results provides a direct extension from local validation to large-scale ecological applications. This extension demonstrates the practical value of VSRE and provides a foundation for future studies of the spatial structure and patterns of coastal vegetation. Second, from the perspective of application and data sharing, the national-scale implementation has a clear and reliable basis. We collected a large number of standard field LiDAR samples with precise geographic coordinates, which provides solid support for large-scale extrapolation. In addition, the release of the AEF embedding dataset enabled us to efficiently complete the inversion and achieve high accuracy without reprocessing large volumes of raw multi-source remote sensing data. In this context, generating and publicly sharing a national-scale data product is also consistent with ESSD's emphasis on data accessibility, reusability, and broad scientific utility.

At the same time, we accept your criticism that the current narrative is not sufficiently focused, and we will make substantial revisions accordingly. Specifically, we will strengthen the main storyline of the manuscript to more clearly focus on the development, validation, and first national-scale application of VSRE in the coastal zone of China. For the sections on vegetation classification and national mapping, we will shorten non-essential descriptions in the main text and move implementation details, parameter settings, model selection procedures, and supplementary results to the Methods and Supplementary Materials. This revision will prevent these supporting components from overshadowing the main theme. We will also more clearly distinguish three levels of content in the Introduction, Methods, and Discussion: the theoretical construction of VSRE, validation using fixed plots and field LiDAR samples, and national-scale wall-to-wall mapping based on AEF data. Through these revisions, we aim to ensure that vegetation classification and national mapping serve the validation and application logic of VSRE more clearly, rather than appearing as independent modules parallel to the main theme.

Comment 6: *Title: The current title doesn't seem like a data paper.*

Response: Thank you for this helpful suggestion. In the revised manuscript, we have changed the title to:"ChinaTidalVSC: a 10 m wall-to-wall dataset of vegetation structural complexity in China's tidal wetlands derived from LiDAR-based relative entropy and AlphaEarth Foundation data".

Comment 7: *Line 38: "the their". Typo.*

Response: Thank you for your suggestion. We have revised this error.

Comment 8: *Line 58-59: Numerous studies have already addressed this question in terrestrial ecosystems. Therefore, the discussion should be more focused on the functional and structural characteristics of coastal ecosystems.*

Response: Thank you for this valuable suggestion. In the revised manuscript, we have strengthened this discussion and improved the transition from the terrestrial to the coastal ecosystem context to clarify the logic.

Revised text:

Main text: Line 63-98

However, most of these LiDAR-derived VSC metrics were developed and validated primarily in terrestrial ecosystems, especially forests (Coverdale and Davies, 2023). Whether they can reliably capture structural complexity in coastal wetlands remains unclear because the structural organization, environmental background, and observation conditions of coastal vegetation differ fundamentally from those of forest systems. There, vegetation is periodically inundated by tides and rooted in soft, muddy, or organic substrates with high water and salt content (He et al., 2025; Yando et al., 2023). It supports vegetation assemblages that often comprise open-canopy succulents, graminoids, and mangroves (Lafond-Hudson and Sulman, 2023). Relative to forests, these communities are typically shorter and more structurally compressed. The close juxtaposition of herbaceous and woody growth forms within a narrow vertical range can cause strong overlap among structural elements, reducing the ability of conventional VSC metrics to resolve subtle differences in three-dimensional organization (Taddeo et al., 2019). Tidal water surfaces further obscure low-stature vegetation and near-ground structure, increasing the likelihood of missing or unstable LiDAR returns (Moffett et al., 2015). These complications propagate from local measurements to regional inference: spaceborne optical and lidar observations cannot be consistently matched to low-tide conditions across repeated overpasses, and the fine-scale mosaics of vegetation, exposed mudflats, and water often result in severe mixed-pixel effects. Together, these features make VSC retrieval in coastal wetlands especially challenging in terms of sensitivity, robustness, and regional scalability.

An equally important limitation is the severe scarcity of VSC data and supporting covariates suitable for model development, accuracy validation, and spatial extrapolation in coastal ecosystems (Weilhoefer, 2011). First, coastal wetlands exhibit rapid dynamics, limited field accessibility, and extensive spatial distributions (Qi et al., 2026). These features increase acquisition costs and make it difficult to obtain medium- to high-density point clouds that can resolve vegetation's three-dimensional structure at ecologically meaningful scales, especially in publicly available datasets (e.g., OpenTopography, NEON, and NOAA Digital Coast) (Krishnan et al., 2011; Keller et al., 2008; Dobson, 1995). Second, many satellite remote sensing products that could potentially support VSC quantification were originally developed for terrestrial ecosystems, and their applicability in intertidal environments remains limited or insufficiently validated. This limitation is particularly relevant for spaceborne LiDAR products such as GEDI and ICESat-2, which still involve substantial uncertainty when applied to low-stature, open wetland vegetation strongly affected by tidal dynamics (Yu et al., 2026). Finally, environmental covariates used for large-scale VSC modeling and spatial extrapolation, including WorldClim and topographic variables (Fick and Hijmans, 2017; Kulp and Strauss, 2018), often face additional constraints in coastal areas, including insufficient spatial resolution, incomplete nearshore coverage, and large errors near land-sea boundaries. Together, these limitations have resulted in a lack of coastal-specific quantitative studies on VSC and of quality-controlled, standardized VSC products that can be used directly for modeling, validation, and regional extrapolation.

Comment 9: *Line 68-71: What are the unique challenges associated with quantifying canopy structural complexity in coastal ecosystems? It would be helpful to include one or two sentences to clarify this point.*

Response: Thank you for pointing this out. In the revised manuscript, we have revised the background section to strengthen this explanation. Specifically, we now clarify these challenges from three perspectives: the technical constraints imposed by the environmental conditions of coastal wetlands, the difficulties arising from the distinctive structural characteristics of coastal vegetation, and the additional challenges associated with large-scale spatial extrapolation. The revised text can be found in **response to comment 8**.

Comment 10: *Line 72-90: This content belongs in the Methods section. In the Introduction, you may briefly summarize the data and overall approach of the study, but detailed procedural steps should not be included.*

Response: Thank you for this helpful suggestion. In the revised manuscript, we have rewritten this section and moved the technical details to the Methods section.

Revised text:

Main text: Line 99-114

Based on the concept of relative entropy (RE, also known as the Kullback–Leibler divergence) (Cover and Thomas, 1991), this study developed a LiDAR point-cloud-derived VSC index, termed vegetation structure relative entropy (VSRE), to characterize heterogeneity in three-dimensional spatial configuration. Using high-precision UAV LiDAR observations and annual vegetation biomass survey data from 18 subplots (60 m × 60 m) at the largest water-level-controlled field experimental site worldwide, located on Chongming Island, Shanghai, China (**Fig. 1**), we systematically tested VSRE and compared its performance with several conventional VSC metrics widely used in terrestrial ecosystems. Specifically, we evaluated the effectiveness and robustness of these metrics in quantifying VSC across typical coastal wetland vegetation scenarios, continuous complexity gradients, and different point cloud densities. We then applied VSRE to a high-density LiDAR dataset from 1,337 coastal vegetation sites spanning China's 18,400 km coastline. We combined the results with corresponding 2022 vegetation-type data to characterize VSC variation across typical natural vegetation communities in coastal wetlands of China. Finally, using the Alpha Earth Foundation (AEF) dataset and a multilayer perceptron (MLP) model, we generated a seamless 10 m spatial map of VSRE along the coast of China with high predictive accuracy ($R^2 = 0.96$).

Comment 11: *Line 92: To be honest, this section is somewhat disorganized. The descriptions of fixed experimental plot data and drone-based LiDAR data should be clearly separated. At present, key information regarding the drone LiDAR data used for national mapping is missing. For example, the manuscript does not specify where these plots are located or what their spatial extent is.*

Response: We apologize for not providing a sufficiently detailed description of the fixed-plot and field-plot data collection in the original manuscript. In the revised manuscript, we have separated the two types of data collection into Sections 1.2.1 and 1.2.2. Specifically, we have added consistent descriptions of the UAV and LiDAR acquisition settings in both sections. We have also included the spatial coordinates of the fixed plots in the Methods section. Because the field plots are numerous, listing all field coordinates in the main text would be impractical. Therefore, detailed sample locations for the field plots will be provided as an SHP vector file in the public data repository.

Revised text:

Main text: Line 126-168

1.2.1 LiDAR data collection in the fixed plot

This study was based on the world's largest water-level-controlled wetland experimental plot, the Dongtan Ecosystem Experimental Plot (**121.94°E, 31.52°N**; Fig. 1). Established in 2018, this fixed plot has allowed vegetation to grow under natural coastal wetland conditions to date. The experimental setup includes three distinct water levels (-30 cm, 0 cm, and +30 cm), randomly distributed across a 130-hectare coastal wetland. The site was divided into 18 secondary plots, each measuring 60 × 60 meters, with two open-top chambers installed within each plot. Under these conditions, the vegetation communities developed distinct structural types: at the +30 cm tidal level, the community is dominated almost exclusively by *P. australis*; at the 0 cm level, diverse herbaceous species form mixed communities; and at the -30 cm level, mixed herbaceous species coexist with woody plants resembling mangrove structures. These naturally formed communities with contrasting vegetation structures provided ideal experimental conditions for our study.

We conducted LiDAR surveys over the fixed plot using a DJI Matrice 300 RTK drone equipped with a DJI Zenmuse L1 LiDAR sensor. Each flight mission covered the entire experimental site to ensure accurate spatial matching. For UAV acquisition, the return mode was set to 3 returns to improve the point cloud's ability to capture vegetation elements at different vertical positions. Point cloud densities were controlled by adjusting flight height and overlap rate, targeting approximate densities of 50, 100, 250, 500, 1000, 1500, and 2000 points m^{-2}. Datasets collected at 50 and 100 points m^{-2} were discarded due to excessive absorption by water surfaces (**Supplementary Fig 1**). Raw LiDAR data were processed in DJI Terra for stitching and denoising, and individual secondary plots were cropped to match the spatial extent of the ground survey plots. During cropping, we prioritized minimizing chamber inclusion while preserving all relevant vegetation features (specific cropping boundaries are shown in **Fig. 1b**).

1.2.2 LiDAR data collection in the field sites

We conducted extensive field surveys along the coast of mainland China from 2022 to 2023, spanning 21.5749◦N-40.9235◦N (**Fig. 1a**). All surveys used the same UAV and LiDAR system, namely a DJI Matrice 300 RTK UAV equipped with a DJI Zenmuse L1 LiDAR sensor. A total of 81 LiDAR scanning missions, accompanied by synchronous optical photography, were conducted in major coastal vegetation hotspots. The LiDAR scans were acquired in three-return mode, and the expected point cloud density was maintained at >500 pt m^{-2} by adjusting flight altitude, flight speed, and side overlap. All data were collected under good visibility and low tide, when vegetation was fully exposed, to ensure simultaneous acquisition of high-quality optical imagery with a spatial resolution of approximately 0.5 m. These optical images supported subsequent accurate point-cloud cropping and vegetation type identification. In addition, we conducted 30 supplementary forest LiDAR surveys in Yunhe City, Zhejiang Province (**Supplementary table S1**), to compare potential differences in point-cloud structural characteristics across ecosystems and further assess the scalability of VSRE.

During data preprocessing, we further cropped the stitched raw point clouds. Based on vegetation patches and corresponding species information identified from high-resolution optical imagery, we extracted 1,337 25×25 m subsamples from the 81 stitched LiDAR datasets. Each subsample was associated with accurate latitude and longitude coordinates and vegetation type information, and adjacent subsamples were separated by at least 25 m. The point cloud density of the coastal vegetation subsamples ultimately ranged from 20.89 to 4,364.33 pt m^{-2}, with a mean value of 790.22 pt m^{-2}. The same cropping procedure was applied to the forest plots, but only one subsample was retained for each plot. The final point cloud density of the forest subsamples ranged from 142.04 to 1,271.73 points m^{-2}.

Comment 12: *Line 93: This sentence is misleading, as it suggests that the entire study was conducted at a single site. In fact, the site was only used for method validation.*

Response: Thank you for this helpful suggestion. We have revised the sentence to avoid any potential misunderstanding. The revised text is provided in **response to comment 11**.

Comment 13: *Line 104-105: Beyond point density, the vertical penetration capability of the LiDAR sensor is critical for accurately measuring canopy structural complexity. To my knowledge, the DJI L1 sensor has limited ability to penetrate dense canopies. It would therefore be helpful to include a vertical profile visualization to illustrate this limitation, allowing readers to better understand the characteristics and potential constraints of the data.*

Response: We appreciate you raising this valuable point. We agree that, in addition to point cloud density, the vertical penetration capability of LiDAR sensors, including the ability to capture returns from the lower canopy and ground surface, is also critical for assessing vegetation structural complexity. In airborne LiDAR surveys, this sampling characteristic can be influenced by multiple factors, including canopy openness, scan geometry, return-recording capability, and flight configuration.

In this study, all surveys were conducted using the same DJI L1 sensor and a consistent acquisition framework. Therefore, sensor-specific properties, such as return-recording capability and scan configuration, were not experimental variables that differed among samples. By contrast, the flight parameters adjusted during data acquisition, including flight altitude, flight speed, and overlap, mainly affected the final point cloud density. We therefore used point cloud density as the primary descriptor of acquisition intensity in our analysis. Nevertheless, we recognize that acquisition and sensor parameters for vertical sampling may be useful to readers with expertise in LiDAR data collection. We have therefore added descriptions of these parameters to the Methods section for reference.

It is also important to note that the target ecosystem of this study is coastal wetlands rather than closed-canopy forests. Most coastal wetland communities in our dataset are characterized by relatively low vegetation height, open canopy structure, and limited vertical overlap among plant elements. Under these conditions, LiDAR pulses can generally sample the lower canopy and, in many cases, the ground surface, especially when point cloud density is high. Therefore, in our study system, point cloud density represents the main source of variation in sampling intensity, whereas penetration limitations are less pronounced than in dense forest canopies. To illustrate this point more clearly, we have added representative vertical-profile visualizations for several coastal vegetation types and discuss this sensor characteristic and its limitations in the revised manuscript. We also clarify that VSRE is most directly applicable to relatively open coastal wetland canopies and should be applied with caution to dense, closed-canopy systems. The revised text is provided in **response to comment 11**.

Revised Figures :

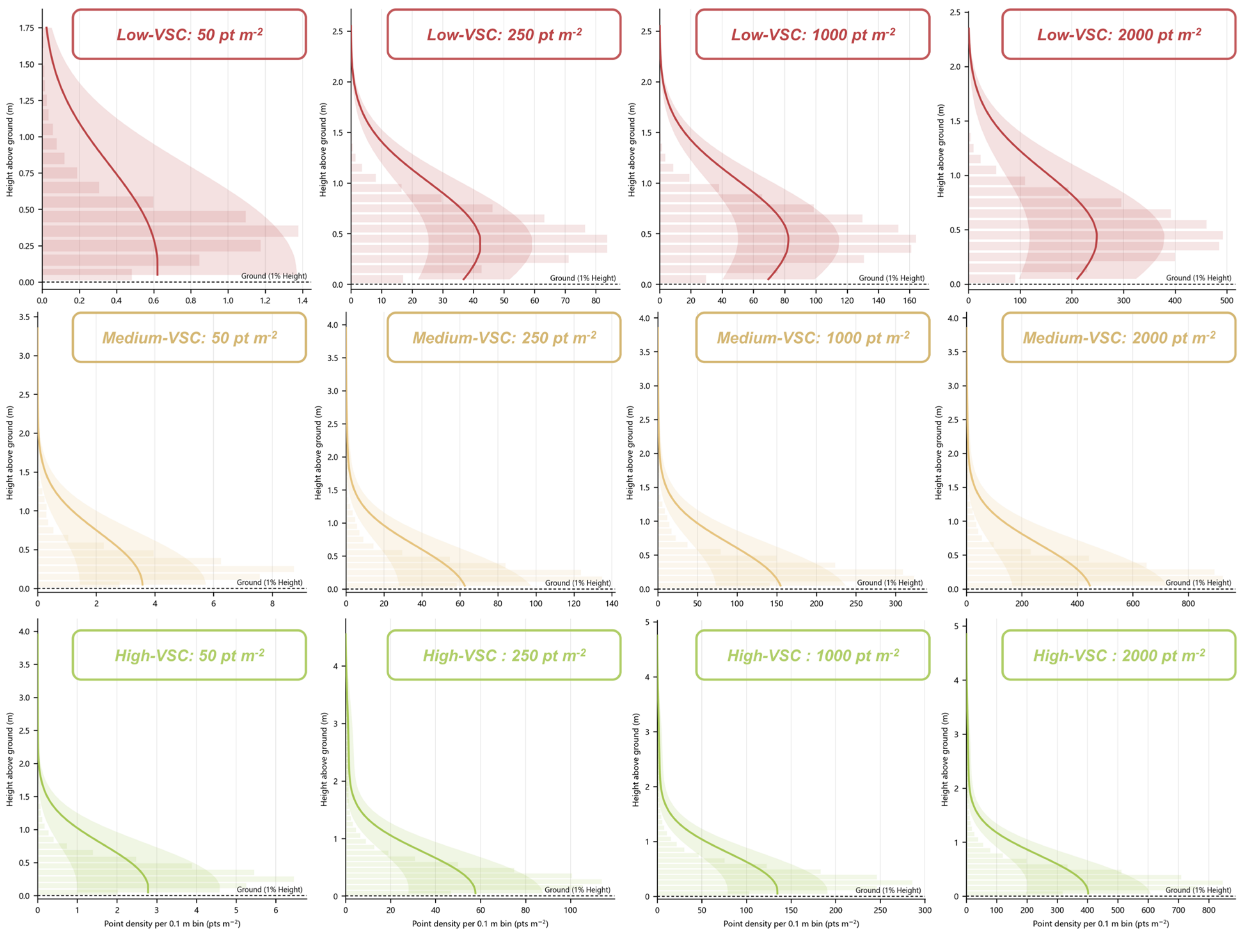


Fig 1 | Vertical point-density profiles of fixed-plot samples across VSC groups and target LiDAR point-cloud densities. Vertical point-density profiles for fixed-plot samples of 25×25 m^2 grouped by vegetation structural complexity (VSC) and target point-cloud density. Rows represent low-, medium-, and high-VSC groups, and columns represent target point-cloud densities of 50, 250, 1000, and 2000 pt m^{-2}. In each panel, horizontal bars show the mean point density within 0.1 m vertical height bins, the solid curve shows the Gaussian-smoothed mean profile, and the shaded envelope indicates variability among samples. Heights were normalized relative to local ground, defined as the 1st percentile of point height and indicated by the black dashed line. The x-axis shows point density per 0.1 m height bin, and the y-axis shows height above ground.

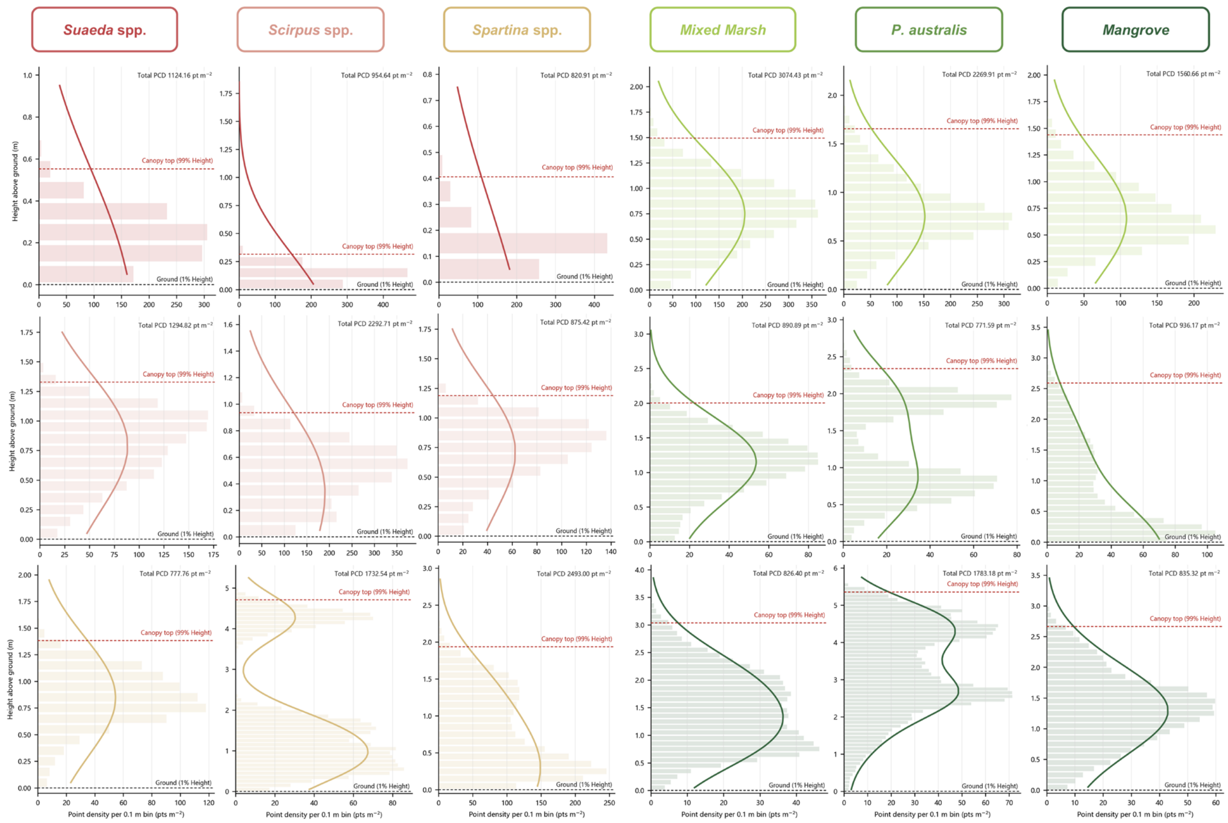


Fig. 2 | Species-specific vertical point-density profiles of field-collected coastal wetland samples. Vertical point-density profiles of individual field-collected 25×25 m^2 m LAS samples across major coastal wetland vegetation types, including Suaeda spp., Scirpus spp., Spartina spp., mixed marsh, Phragmites australis, and mangrove. Each panel represents one field sample. Horizontal bars show point density within 0.1 m vertical height bins, and the solid curve shows the smoothed vertical distribution of point density. The PCD values in the upper-right corner indicate the total point-cloud density for each sample, calculated as the total point count divided by the plot area. Heights were normalized using the 1st percentile of point height as local ground, indicated by the black dashed line. The red dashed line marks canopy top height, defined as the 99th percentile of normalized point height.

Comment 14: *Line114: "numerous" It would be better to provide a specific number.*

Response: Thank you for this helpful suggestion. We have revised the description to include the exact number of samples.

Revised text:

Main text: Line 151-152

A total of 81 LiDAR scanning missions, accompanied by synchronous optical photography, were conducted in major coastal vegetation hotspots.

Comment 15: *Line 119: This represents a very wide range of point densities. Additional information is needed to justify the experimental design and the selection of point density levels.*

Response: We thank you for this comment. We agree that reporting a broad range of point cloud densities without explaining their source and selection logic could raise reasonable concerns about the experimental design.

First, we clarify that this broad range mainly reflects the overall distribution of raw data from the nationwide field sampling campaign, and does not mean that all density levels were used equally in the vegetation structural complexity analysis. In the nationwide field survey, the raw point cloud density ranged from 20.89 to 4364.33 pt m m^{-2}, with a mean value of 790.22 pt m m^{-2}. This range reflects raw sampling conditions across different regions, vegetation types, and land-cover backgrounds, rather than a homogeneous dataset used as the basis for the final structural analysis.

Second, we retained this overall range to represent the variability of real field acquisition conditions transparently. However, the data used in the actual analysis were further quality controlled. For the core analysis of vegetation structural complexity, we focused on samples with sufficient information to characterize three-dimensional vegetation structure effectively (PCD > 250 pt m^{-2}). Low-density samples (PCD = 20-250 pt m-2) were mainly found in structurally simple settings, such as bare mudflats. In other words, the reported wide density range should be understood as the overall coverage of the raw sampling background, rather than as evidence that all effective vegetation samples used for structural comparison spanned this range without quality constraints.

More importantly, our results show that VSRE is robust to variation in point cloud density. Therefore, a wide range of point cloud densities does not necessarily imply systematic distortion of the results. Methodologically, VSRE does not directly depend on the raw number of points within a single layer. Instead, it first normalizes voxel distributions within sliding windows to reduce the influence of local anomalies and overall point cloud density variation, and then compares the relative entropies of these normalized distributions. Empirically, we evaluated the discriminatory ability of VSRE at different PCD levels and further tested its stability under a mixed-PCD scenario. The results showed that VSRE could consistently distinguish between different complexity groups, even when point cloud density varied or when samples with different densities were combined, whereas several conventional metrics showed more pronounced misclassification or density sensitivity under these conditions.

Therefore, we reported this point cloud density range for two main reasons: to reflect objective variation in data acquisition under real field conditions, and to test the applicability of VSRE under non-ideal and non-uniform sampling conditions. Our results indicate that VSRE can maintain stable performance under relatively flexible conditions, provided that individual samples meet a usable density threshold or that sufficient replicated samples are available in mixed-PCD scenarios. To avoid misunderstanding, we will clarify in the revised manuscript that this broad range primarily reflects the raw field data distribution, whereas the data used for vegetation structural analysis were subject to quality control. We will also clarify the main sources of low-density samples and strengthen the explanation of PCD selection criteria and the applicable scope of VSRE in the Methods and Results sections.

Revised text :

Main text: Line 161-178

During data preprocessing, we further cropped the stitched raw point clouds. Based on vegetation patches and corresponding species information identified from high-resolution optical imagery, we extracted 1,337 25×25 m subsamples from the 81 stitched LiDAR datasets. Each subsample was associated with accurate latitude and longitude coordinates and vegetation type information, and adjacent subsamples were separated by at least 25 m. The point cloud density of the coastal vegetation subsamples ultimately ranged from 20.89 to 4,364.33 pt m^{-2}, with a mean value of 790.22 pt m^{-2}. The same cropping procedure was applied to the forest plots, but only one subsample was retained for each plot. The final point cloud density of the forest subsamples ranged from 142.04 to 1,271.73 points m^{-2}.

Comment 16: *Line 141: Did you measure tree height manually in the field? If so, what is the purpose of using LiDAR-segmented individual trees?*

Response: We thank you for this question. In this study, we did not conduct manual height measurements for all trees. The main reason is that the fixed plots contained numerous soil-monitoring instruments, and most trees were distributed within them. Manual height measurement for each tree would not only have been technically challenging, but could also have disturbed the plots and related monitoring facilities. Therefore, we used high-density UAV LiDAR data, combined with an individual-tree segmentation algorithm, to extract trees and estimate tree heights within the plots in a non-destructive manner. We also measured the location, height, and DBH of 7 trees at the edge of the plots and compared them with vegetation parameters calculated after individual tree segmentation. The results showed that the errors were extremely small ($nRMSE_{CH}$ = 5.7%, $nRMSE_{DBH}$ = 2.4%).

Specifically, we segmented individual trees in the fixed plots using the canopy height model (CHM) in LiDAR360, assigned each segmented tree to its corresponding plot, and then extracted structural parameters such as tree height. Based on these results, we estimated tree biomass by combining tree species information with allometric equations. Such an approach is widely used in forest biomass surveys, and the allometric equations and parameters adopted here are available for common tree species in our plots, which were dominated by Chinese tallow trees. We therefore consider this method to provide reliable support for extracting tree height within the plots.

In the revised manuscript, we will further clarify that comprehensive manual height measurements were not conducted for trees within the sample plots. Instead, tree height information was derived from high-density LiDAR point clouds and individual-tree segmentation results. We will also explain the rationale for adopting this method, namely to minimize disturbance to the fixed plots while maintaining reliable height estimation.

Revised text:

Main text: Line 194-206

For woody plants growing in the center of the plots, considering the presence of sophisticated equipment monitoring soil respiration and vegetation carbon flux, we refrained from entering the plots for measurement to avoid interference and damage. Therefore, based on the highest point cloud density (2000 pt m^{-2}), we used the canopy height model (CHM) in LiDAR 360 software to segment individual trees within the fixed plots and assigned each segmented tree to its corresponding secondary plot (Fischer et al., 2019). The diameter at breast height (DBH) and crown height (CH) were recorded for each tree extracted using the segmentation algorithm. We measured the location, height, and DBH of 7 trees at the edge of the plots and compared them with vegetation parameters calculated after individual tree segmentation. The results showed that the errors were extremely small ($nRMSE_{CH}$ = 5.7%, $nRMSE_{DBH}$ = 2.4%). Furthermore, we identified tree species (mainly *Sapium sebiferum*) using UAV optical imagery and selected a matching allometric growth model to estimate biomass. Subsequently, we used a species-specific binary allometric growth model based on DBH and CH (Jucker et al., 2022) to calculate the total tree biomass of each secondary forest plot.

Comment 17: *Line 155: I am not convinced that this index effectively quantifies canopy structural complexity. Rather, it appears to primarily capture the dissimilarity in vertical canopy distribution. Please see my general comment.*

Response: We thank you for this comment. We understand the concern regarding whether VSRE can effectively characterize canopy structural complexity. In our view, the key issue is how the conceptual scope of VSC is defined. From an ecological perspective, structural complexity is generally understood as the spatial organization of structural elements and the degree of heterogeneity in that organization. It therefore includes not only the presence or abundance of structural elements, but also their arrangement and variation in three-dimensional space. VSRE was developed based on this understanding. By voxelizing local point clouds into three-dimensional distribution functions and comparing differences in these functions among spatial locations, VSRE quantifies configurational differences in the spatial arrangement of structural elements. Therefore, VSRE corresponds to the dimension of structural complexity related to spatial configurational heterogeneity, and provides a direct quantitative expression of this dimension rather than an indirect proxy for other structural metrics.

We agree that VSRE uses information on vertical point distributions during its calculation and is therefore sensitive to vertical structural differences. However, interpreting VSRE solely as a measure of vertical distribution differences would be incomplete. VSRE does not describe the vertical distribution at a single location. Instead, it compares three-dimensional distribution patterns across multiple local regions using a sliding-window framework. In other words, this metric evaluates whether the spatial organization of structural elements is consistent among local regions, rather than describing only the shape of the vertical profile at a given location. Thus, even if two regions have similar vertical layering, VSRE can still distinguish them when their three-dimensional configurational patterns differ.

In our **response to the general comment 2**, we provide a more detailed explanation of the relationship between VSRE and the concept of structural complexity, the specific structural dimension quantified by VSRE, and the differences between VSRE and conventional metrics. That explanation is consistent with the response provided here. We hope these revisions clarify that VSRE is not intended merely to describe differences in vertical distribution, but rather to quantify heterogeneity in the three-dimensional configuration of local vegetation structures.

Comment 18: *Fig. 2: This figure is not an effective illustration. It does not clearly convey how the metric is designed or calculated, and instead only shows a set of voxels without sufficient explanation.*

Response: Thank you for this helpful suggestion. We have revised the technical workflow figure to provide a more detailed and transparent illustration of the VSRE calculation process. The revised figure now includes the specific processing steps and procedures, thereby addressing the missing information in the original conceptual illustration.

Revised Figure:

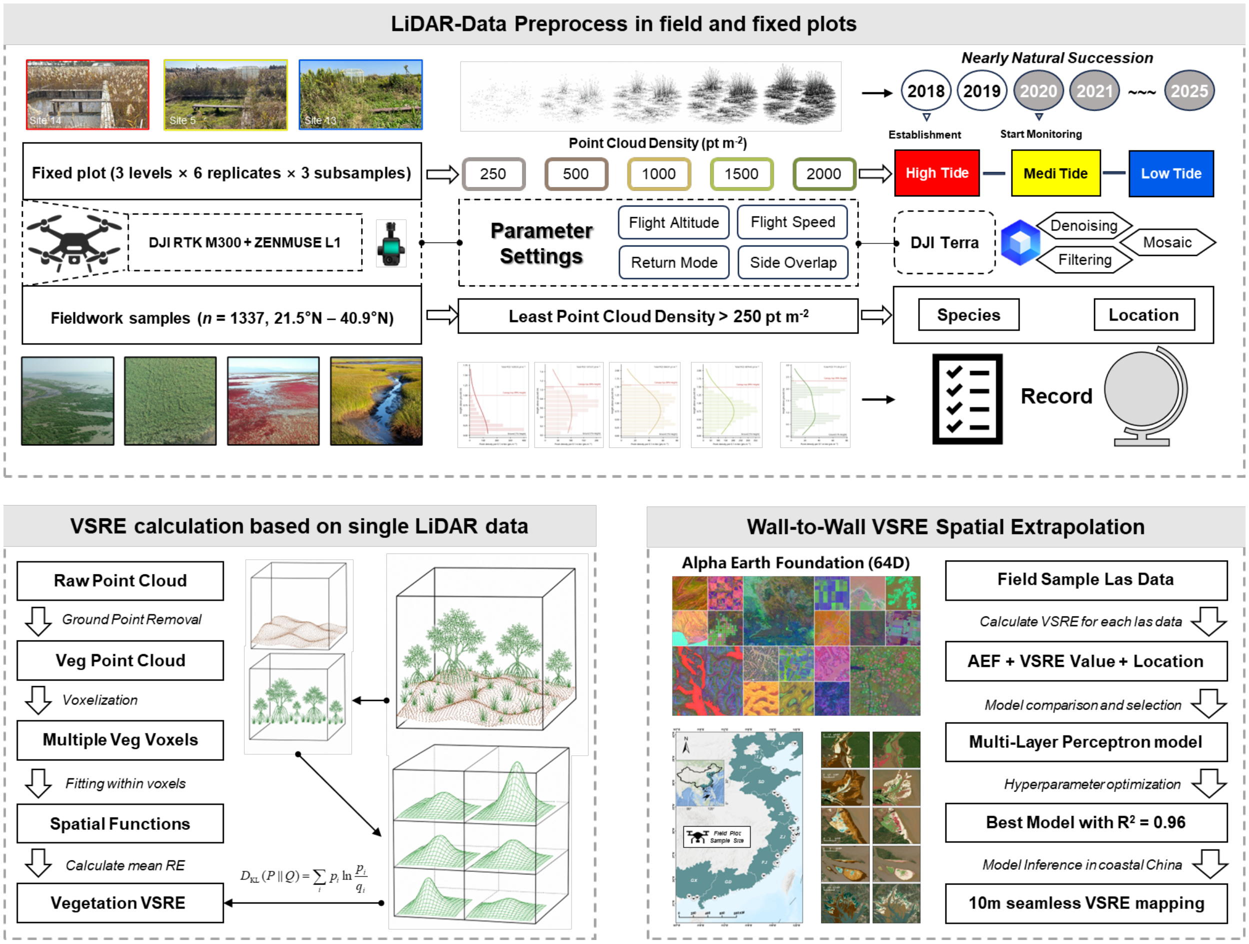


Fig. 3 | The Overall workflow of this study.

Comment 19: *Line 233: Five? But you only mentioned four here.*

Response: We thank you for the careful reading. We would like to clarify that the phrase"All **five** structural metrics were calculated for the same LiDAR samples and spatial extents as VSRE. By comparing VSRE with metrics emphasizing horizontal structure (**canopy cover**), vertical structure (**mean vegetation height** and **FHD**), and integrated canopy structure (**rugosity** and **canopy entropy**), this analysis provides a systematic evaluation of whether VSRE captures structural information beyond that represented by conventional vegetation structural complexity indices, particularly in the context of coastal saltmarsh ecosystems." in the original text refers to five conventional structural metrics, namely mean

- mean vegetation height
- canopy cover
- FHD (foliage height diversity)
- canopy rugosity
- canopy entropy

VSRE is the new metric proposed in this study and was compared against these five existing metrics. Therefore, the intended comparison was between five conventional structural metrics and VSRE.The latter part of the original sentence was intended to describe the structural dimensions represented by these five conventional metrics:

- horizontal structure: canopy cover (1)
- vertical structure: mean vegetation height and FHD (2)
- integrated canopy structure: rugosity and canopy entropy (2)

Together, these correspond to five conventional structural metrics. We recognize that the original wording may not have been sufficiently clear. In the revised manuscript, we will explicitly state ``five conventional structural metrics" and list these metrics where appropriate to avoid ambiguity or the mistaken inclusion of VSRE in this count.

Comment 20: *Line 239-306: This is an interesting study; however, the manuscript does not allocate sufficient space to adequately present the results. Key outcomes, such as classification and mapping accuracy, are only mentioned in the Methods section, which is inappropriate. Please refer to my general comments for further details.*

Response: We appreciate you raising this important point. We agree that the presentation of this section in the original manuscript was not ideal. In particular, the key results of vegetation classification and national-scale mapping were described primarily in the Methods section rather than clearly summarized in the Results section. This organization may have weakened the clarity of the manuscript structure and made it difficult for readers to understand the role of this component within the overall study.

We want to clarify that this component is not a core research objective in itself, but rather a supporting element for the national-scale application of VSRE. Specifically, vegetation classification provides essential background information for subsequent structural interpretation and ecological validation, whereas national-scale mapping is included not to develop an independent classification study, but to demonstrate the applicability of VSRE in real-world, large-scale settings. For this reason, we initially did not intend to discuss these two components in the main text with the same level of detail as the central VSRE development and validation framework.

One reason that we retained a relatively brief but complete methodological description in the submitted manuscript was that the related vegetation classification study had not yet been formally published at the time of submission. To ensure the workflow remained understandable, we included methodological descriptions and accuracy information so readers could understand the data basis and the technical sources supporting national-scale VSRE mapping. During the review process, this independent study was published online. Therefore, in the revised manuscript, we will treat this section primarily through citation, supplemented by only brief necessary explanations, thereby reducing unnecessary interference with the main storyline.

Following your suggestion, we will make several revisions. We will further shorten the non-core descriptions of vegetation classification and mapping in the main text, move detailed technical implementation details, parameter settings, and supplementary results to the Supplementary Materials, and provide a clearer, more concise summary of the key classification and mapping results in the Results section. We will also more explicitly emphasize the auxiliary role of these components, so that they serve the main storyline of VSRE development, validation, and application rather than appearing as independent modules parallel to the manuscript's central focus.

This revision strategy is consistent with our **response to comment 5**. We believe that these adjustments will make the manuscript more focused and allow the vegetation classification and national-scale mapping components to better support the study's core objectives, with more appropriately proportioned coverage.

Comment 21: *Line 305: This level of accuracy suggests potential overfitting, which is a known issue for MLP models when trained on a limited number of samples.*

Response: We thank you for this important comment. We agree that MLP models can be prone to overfitting when sample sizes are limited. We also acknowledge that the description of this part in the original manuscript was not sufficiently clear, which may have led readers to confuse the cross-validation results used for model selection with the performance of the final tuned model on the independent test set.

We would like to clarify that our modeling workflow consisted of two stages. First, all 1,337 samples were divided into training and test sets at a ratio of 7:3. In the first stage, we performed 10-fold cross-validation on the training set for all candidate models and used cross-validation MAE as the primary criterion to compare the generalization ability of different algorithms. This procedure identified MLP as the best-performing model. In the second stage, after MLP was selected, we further optimized its hyperparameters using grid search and then evaluated the final tuned model on an independent test set.

Based on this workflow, we do not think the current results indicate substantial overfitting for three main reasons. First, model selection was based on the average performance of candidate models under tenfold cross-validation within the training set, and final predictive performance was evaluated on test samples independent of the training process. This is a standard modeling strategy that reduces the risk of model selection bias arising from random data partitioning. Second, the dataset used in this study comprised 1,337 in situ LiDAR quadrats distributed across the coast of China. For the task addressed here, namely the spatial extrapolation of VSRE, this sample size provides a reasonable basis for model training and evaluation, and the samples also have broad spatial representativeness. Third, the AEF embeddings integrate multi-source remote sensing data closely related to vegetation structure, including optical, LiDAR, and radar data. Therefore, the model's strong predictive performance is methodologically plausible and supported by the data, and does not necessarily indicate overfitting.

To avoid misunderstanding, we will further clarify in the revised manuscript which results were used for model selection and for comparing generalization ability, and which were used to demonstrate the predictive performance of the final tuned model on the independent test set.

Revised text:

Main text: Line 297-311

To evaluate model performance while reducing the risk of overfitting, all samples were first randomly divided into training and independent test sets at a ratio of 7:3. Within the training set, several mainstream machine learning and deep learning models were compared using tenfold cross-validation, with cross-validation MAE used as the primary criterion for model selection. After the Multilayer Perceptron (MLP) was identified as the best-performing candidate model(Pinkus, 1999), its hyperparameters were further optimized using grid search within the training workflow. The final hyperparameter-tuned MLP model was then evaluated on the independent test set and applied to generate the

2022 wall-to-wall VSRE map of coastal China at 10 m spatial resolution. The model comparison showed that MLP achieved the lowest cross-validation MAE among the candidate algorithms, indicating the strongest generalization ability during model selection (Supplementary Table S5). After hyperparameter tuning, the final MLP model achieved high predictive accuracy on the independent test set, with R2=0.9613, RMSE=2.812, and MAE=1.946 (**Supplementary Table S5, Supplementary Figure S6**). This performance suggests that the AEF embeddings contain structural information relevant to VSRE prediction and can support national-scale extrapolation from field LiDAR samples. Based on this model, we generated a seamless 10 m VSRE map for coastal vegetation across China in 2022.

Comment 22: *Line 332: you have defined the abbreviation of VSC before.*

Response: Thank you for reminding. We have revised this error.

Comment 23: *Fig. 3: How were the three VSC groups defined? I could not find sufficient details on this. Notably, most existing metrics indicate that the "medium" group corresponds to relatively low VSC, whereas only your metric suggests otherwise. This raises questions about the criteria used to establish these groupings, particularly considering the difficulty to quantify VSC in real world.*

Response: We thank you for this question. The three VSC plot groups are defined in detail in our **response to comment 3**; we briefly clarify them here. The low-, medium-, and high-VSC groups in this study were not defined by subjective visual assessment. Instead, they were derived from three typical community-structure scenarios generated within a controlled, near-natural experimental platform and supported by independent field survey data. Specifically, these three groups correspond to a monodominant herbaceous community, a mixed herbaceous community, and a herbaceous--woody community, respectively, representing a structural gradient from simple to complex. In addition, we used a biomass-weighted Shannon index as an independent external proxy to evaluate the rationale for this gradient; the results are shown in **Fig. S3**. Given the absence of a mature, unified framework for defining coastal vegetation structural complexity, we believe that this experimentally generated structural gradient, consistent with field observations and the logic of community succession, provides an ecologically meaningful and important baseline for metric evaluation.

Regarding the point that most existing metrics classified the medium group as having relatively low complexity, whereas VSRE did not, we do not think that this pattern indicates a problem with the grouping criteria. On the contrary, it reflects one of the key findings that this study aims to highlight: some conventional metrics cannot consistently capture the expected structural complexity gradient in coastal wetlands, which are open, low-stature, and spatially patchy ecosystems. As a result, these metrics may misclassify the medium-VSC group. By contrast, VSRE more accurately distinguishes the three predefined structural scenarios that are supported by independent external evidence.

To avoid similar confusion, we will further clarify the definitions of the three plot groups in the revised manuscript. We will also explicitly cross-reference the explanation provided in our **response to comment 3** and **Fig. S3** in the text related to **Fig. 3** to improve clarity.

Revised text and Figure:

Main text: Line 340-347

Across the low-, medium-, and high-water-level treatment groups, the VSC of the secondary plots showed a clear decreasing gradient (***Methods*, Fig. 1b**). This gradient was reflected not only in community composition, but also in the intuitive structural differences observed in the field and in plot photographs. It was further supported by the frequency distribution of the VSC proxy derived from the biomass-weighted Shannon index (**Supplementary Figures S3**). We therefore consider the structural complexity gradient formed under the water-level treatments to provide a reasonable baseline for evaluating the discriminatory ability of different VSC metrics. This baseline can also be used to compare the performance of different metrics in distinguishing among levels of vegetation structural complexity.

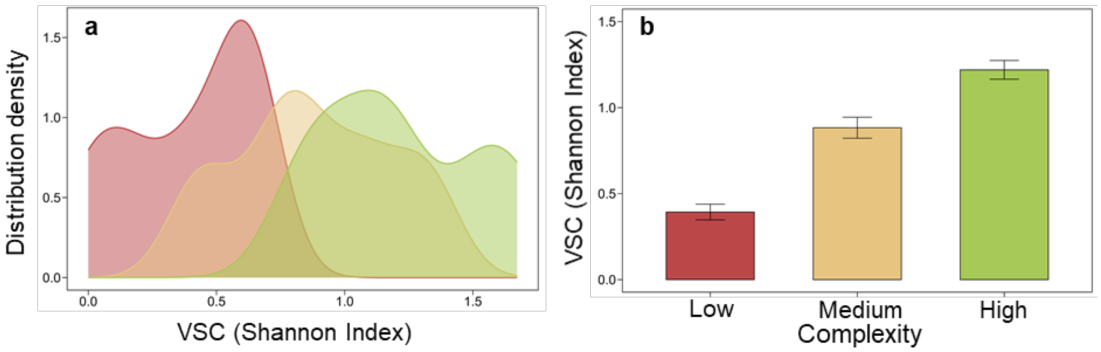


Fig. S3 | VSC index distribution characteristics constructed based on the Shannon index. a, the VSC distribution curve was fitted using kernel density estimation. **b,** Mean values of VSC in groups with different human-defined complexity. Error bars indicate standard deviation.

Comment 24: *Line 362: Point density is not the only factor that should be considered (see my previous comments). It would be helpful to include a vertical profile of the LiDAR data to better illustrate its structural characteristics. To my knowledge, the DJI L1 sensor primarily captures returns from the upper canopy and has limited penetration into lower layers. As a result, even with increasing point density, the additional points may still be disproportionately concentrated in the upper canopy. This could artificially increase relative entropy by enhancing apparent dissimilarity between layers, without necessarily reflecting changes in VSC.*

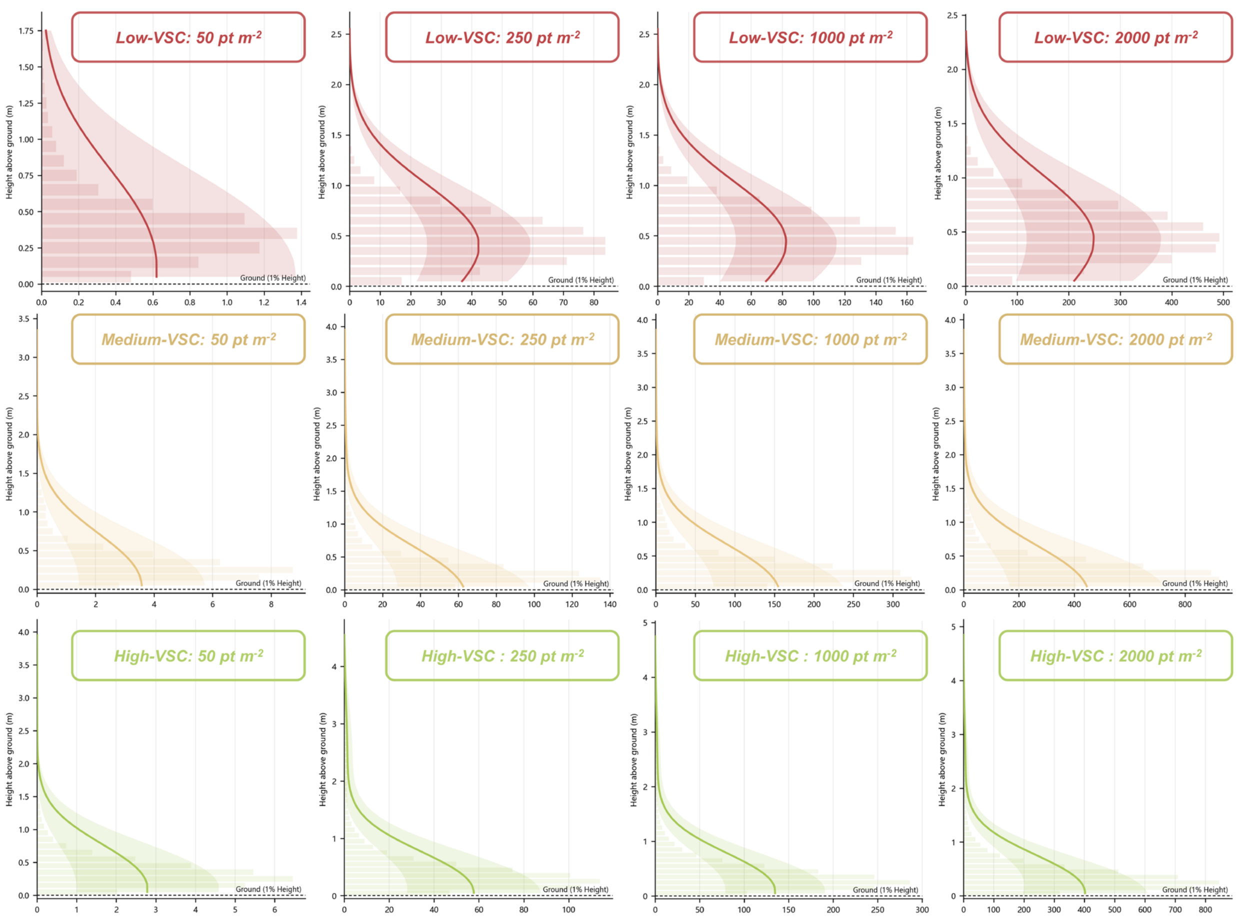
Response: We appreciate your valuable comment. We agree that when LiDAR is applied to dense, closed vegetation, vertical sampling bias and insufficient penetration into the lower canopy can substantially affect structural characterization. However, this issue is less pronounced in the coastal wetland system examined in this study. As described in the manuscript, the coastal wetland vegetation in our dataset is generally low in stature and has a relatively open canopy structure, in contrast to the strongly vertically closed structure typical of mature forests. Under these conditions, when point cloud density is sufficient, the lower canopy and, in many plots, the ground surface can still be adequately sampled. This pattern is directly evident in the vertical-profile visualizations of many of our plots. Therefore, we will add representative vertical profiles for several typical vegetation types in the revised manuscript to more clearly illustrate this data characteristic and its limitations.

More importantly, we would like to clarify that the potential bias noted by you is one reason why VSRE showed more stable performance than several conventional metrics. Traditional metrics such as canopy cover, FHD, and canopy entropy are more directly affected by the vertical distribution of returns. For example, canopy cover depends on the proportion of returns above a fixed height threshold, whereas FHD is calculated from the occupancy distribution of returns among vertical layers. Although canopy entropy attempts to reduce the effect of excessive point cloud concentration in the upper canopy through resampling, as discussed in the manuscript, this procedure may also remove important structural information and introduce additional noise.

By contrast, VSRE is not calculated directly from the raw return abundance within a single layer. Instead, it characterizes structural differences based on normalized voxel-based spatial distributions within sliding windows. This normalization step is intended to reduce the influence of local anomalies and overall variation in point cloud density before relative entropy is compared. In this sense, VSRE cannot completely eliminate density-related effects, but it can substantially reduce the risk of misinterpreting the enrichment of upper-layer returns, which may arise from the inherent sampling tendency of UAV LiDAR toward upper-canopy elements, as an increase in structural complexity.

This interpretation is also consistent with our empirical results. If increasing point cloud density mainly amplified artificial interlayer differences, VSRE would be expected to become less stable as sampling density increased. However, we observed the opposite pattern. Under varying or mixed point cloud density conditions, several conventional metrics showed unstable or even misleading responses, whereas VSRE consistently maintained the clearest and most coherent discrimination among structural complexity groups.

Revised Figures :



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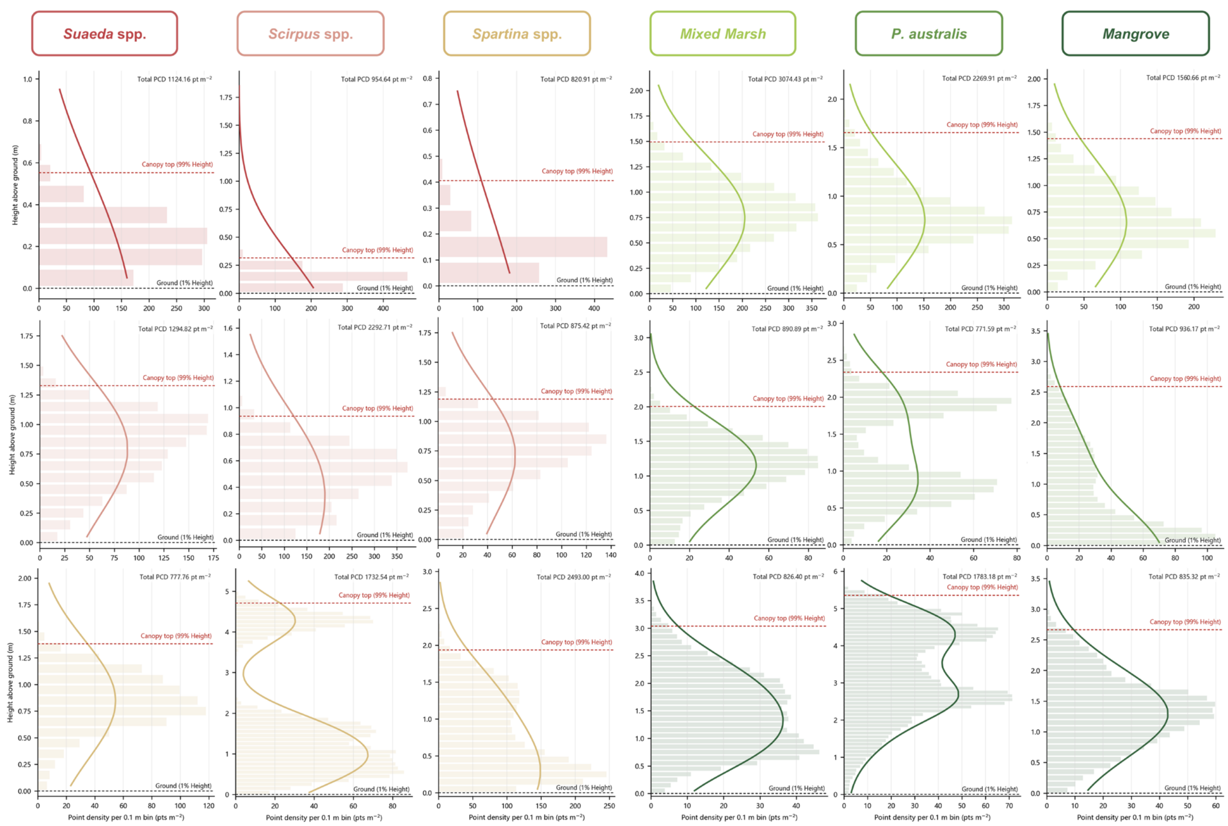
cloud densities. Vertical point-density profiles for fixed-plot samples of 25×25 m^2 grouped by vegetation structural complexity (VSC) and target point-cloud density. Rows represent low-, medium-, and high-VSC groups, and columns represent target point-cloud densities of 50, 250, 1000, and 2000 pt m^{-2}. In each panel, horizontal bars show the mean point density within 0.1 m vertical height bins, the solid curve shows the Gaussian-smoothed mean profile, and the shaded envelope indicates variability among samples. Heights were normalized relative to local ground, defined as the 1st percentile of point height and indicated by the black dashed line. The x-axis shows point density per 0.1 m height bin, and the y-axis shows height above ground.



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Comment 25: *Line 386: High species diversity does not necessarily mean high canopy structural complexity. Please see my general comment.*

Response: We appreciate you raising this point. We agree that higher species diversity does not necessarily imply higher canopy structural complexity, and that these two concepts are not ecologically equivalent. Our intention was not to use biodiversity, especially species diversity, as a direct definition or ground truth of canopy structural complexity.

As clarified in our responses to Comments 3 and 4, the structural gradient among the three plot groups in this study was primarily derived from three typical community-structure scenarios formed within a controlled near-natural experimental platform, rather than being directly defined by biodiversity metrics. In addition, the continuous-gradient analysis was not based solely on species richness, but on a biomass-weighted Shannon index. This index was used only as an independent external ecological reference to examine whether different structural metrics could respond to objectively existing continuous gradients among communities, rather than as a direct substitute for VSC.

We acknowledge that the original wording may have led readers to interpret the analysis as implying that higher species diversity is equivalent to higher structural complexity. In the revised manuscript, we will further clarify the distinction between biodiversity and canopy structural complexity. We will also emphasize that the purpose of this analysis is to provide supplementary support for the ecological relevance and gradient sensitivity of VSRE, rather than to use biodiversity-based comparisons as direct evidence of VSRE's superiority.

Comment 26: *Line 471-484 and Fig. 9: I may be misunderstanding something here, but I am not clear how these conclusions are derived. Wouldn't a mature forest with strong canopy complementarity exhibit a near-random distribution of canopy elements, and therefore correspond to high entropy.*

Response: We appreciate this important and insightful comment from you. We agree that, in mature forests, strong canopy complementarity may cause the point-cloud distribution to approach spatial saturation or a relatively uniform distribution. Under such conditions, entropy-based metrics may yield high values, and this high entropy can, to some extent, reflect the high canopy structural complexity of mature forests. Therefore, our original manuscript did not intend to deny the possibility that mature forests may exhibit high entropy.

What we intended to emphasize is that high information entropy is not necessarily equivalent to high ecological vegetation structural complexity. Information entropy primarily measures whether the occupancy probability of point clouds within predefined spatial units, voxels, or height layers is uniform. In other words, it quantifies the uncertainty of a point occurring at a particular spatial location. When point clouds are more uniformly distributed among spatial units, information entropy generally increases. However, ecologically meaningful VSC depends not only on whether space is uniformly occupied, but also on whether vegetation structures exhibit multilayered, multicomponent, multiscale, and locally heterogeneous three-dimensional organization.

The mature forest example raised by you helps clarify this distinction. High information entropy in mature forests often does not arise from completely unconstrained random arrangements. Rather, it can result from structural complementarity among tree crowns, trunks, understory vegetation, gaps, and different height layers. These structural elements are organized under ecological and architectural constraints, including competition for growth, light resource use, and spatial niche differentiation. As a result, complex local structures may ultimately produce relatively full and uniform spatial occupation at the point-cloud or voxel scale. In this case, high entropy can be understood as a consequential expression of complex structures approaching spatial saturation.

The key limitation is that information entropy primarily focuses on the final uniformity of occupancy and does not distinguish whether this uniformity arises from the complementary stacking of diverse structural units or from the repetitive arrangement of simple structural units. For example, a mature forest may show high entropy because many different local structural configurations complement one another in three-dimensional space. However, a dense, fast-growing monospecific stand may also produce relatively uniform voxel-scale point-cloud occupancy because many similar structural units are repeatedly arranged in space. The high entropy of the former reflects structural complementarity and local configurational diversity, whereas the latter's high entropy reflects dense repetition and uniform filling. Although these two cases may appear similar in terms of information entropy, they are not equivalent in ecological VSC.

This issue is particularly relevant in coastal wetlands. Unlike mature forests, many coastal wetland communities are dominated by one or a few species, such as dense *Phragmites australis*, *Spartina alterniflora* or other graminoid saltmarsh communities. Although these communities may consist of relatively simple and repetitive structural units, their point clouds may still show relatively uniform occupancy across many spatial units when vegetation density is high and voxel size or vertical stratification is coarse. In such cases, entropy-based metrics may mistakenly interpret dense, uniform, and repetitive occupancy as high structural complexity. Conversely, some multispecies mixed communities may not have the most uniform overall spatial occupancy, but may exhibit higher ecological structural complexity because local windows differ substantially in their three-dimensional configurations, including differences in height-layer combinations, gap structure, and herbaceous--woody organization.

By contrast, VSRE was not designed to measure whether the entire plot space is uniformly filled. Instead, it constructs local voxel distributions using three-dimensional sliding windows and compares spatial distribution differences among local windows. Thus, VSRE focuses on differences in local structural configurations rather than on the uniformity of global spatial occupancy. If a community has a relatively uniform point-cloud distribution but highly repetitive local structures, VSRE will not be strongly inflated by uniform occupancy alone. If different local windows contain substantially different three-dimensional structural configurations, VSRE will more sensitively capture this configurational heterogeneity. We believe that this is an important reason why VSRE distinguished different VSC gradients in coastal wetlands more consistently than conventional metrics such as CE and FHD in this study. Our results also show that FHD, canopy cover, and canopy entropy were prone to misclassifying moderately complex communities under varying point cloud densities, whereas VSRE more stably distinguished low-, medium-, and high-VSC groups.

Therefore, we agree that the mature forest scenario noted by you is an important case in which information entropy can closely match VSC, especially when canopy structure is highly developed and approaches spatial saturation. However, across the continuous transition from simple to complex communities, particularly in coastal wetlands where dense monospecific communities are common, the relationship between information entropy and VSC is not necessarily strictly monotonic. Our original intention in Fig. 9 was to express this potential inconsistency.

However, we agree that the wording in the original manuscript was too simplified and may have led readers to infer that mature forests always have low entropy or that entropy-based metrics are generally ineffective.

Accordingly, we will revise the relevant text in the revised manuscript. First, we will delete or weaken the overgeneralized statement that mature forests may have lower information entropy than secondary forests, and we will explicitly acknowledge that mature forests may indeed exhibit high information entropy under conditions of spatial saturation and strong canopy complementarity. Second, we will emphasize that Fig. 9 is a conceptual diagram rather than a universal empirical rule. Its purpose is not to suggest that CE or FHD necessarily follows a fixed curve, but to illustrate that entropy-based metrics primarily reward spatial occupancy uniformity. Therefore, VSC may be overestimated in communities with repetitive structures but uniform point-cloud occupancy. Third, we will further distinguish spatial occupancy uniformity from ecological structural complexity by explaining that high entropy may arise from either the multilayered, complementary structure of mature forests or the uniform occupancy of simple, repetitive communities. For this reason, entropy alone should not be used as a sufficient criterion for ecological VSC.

We are therefore grateful for your reminder. This comment helped us recognize that the original description of the relationship between information entropy and VSC was too absolute. In the revised manuscript, we will explain more cautiously that information entropy can effectively reflect complexity in spatially saturated and multilayered canopy structures, but in coastal wetlands, especially in dense, repetitive, monospecific communities, it may reflect spatial occupancy uniformity more than local structural heterogeneity. We will also revise the description of Fig. 9 accordingly, presenting it as a conceptual illustration of the possible nonmonotonic or context-dependent relationship between entropy-based metrics and ecological VSC.

Revised text:

Main text: Line 481-521

The concept of entropy originates from physics, where it describes the degree of disorder within a system. Since Shannon introduced it into information theory, information entropy (IE) has been widely applied in digital information processing (Cover and Thomas, 1991). More recently, following previous work using IE (FHD, CE) to point cloud data to quantify forest canopy complexity (Liu et al., 2022), many studies have been conducted in-depth analyses of the ecological functions and structural characteristics of forest canopies based on this concept (Liu et al., 2024; De Conto et al., 2024; Wang et al., 2023).

However, when point-cloud IE is used directly as a proxy for VSC, an important conceptual limitation arises. In voxelized point clouds, IE primarily quantifies the evenness or uncertainty of point occupancy within predefined spatial units, such as voxels or height layers. It reaches its maximum when point occupancy is uniformly distributed and its minimum when points are concentrated in a small number of spatial units. Thus, high IE indicates uniform spatial occupancy, but such uniformity is not necessarily equivalent to ecological structural complexity. Mature forests provide an important case in which high IE may correspond well with high VSC, because canopy complementarity, vertical stratification, crown packing, trunks, understory vegetation, and gaps can jointly produce a saturated, spatially uniform point-cloud distribution. Yet IE does not distinguish between uniformity arising from complementary arrangements of diverse structural units and that arising from repetitive arrangements of simple structural units (**Fig. 10**).

This distinction is particularly important in coastal wetlands, where dense reed stands, Spartina alterniflora marshes, and other graminoid communities may consist of simple, repetitive structures yet exhibit uniform occupancy across voxels or height layers. In such cases, entropy-based metrics may overestimate VSC by interpreting dense, repetitive filling as structural complexity. Conversely, multispecies mixed communities may show lower global occupancy evenness but higher ecological VSC because their local structural configurations vary across space. Therefore, the relationship between entropy-based metrics and ecological VSC is context-dependent rather than universally monotonic. Fig. 10 illustrates this potential mismatch and helps explain why the high-water-level group in our results showed lower ecological VSC but higher CE and FHD values than the medium-water-level group (**Fig. 4b**).

A further limitation of information-entropy-based metrics is their sensitivity to point cloud density and sampling distribution. Ideally, once point cloud density is sufficient to characterize vegetation three-dimensional structure, additional points should mainly reduce measurement noise rather than systematically alter the estimated VSC. However, IE is calculated from point-occupancy probabilities within voxels or height layers and therefore assumes that the observed point-cloud distribution accurately reflects the underlying vegetation structure. This assumption is often difficult to satisfy in LiDAR data, because point clouds are influenced by flight altitude, scan angle, return mode, canopy occlusion, sensor penetration, and surface reflectance. As point cloud density increases, newly added points may be disproportionately concentrated in upper canopies, outer surfaces, or high-reflectance regions rather than being distributed proportionally across all structural elements. In addition, IE has an upper bound determined by voxel size, vertical stratification, and plot extent; increasing point cloud density may fill more voxels and move the observed distribution toward this saturation limit. As a result, changes in IE may reflect a mixture of true structural variation, density effects, and sampling bias, rather than ecological structural complexity alone (**Fig. 10**).

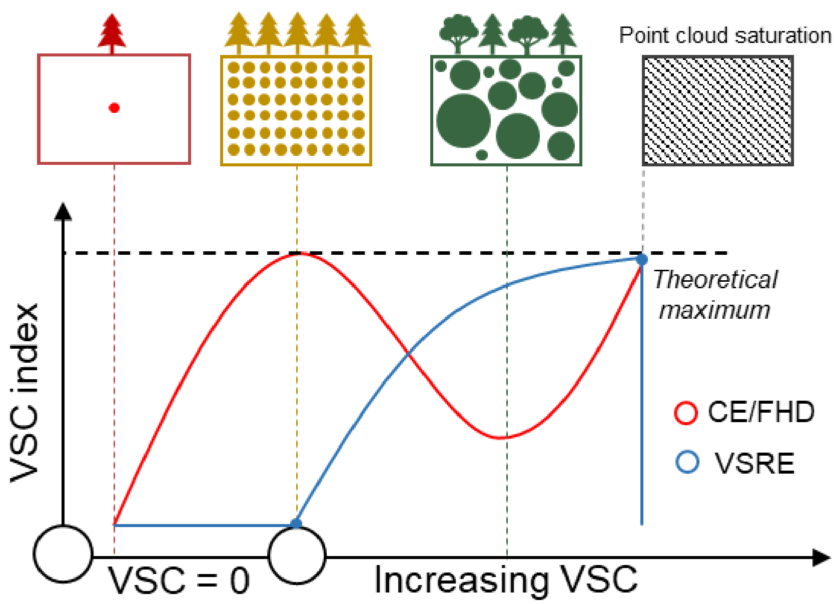

Fig. 10 | Theoretical trends of VSRE and CE/FHD as VSC increases.

Comment 27: *Line 493-494: I am lost again here. What do you mean by structural reproducibility?.*

Response: We appreciate you pointing out the ambiguity of this statement. We agree that the term ``structural reproducibility" may be misunderstood. Our intention was not to refer to repeated measurement of the same structure or to experimental reproducibility. Rather, we intended to describe whether similar structural configuration patterns repeatedly occur across different local spatial windows.

More specifically, the VSRE calculation does not focus on the uniformity of the point cloud within a single window. Instead, it compares three-dimensional voxel distributions across multiple local windows. If local structures at different positions within an ecosystem are highly similar, for example, if similar layering patterns, spatial filling modes, and local organizational forms repeatedly appear across windows, then the distributional differences among these windows will be small, and the corresponding relative entropy will be low. This was the intended meaning of our original statement that greater structural reproducibility indicates lower VSC: when local structures are highly repetitive in space and show limited configurational variation, spatial heterogeneity is low, and VSRE is therefore also low.

Conversely, if structural configurations differ substantially among local windows, for example, if some windows contain tall and dense canopy elements, some contain clear gaps, and others contain mixed herbaceous--woody structures, then the distributional differences among local structures will increase, and the corresponding relative entropy will also increase. In this case, VSRE reflects stronger heterogeneity among local structural configurations.

We therefore agree that structural reproducibility" is not sufficiently intuitive. To avoid further confusion, we will replace this term in the revised manuscript with the clearer phrase similarity among local structural configurations". This wording better conveys our intended meaning: VSRE measures the degree of difference among local structural configurations, rather than the randomness or uniformity within a single local structure.

Comment 28: *Line 507: I did not put too much focus on the discussion on the national mapping here, because I think this should be put in a separate paper.*

Response: We appreciate you raising this point. We understand the concern that the national-scale mapping component could be developed into a separate article, which is consistent with the suggestion raised in the general comments. As explained in our responses to Comments 5 and 15, we agree that this component occupied a substantial portion of the original manuscript and may have partly distracted from the main storyline.

However, we still believe that national-scale mapping plays a necessary supporting role in this study. Its primary purpose is not to present an independent mapping study, but to demonstrate the applicability of VSRE in a real-world, large-scale setting. By extending VSRE from local development and validation to regional-scale data production, this component illustrates the practical potential of the metric and its value for broader ecological applications.

In response to the this suggestion, we will further shorten this section in the revised manuscript. We will reduce its appearance as an independent module and more clearly position it as supplementary evidence for the application potential of VSRE, rather than as a core research section parallel to the methodological development. A more detailed explanation of these structural adjustments is provided in our **responses to comments 5 and 15**.

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