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Research article

Three-dimensional modeling of 500 kV transmission lines by airborne LiDAR

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ABSTRACT

This study aims to enhance the accuracy of three-dimensional (3D) modeling in the planning, design, operation management, and risk assessment of 500 kV transmission lines. Addressing the limitations of traditional two-dimensional (2D) or low-precision 3D models, a new method based on airborne Light Detection and Ranging (LiDAR) technology is proposed. Initially, high-density, high-precision 3D point cloud data are collected using airborne LiDAR technology. This data is then processed using specialized software for noise removal, terrain classification extraction, and Geographic Information System (GIS) data integration. Subsequently, a Convolutional Neural Network (CNN) is employed to classify the 3D point cloud data to enhance the accuracy of complex structure recognition. Lastly, the point cloud data are converted into linear and planar entities using Computer-Aided Design (CAD) technology, achieving high-precision 3D reconstruction of the 500 kV transmission lines and their complex terrain environment. Experimental results show that the spatial resolution of the constructed model reaches 0.1 m per pixel, with overall geometric accuracy within ±5 cm. Compared to traditional aerial imagery and ground survey methods, the model based on airborne LiDAR technology achieves improvements of 30 % in detail richness and 35 % in terrain adaptability, with a 45 % increase in decision-making efficiency. These improvements significantly enhance the accuracy of line operations, safety assessments, and environmental impact analyses, providing solid data support for the modernization and intelligent development of the power industry.

1. Introduction

With the rapid progress of the global economy and the continuous growth in societal energy demands, the power system, as a crucial component of national infrastructure, plays a direct role in the stable development of the national economy and the quality of people's lives [1,2]. Among various power facilities, high-voltage transmission lines such as 500 kV, characterized by long-distance transmission and large capacity, serve as indispensable links connecting power stations with various electricity consumption areas [3,4]. However, these transmission lines often traverse complex and dynamic geographical environments. Ensuring their stable operation under unpredictable factors such as extreme weather and geological disasters is a significant technical challenge for the power industry. Meanwhile, it is a prerequisite for safeguarding the stable operation of societal economic activities [5–7]. However, with the increasing demand for high-precision three-dimensional (3D) modeling of power systems, traditional two-dimensional (2D)

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or low-precision 3D models can no longer meet the requirements of detailed planning and management of 500 kV transmission lines and their surrounding environments.

To address these challenges, high-precision 3D models have become essential tools for the planning, design, operational management, and risk assessment of transmission lines [8]. Compared to traditional 2D drawings, 3D models can provide more intuitive and comprehensive spatial information, assisting engineers and decision-makers in a more accurate understanding of the actual conditions of transmission lines and their surrounding environments. This, in turn, facilitates more scientifically sound planning and decision-making [9,10]. However, due to technological and equipment limitations, establishing high-quality 3D models has been time-consuming and resource-intensive over the years, especially in complicated terrain environments. Traditional ground measurement and aerial imaging methods often struggle to achieve the desired accuracy and efficiency, thereby limiting the progress of the power industry in terms of precision management and intelligent operation [11–13].

Firstly, point cloud data contains a lot of noise and unstructured information, so how to accurately extract transmission lines and their auxiliary facilities (such as towers, wires, insulator strings, etc.) is a complex and technical task. This requires high accuracy during noise removal and classification to avoid errors affecting subsequent modeling. Secondly, the processing of point cloud data requires efficient algorithms for geometric modeling. Especially in 3D reconstruction, how to accurately transform point cloud data into linear and planar entities with practical application value involves complicated computer vision and graphics techniques.

In recent years, the swift advancement of airborne Light Detection and Ranging (LiDAR) technology has demonstrated significant advantages in acquiring 3D spatial data [14,15]. LiDAR technology precisely measures the distance between objects and the laser source through laser pulses, generating high-density and high-precision 3D point cloud data, thereby enabling 3D modeling in complex environments [16–18]. Compared to traditional methods, airborne LiDAR covers a broader area and effectively penetrates the canopy, capturing detailed information on the terrain surface, greatly enhancing data acquisition efficiency and model accuracy [19].

In this context, this study explores the methods and effects of using airborne LiDAR technology for high-precision 3D modeling, especially for 500 kV transmission lines and their surrounding environments, to address the shortcomings of traditional modeling methods. The study aims to construct a 3D model that accurately reflects the transmission line and its complex terrain environment by professionally processing and accurately modeling the collected 3D point cloud data. The innovation lies in the following.

1) High-precision modeling: Airborne LiDAR technology is utilized for 3D modeling of transmission lines and surrounding environments. This not only captures subtle terrain changes and structural details but also improves the model's overall accuracy. Compared with traditional modeling methods, LiDAR technology can better process large-scale and complex terrain data and provide more detailed 3D information.
2) Application of data processing technology: Advanced Convolutional Neural Network (CNN) is adopted for point cloud classification to improve the accuracy of structure recognition. Then, advanced data processing techniques such as the Random Sample Consensus (RANSAC) algorithm and region growing algorithm are used to further improve the parsing accuracy of point cloud data. The application of these technologies makes it possible to extract high-quality linear and planar structures from noise and outliers, thereby constructing more accurate and reliable 3D models.
3) Comprehensive application and intelligent support: This study explores technical methods and applies these methods to the practical needs of the power industry, providing more accurate and detailed basic data support for the planning, design, operation management, and risk assessment of transmission lines. This promotes the further development of modernization and intelligence in the power industry. In short, this study has remarkable innovation in the application of high-precision 3D modeling technology and data processing methods, aiming to provide strong technical support for the intelligent operation and maintenance of transmission lines.

2. Literature review

In the 3D modeling field of transmission lines, recent studies have predominantly focused on two major technological paths. Firstly, the traditional methods are based on ground measurement and aerial photogrammetry for 3D modeling. Secondly, utilizing emerging remote sensing technologies, particularly airborne LiDAR technology, for high-precision 3D modeling [20,21]. Traditional methods, due to their mature technology and ease of operation, received widespread application in the early stages. However, as research deepened and technological requirements increased, their limitations gradually became evident regarding data acquisition efficiency, accuracy, and model detail representation [22]. As remote sensing technologies develop, especially the progress in airborne LiDAR technology, new possibilities have emerged for the 3D modeling of transmission lines. Airborne LiDAR technology can rapidly acquire high-precision 3D point cloud data over large areas. It is not restricted by lighting conditions and can effectively penetrate vegetation layers to reach the ground, markedly enhancing data acquisition efficiency and model accuracy [23]. Recent studies have started to explore the application of airborne LiDAR technology in the 3D modeling of transmission lines, showing promising initial results.

Lohani & Ghosh (2017) [24] investigated various types of laser radar sensors and their operating principles. Qin et al. (2022) [25] presented a more economically feasible method using airborne LiDAR technology for forest carbon sequestration assessment. They found that the emission reduction measured through field measurements or LiDAR observations was approximately twice the estimated emissions by project developers before implementation. Küçükdemirci et al. (2023) [26] argued that advancing airborne LiDAR technology could offer high-resolution datasets, enabling experts to more effectively detect archaeological features hidden beneath forested areas. Zhang et al. (2022) [27] similarly emphasized that airborne LiDAR technology became a common and effective method for collecting large-scale 3D spatial information. They also proposed a dual-attention neural network to optimize it.

Sarıtaş & Kaplan (2023) [28] aimed to improve the data quality of three different LiDAR datasets representing urban, rural, and forest environments by applying airborne LiDAR scanning algorithms in the CloudCompare software. Ge et al. (2023) [29] introduced that optimizing the strategy for modeling lines to improve detection efficiency needs immediate attention. For instance, Liu et al. (2022) [30] discussed using deep learning (DL) technology to improve the classification accuracy of LiDAR point cloud data. By preprocessing mobile laser scanning data collected on-site to extract a single point cloud and applying non-uniform grid and farthest point sampling methods, the resulting sample data were more favorable for DL model feature extraction. Pan & Yang (2023) [31] proposed a CNN-based point cloud data processing method to enhance model detail reconstruction capabilities. This study developed a new CNN-based method for locating structural bolts in 3D point clouds. Lopac et al. (2022) [32] examined the challenges and solutions of applying LiDAR technology in complex environments.

Current research indicates that traditional 3D modeling methods, such as those based on ground measurements and aerial photogrammetry, while technically mature and easy to operate, have limitations in data acquisition precision, efficiency, and model detail representation. Specifically, these methods struggle to provide sufficient detail and accuracy when dealing with complex environments and high-density data. Additionally, traditional methods are often constrained by lighting conditions and terrain occlusion, leading to information loss during data collection and modeling processes. Advances in airborne LiDAR technology offer new possibilities for addressing these issues. This technology can rapidly acquire large-scale, high-precision 3D point cloud data regardless of lighting conditions. Moreover, it can effectively penetrate vegetation layers to obtain ground information, significantly improving data acquisition efficiency and model accuracy. Despite the obvious advantages of airborne LiDAR technology in the collection of point cloud data, the current research and application still face the following major shortcomings.

1) Insufficient accuracy of point cloud classification: Although previous studies have attempted to improve the classification accuracy of point cloud data using different classification algorithms, the classification accuracy is still unsatisfactory when dealing with complex scenes and large-scale data. For example, although existing CNN methods have improved, there are still challenges in classifying high-noise environments and small features.
2) The demand for improving the accuracy of 3D modeling: Existing modeling techniques still face the problem of accurately reproducing complex structures and details when converting point cloud data into linear and planar entities. Although the study has proposed improved modeling methods such as dual attention neural networks, the model's accuracy and detail restoration ability still need to be enhanced when handling complex terrain and large-scale data.
3) Modeling challenges in complex environments: In highly complex environments such as forests or urban areas, existing LiDAR technologies still have shortcomings in terms of data processing and modeling efficiency. This requires further optimization of point cloud processing algorithms and modeling strategies to adapt to the data characteristics in different environments.

This study aims to address gaps in current technology by incorporating advanced point cloud classification techniques, such as CNN-based methods, and improved 3D modeling methods. Specifically, it explores how to enhance the classification accuracy of point cloud data, optimize the process of converting point clouds into 3D models, and enhance modeling accuracy and efficiency in complicated environments. Through these innovative approaches, the study seeks to provide more reliable data support for the design, planning, operation management, and risk assessment of transmission lines, further advancing the modernization and intelligence of

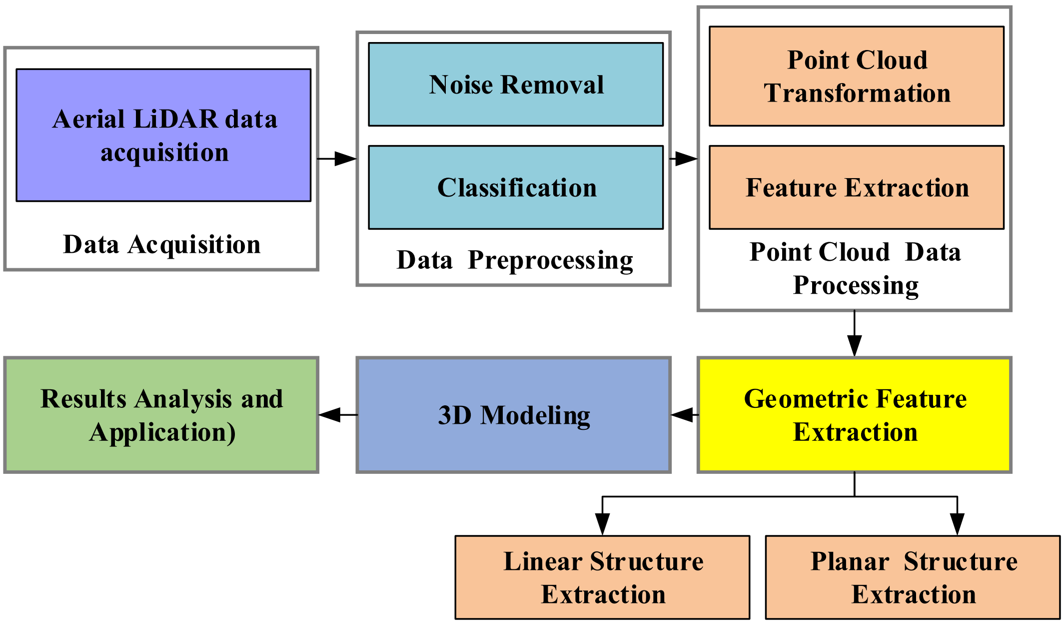

Fig. 1. The research framework.

the power industry.

3. Research methodology

To achieve the above research objectives, this study's overall workflow covers the key steps from data acquisition to 3D model construction, including data preprocessing, feature extraction, 3D modeling, etc., as displayed in Fig. 1. Then, the details contained in each workflow are shown in sub-sections to better demonstrate the research process.

3.1. Airborne LiDAR data acquisition

This study employs a high-precision airborne LiDAR system to conduct aerial scans of the target area, aiming to acquire 3D point cloud data of the 500 kV transmission lines and their surrounding environment [33–35]. Point cloud data is a dataset composed of a series of points in 3D space, each containing its positional coordinates. LiDAR is a remote sensing technology that utilizes lasers to measure the distance between objects and the laser emission source.

Point cloud data can precisely describe the shape, dimensions, and other characteristics of scanned objects, making it a crucial foundational data type for areas such as 3D modeling, mapping, and visual reconstruction. In airborne LiDAR systems, laser scanners mounted on aircraft or unmanned aerial vehicles (UAVs) emit laser pulses and receive reflected laser signals. The positional coordinates of the ground or object surface are calculated based on the laser's round-trip time, generating large-scale, high-precision 3D point cloud data. These data can encompass terrain and topography information and capture details such as buildings, vegetation, and transmission lines. They hold significant value for accurately reconstructing 3D models and conducting further analysis.

During the data collection, parameters such as flight altitude, speed, and laser scanning frequency are tightly controlled to ensure high-density and high-precision data. Flight altitude directly impacts the coverage area of laser pulses and the density of the point cloud. Lower flight altitudes yield higher-density point cloud data but reduce coverage range, increasing flight costs. Flight speed affects data acquisition efficiency and point cloud density. A slower speed can result in denser point cloud data, but it can also prolong operation time and cost. Laser scanning frequency, or the emission frequency of laser pulses, determines the number of laser pulses emitted per unit time, thus influencing point cloud density and measurement accuracy. Higher scanning frequencies result in denser point cloud data. The data acquisition process is presented in Fig. 2.

In Fig. 2, the aircraft/UAV path represents the flight path of an aircraft or UAV equipped with LiDAR devices flying along a predetermined route in the air. The flight path is planned based on the geographical area to be covered and specific requirements for data collection. The airborne LiDAR system is the core equipment mounted on the aircraft, responsible for emitting laser pulses and receiving pulses reflected from the ground or object surfaces. The LiDAR system comprises a laser emitter, a receiver, and a computational unit for data processing. Laser pulses are beams emitted from the airborne LiDAR system, capable of penetrating obstacles such as vegetation to reach the ground or object surfaces. The characteristics of laser pulses, such as wavelength and power, may vary according to specific application requirements.

The laser pulse reaches and illuminates the actual ground or other objects (e.g., transmission towers, trees). These surfaces reflect laser pulses, which are captured by the LiDAR system's receiver. Reflection denotes the event where the laser pulse strikes the ground or an object, and the reflected signal is acquired by the LiDAR system's receiving part. The distance between the laser pulse and the object can be calculated by analyzing these reflection signals. This process is repeated continuously during the flight, allowing the airborne LiDAR system to emit and receive thousands of laser pulses, generating a detailed 3D point cloud map covering a vast area. Each point in the point cloud data represents a specific location on the ground or object surface. Through these data points, an accurate reconstruction of the terrain, building structures, and other geographical features in three dimensions can be achieved.

The calculation of the positional coordinates for each point in the point cloud data can be written as equation (1):

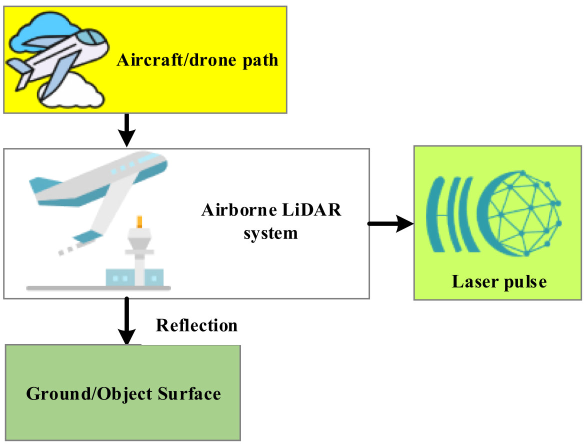

Fig. 2. Schematic diagram of data acquisition.

$$D = \frac{c \times \Delta t}{2} \tag{1}$$

D represents the distance from the laser pulse emission to reception (i.e., the distance from the object to the LiDAR device); c refers to the speed of light (approximately 3.00 × 10ˆ8 m per second); Δt denotes the time difference experienced by the laser pulse from emission to reflection back to the receiver. By measuring a large number of laser pulse reflection events, the airborne LiDAR system can rapidly obtain detailed 3D spatial information, encompassing transmission towers, power lines, terrain, etc. This process generates a high-density, high-precision point cloud dataset, serving as the foundation for subsequent analysis and model reconstruction.

3.2. Point cloud data processing workflow

The processing of point cloud data is a crucial step in transforming raw data collected by airborne LiDAR into accurate and high-quality 3D models. This section provides a detailed explanation of the three main stages in point cloud data processing: noise point removal, extraction of terrain information, and geographic coordinate correction and fusion. The specific workflow is drawn in Fig. 3:

Fig. 3 indicates that following the data collection, the experiment further processed the data to enhance its quality. The raw point cloud data collected by airborne LiDAR contains noise points from various sources, caused by atmospheric disturbances, equipment errors, or non-target reflections (such as birds or aircraft). To ensure the accuracy of subsequent processing, it is essential to preprocess the data and remove these noise points. This study utilizes the Statistical Outlier Removal (SOR) algorithm, which effectively identifies and eliminates outliers in the data. The basic principle of this algorithm is expressed in equation (2):

$$p_d = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{2}$$

p_d represents the standard deviation of the point-to-nearest-neighbor distance; N means the number of neighboring points for a given point; x_i refers to the coordinates of the neighboring points; $\overline{x}$ is the average of all neighboring point coordinates. By setting a threshold, points with a standard deviation greater than this threshold can be identified as noise and removed. Through this step, the experiment significantly improved the point cloud data's quality and usability.

After noise removal, the study proceeds to the extraction of terrain information from the cleaned point cloud data. Advanced machine learning (ML) and deep learning (DL) technologies, particularly CNN, are employed for the analysis and classification of point cloud data. The primary goal of this phase is to classify the point cloud data according to representative physical entities (such as transmission towers, power lines, trees, buildings, etc.), offering a solid information foundation for subsequent modeling and analysis. Before classification, the point cloud data undergoes a series of preprocessing steps, including removing isolated noise points, smoothing the data, and filling in missing areas. Preprocessing improves the quality of the point cloud data and ensures the accuracy of subsequent classification.

The point cloud data can be converted into a voxel grid or directly input into the CNN model in its raw form. A voxel grid divides the

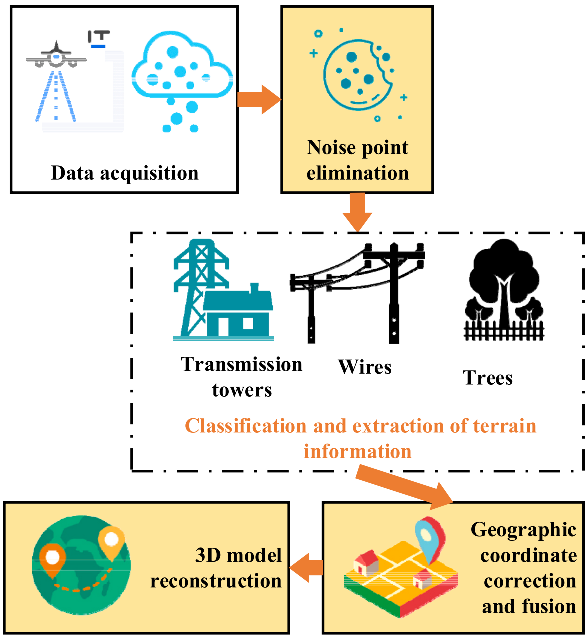

Fig. 3. Workflow of point cloud data processing.

point cloud data into regular 3D grids, with each voxel representing a spatial unit. This method transforms the point cloud data into a uniform grid structure, facilitating DL processing. Alternatively, using the raw point cloud data preserves the original details, suitable for applications requiring fine structural information.

Next, CNNs are used for point cloud classification. CNNs excel in handling image data by extracting local features through convolutional layers and reducing the computation and feature dimensions through pooling layers. In point cloud classification, CNNs can effectively recognize different land cover types by extracting local geometric features and spatial relationships from the point cloud data. The CNN model includes multiple convolutional layers, activation functions (such as ReLU), pooling layers, and fully connected (FC) layers. Convolutional layers extract local features of the point cloud, pooling layers reduce dimensionality and computational complexity, and FC layers map the extracted features to specific categories.

The CNN model is trained using a labeled point cloud dataset, which includes samples of different categories such as transmission towers, power lines, and trees. By training on these datasets, the model learns to distinguish between different land cover types. During training, cross-validation and performance evaluation metrics are employed to monitor the model's performance. The model parameters and structure are continuously optimized to improve classification accuracy. The trained CNN model is then applied to classify new point cloud data. The model assigns each point cloud point to a category, such as power lines, transmission towers, or trees. These classification results provide the foundational data for subsequent 3D modeling. The model's output is the category label for each point, which can be used to generate detailed terrain models and analysis reports. During the training process, the loss function adopts the Cross-Entropy Loss, as shown in equation (3):

$$L = -\sum_{c=1}^{M} y_{o,c} \log\left(p_{o,c}\right) \tag{3}$$

M stands for the number of categories; y means the true value of the label (0 or 1); p represents the predicted probability by the model; o and c refer to the index of the data point and category. This process relies not only on the point cloud's spatial distribution characteristics but also utilizes additional information such as its reflection intensity to enhance the classification accuracy. Accurate classification of features is fundamental to the subsequent reconstruction of the 3D model, directly influencing the model's accuracy and detailed representation.

To accurately map point cloud data to real-world geographic coordinates, precise geographic coordinate correction is necessary. This study achieves accurate geographic coordinate correction of point cloud data by combining it with data from a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU), which are simultaneously collected during the point cloud acquisition. The specific process is outlined in equation (4):

$$P_{corrected} = P_{raw} + \Delta P_{GPS} + \Delta P_{IMU} \tag{4}$$

$P_{corrected}$ represents the corrected point coordinates; P_{raw} means the coordinates of the original point cloud data; ΔP_{GPS} and ΔP_{IMU} refer to the coordinate correction values calculated based on GPS and IMU data, respectively. After the correction, using GIS technology, the corrected point cloud data is fused with other geographical data. This step not only enhances the 3D model's geographical accuracy but also provides more comprehensive background and environmental information for this model, such as terrain features, vegetation

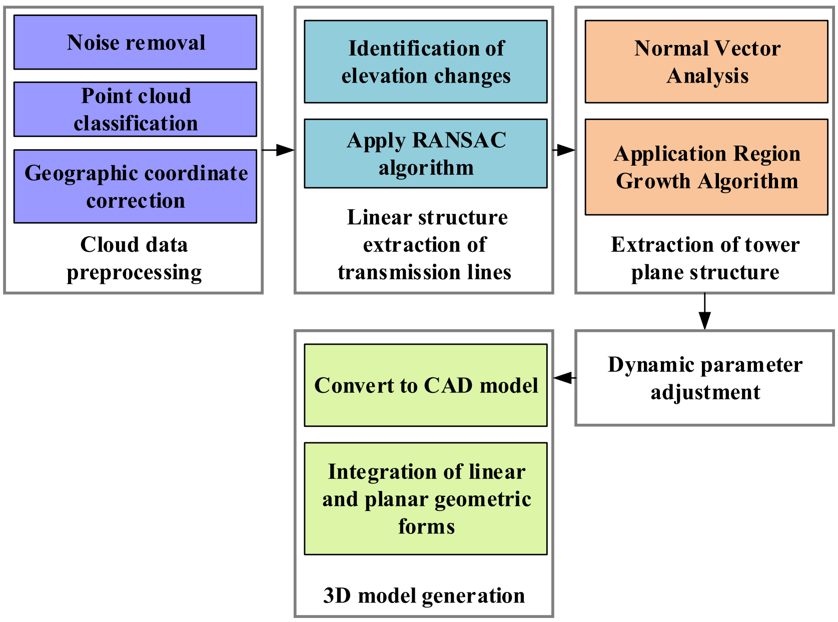

Fig. 4. The process of extracting linear and planar entities of transmission lines from ALS point clouds.

coverage, etc., making the final 3D model more realistic and reliable.

3.3. Application of CAD technology

After completing the preprocessing, noise removal, classification extraction, and geographical coordinate correction of point cloud data, the next step is to transform these accurate and rich point cloud data into practical 3D models. This transformation process relies mainly on CAD technology. The first step is the conversion from point clouds to vectors. This process's core objective is to integrate and transform scattered point cloud data into vector lines or surfaces with clear geometric significance. To achieve this goal, this process relies on the RANSAC algorithm to identify geometric patterns, edges, and shapes in the point cloud. The RANSAC algorithm is employed to estimate the parameters of a mathematical model from a set of observation data that may contain outliers. In this scenario, it is used to identify and extract linear structures, such as the edges of transmission lines and towers. In this way, the RANSAC algorithm lays the foundation for subsequent geometric modeling. The specific process is plotted in Fig. 4:

In Fig. 4, the RANSAC algorithm is applied to the linear structures of transmission lines. This algorithm iteratively selects a subset of sample points from the point cloud to fit a mathematical model. In the 3D modeling of transmission lines, RANSAC is used to identify linear structures, particularly in the presence of noise and outliers. Initially, a suitable linear model is defined based on the geometric characteristics of the transmission line, and elevation changes in the point cloud serve as preliminary cues for fitting. In each iteration, the algorithm randomly selects a set of sample points from the point cloud data and assumes that these points conform to the target linear structure. RANSAC then fits a linear equation based on the selected sample points, and evaluates its match with the remaining data points. Ultimately, it determines the optimal linear model by maximizing the number of inliers (i.e., points that fit the linear model).

To further enhance accuracy, a dynamic threshold adjustment mechanism is incorporated into the RANSAC process, allowing the algorithm to adapt to the density distribution of the point cloud. This is particularly important for handling linear structures with long spans of transmission lines, as point cloud density may vary significantly across different regions. Through this dynamic adjustment, RANSAC maintains high recognition accuracy on both sparse and dense datasets while effectively filtering out ground noise and other irrelevant background points.

For parts with planar structures, such as towers, a region-growing algorithm is used. This algorithm starts with an initial seed point and progressively expands the region by incorporating neighboring points until a certain similarity criterion is met. In this study, the normal vectors of the point cloud are first analyzed to estimate the normal direction of each point, and points with consistent normal directions are selected as initial seed points. The region-growing algorithm then continues to expand based on the consistency of the normal vectors, extracting the planar structure of the towers. To improve extraction robustness, a multi-scale analysis mechanism is introduced in the algorithm, which can detect the local and overall geometric features of the towers at different resolutions, ensuring accurate extraction even in noisy datasets.

Throughout the extraction process, parameters for RANSAC and the region-growing algorithm are dynamically adjusted based on the varying density and complexity of the point cloud data. For example, in high-density point clouds, the number of sample points for RANSAC is increased to ensure stability in fitting results; for planar extraction, the similarity criteria of the region-growing algorithm are relaxed to tolerate a certain degree of noise. This dynamic adjustment mechanism allows the algorithm to accommodate different types and distributions of point cloud data, thereby enhancing extraction accuracy and robustness. Ultimately, the combination of RANSAC and the region-growing algorithm successfully extracts both the linear structures of transmission lines and the planar geometric forms of towers. Meanwhile, it ensures stable and high-precision results, providing a reliable foundation for subsequent 3D modeling.

Once the transformation is complete, this study proceeds with the construction of 3D entities, as illustrated in Fig. 5:

In Fig. 5, the first step is data transformation. After completing the conversion from point cloud to vectors, the subsequent process

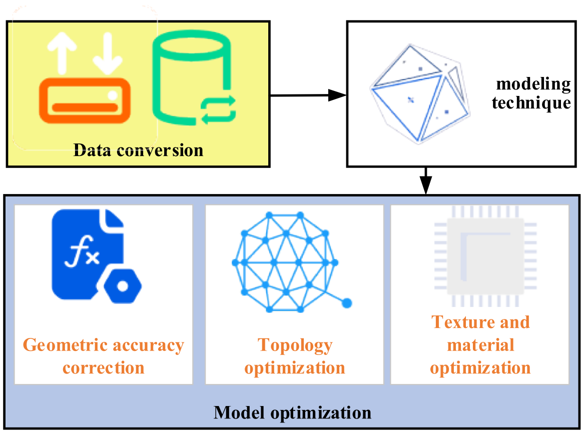

Fig. 5. Construction and optimization of 3D entities of transmission lines.

involves leveraging the powerful capabilities of CAD software to transform the vectorized lines and shapes into 3D entities. This process includes but is not limited to the precise simulation of the conductors, tower bases, and other key components of transmission lines. It also encompasses the interactions and manifestations of these structures in their natural environment. Advanced geometric modeling techniques such as Non-Uniform Rational B-Splines (NURBS) are then employed to construct complex surfaces, achieving precise reconstruction of transmission lines and their intricate terrain environments.

Following the 3D model's initial construction, optimization is carried out. Firstly, detailed geometric accuracy correction is performed on the preliminary 3D model to ensure perfect alignment with the dimensions and shapes of real-world objects. Secondly, the model's topology is optimized to ensure data consistency and accuracy while reducing unnecessary complexity to enhance processing efficiency. Finally, based on the characteristics of actual objects, textures, and materials are added or refined to make the model visually more realistic and vivid. This step not only enhances the visual appeal of the model but also increases its accuracy and credibility when simulating real scenarios.

3.4. Experimental design

The designated 500 kV transmission line and its surrounding environment are subjected to aerial scanning using the airborne LiDAR system to collect the required 3D point cloud data. Tools such as Point Data Abstraction Library (PDAL) are employed to perform noise removal and filtering on the collected raw point cloud data, improving data quality and usability. ML and DL algorithms are applied to classify the processed point cloud data, identifying different features such as transmission towers, conductors, and trees. Subsequently, geographical coordinate correction of the point cloud is carried out using data recorded by the GPS and IMU systems. The point cloud data is then fused with other geographical data to provide richer environmental information for the 3D model. Finally, CAD technology is utilized to transform the classified and extracted point cloud data into accurate 3D models, encompassing the construction of linear and planar entities for transmission lines, model optimization, and detail processing. The model validation and analysis section compares the reconstructed 3D model with the actual environment to assess its accuracy and practicality. Based on this evaluation, the study conducts state assessments, hazard analyses, and optimization recommendations for the transmission lines. The experimental environment and parameter settings are exhibited in Table 1.

4. Results and discussion

4.1. 3D model detection performance

Fig. 6 provides a detailed overview of three different data categories, namely conductor segments, tower bases, and terrain features, in terms of point cloud density, noise point removal ratio, number of classified features, minimum point spacing, and average point spacing:

In Fig. 6, the point cloud density is highest for the tower base segment (10,000 points/m^2), indicating the high precision requirement for modeling tower bases. Conversely, the point cloud density for terrain features is lower (2000 points/m^2), possibly due to the relatively gradual changes in terrain features that do not necessitate high-density point clouds to capture details. The noise point removal ratio varies among the three data categories, with terrain features having the highest removal ratio (20 %), possibly due to more interference from surface clutter in terrain features. The number of classified features reflects the model's complexity, with terrain features having the highest number of classifications (10 categories), illustrating the need to consider more types of features when processing terrain features. The data for minimum point spacing and average point spacing demonstrate the spatial resolution of the point cloud, with the tower base segment having the smallest minimum and average point spacing, demonstrating the high-resolution capture requirements for its details. The results of the geometric accuracy verification of the 3D model are suggested in Fig. 7:

Fig. 7 displays the actual values, measured points, calculated values, geometric errors, and compliance rates for three model components: the tower base center coordinates, conductor suspension point heights, and insulator string lengths. The geometric errors are relatively small (within 2.3 cm), indicating the high accuracy of the 3D model in geometric precision. Specifically, the geometric error for the insulator string length is only 1.5 cm, with a compliance rate of 100 %, demonstrating the model's high reliability. This high-precision geometric verification is crucial for ensuring the safe operation and maintenance of transmission lines. Fig. 8 illustrates the resolution of key components in the 3D model of the 500 kV transmission line:

In Fig. 8, the insulator string exhibits the highest minimum resolution (0.02m/pixel) and average resolution (0.03m/pixel), highlighting the meticulous attention to detail in the model, crucial for ensuring the safety of transmission lines. In contrast, the

Table 1
Experimental environment and parameter settings.

Parameter item	Illustration
Lab environment	High-performance computing workstation with multi-core processors, high-speed memory, and professional GPUs
Flight altitude	about 600 m
Laser scanning frequency	200 kHz
Flight speed	150 km per hour
Software tools	point cloud preprocessing (PDAL), GIS analysis, and CAD design (ArcGIS and AutoCAD)

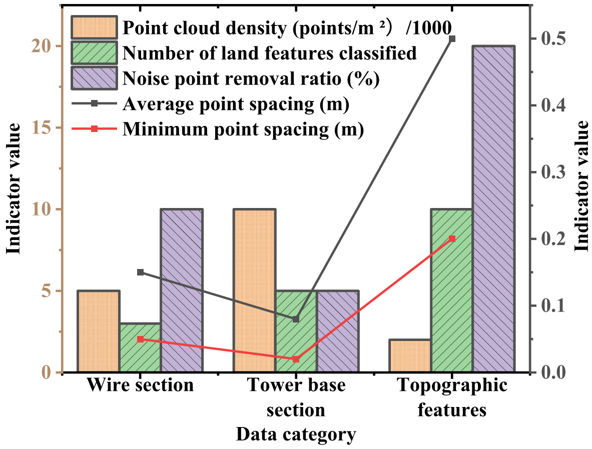

Fig. 6. Statistics of 3D point cloud data quality.

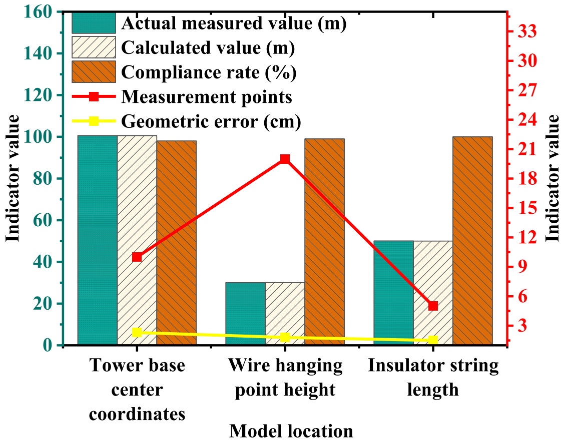

Fig. 7. Geometric accuracy verification of the 3D Model.

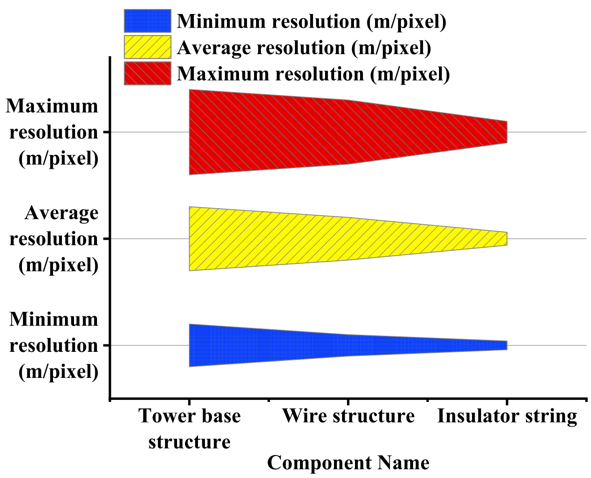

Fig. 8. Resolution of key components in the 3D Model of 500 kV transmission line.

resolution of the tower base structure and conductor structure, while lower, still meets engineering requirements, demonstrating the model's capability to optimize different components according to practical needs.

4.2. Comparison of effects of different modeling methods

The comparison of the effects of different modeling methods is depicted in Fig. 9:

In Fig. 9, the advantages of the airborne LiDAR model are very apparent, particularly in terms of detail richness (30 %) and decision-making efficiency (45 %), where it outperforms both the UAV oblique photography model and the ground-based radar model. Specifically, the airborne LiDAR model shows a 30 % improvement in detail richness, significantly higher than the other models. This enhancement is attributed to LiDAR technology's high-precision capturing capability of complex 3D structures, which allows for more detailed modeling of transmission lines. The ground-based radar model exhibits a 20 % improvement in detail richness, slightly lower than that of the LiDAR model. In terms of terrain adaptability, the airborne LiDAR model's improvement is 30 %, closely matching the 25 % improvement of the ground-based radar model. Although the radar model performs better in complex terrain adaptability, the LiDAR model demonstrates stronger adaptability across various terrain conditions. The airborne LiDAR model excels particularly in decision-making efficiency, with a 45 % increase, far surpassing the other models. This indicates that LiDAR technology not only achieves precise 3D modeling but also significantly enhances the efficiency of decision-making related to transmission lines. Additionally, the airborne LiDAR model presents a 35 % improvement in safety assessment accuracy, slightly above the 30 % improvement of the ground-based radar model. This further confirms the reliability and accuracy of LiDAR technology in safety assessments for transmission lines.

The comparison reveals that the airborne LiDAR model stands out in detail richness and decision-making efficiency, making it an ideal choice for 3D modeling of complex power transmission lines. In contrast, while the ground-based radar model excels in terrain adaptability, its overall performance is somewhat inferior, particularly in detail capture and decision-making efficiency compared to the LiDAR model. Therefore, the airborne LiDAR model is better suited for high-precision modeling and applications requiring rapid decision support.

4.3. Validation with typical engineering cases

Fig. 10 further compares the modeling time differences between using airborne LiDAR technology and a combination of aerial imagery with traditional survey methods in three typical engineering cases. Case A includes a transmission line project traversing complex terrain. Case B pertains to the upgrade and renovation of an urban or suburban transmission line project. Case C involves transmission line construction projects in special environments, such as wetlands, rivers, or other sensitive ecological areas. Without exception, airborne LiDAR technology saves approximately 33.33 % of the time, prominently improving modeling efficiency. This time-saving reduces project costs and accelerates project timelines, which is particularly crucial for urgent or time-sensitive transmission line construction and maintenance projects.

Figs. 11 and 12 respectively show the raw point cloud data of some study areas and the visualization images of the final 3D model:

Fig. 11 presents the raw point cloud data of the study area. This data includes high-density 3D point clouds collected through airborne LiDAR technology, covering the basic structures of transmission lines, towers, and surrounding terrain. These point cloud data reflect the study area's overall terrain and structural complexity. Due to the unprocessed raw data, some noise points and redundant data can be observed, especially in areas with complex terrain and high vegetation coverage. The raw point cloud data's density, distribution, and complexity provide a foundation for subsequent noise removal, classification, and 3D modeling.

Fig. 12 demonstrates the 3D model of the study area, which is generated based on airborne LiDAR technology. After data

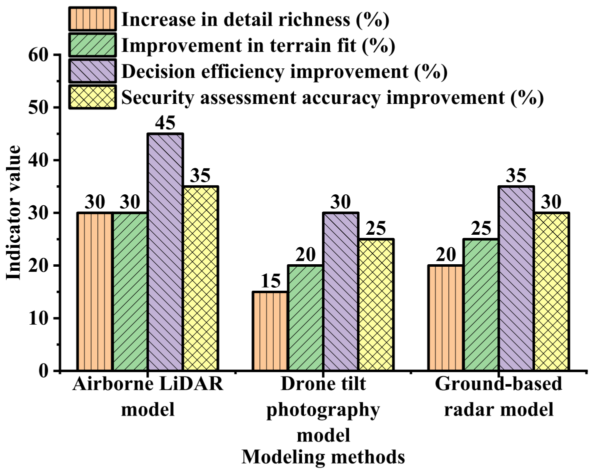

Fig. 9. Comparison of effects of different modeling methods.

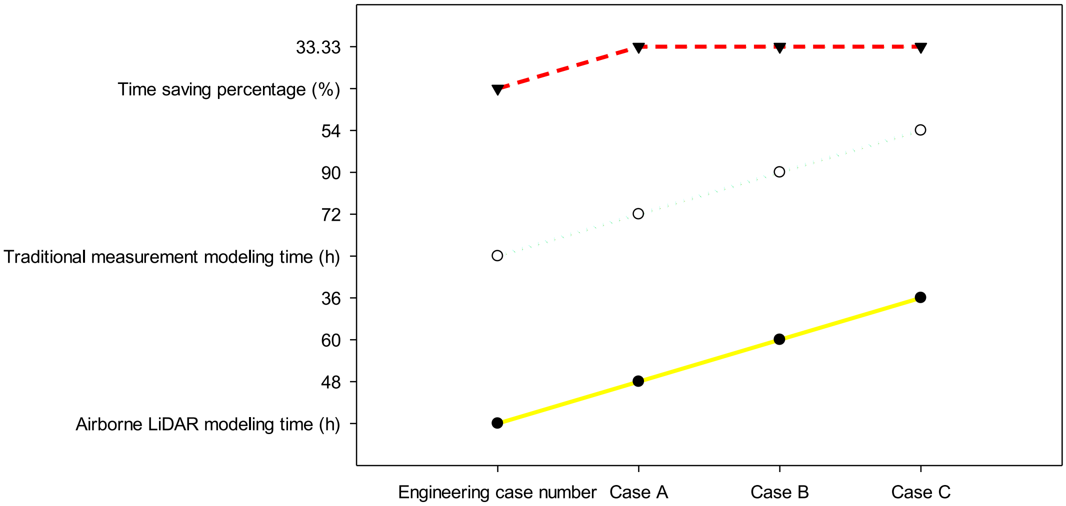

Fig. 10. Comparison of 3D Model construction time in typical engineering cases.

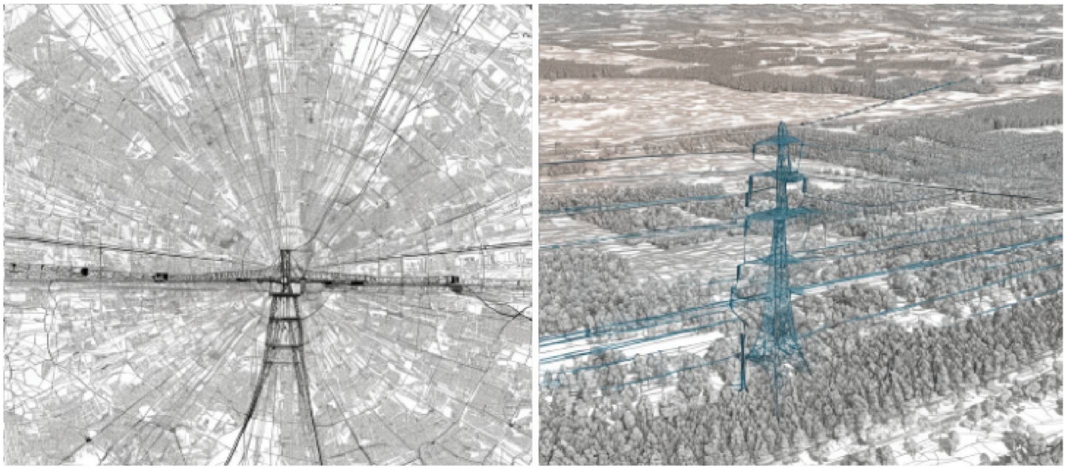

Fig. 11. Raw point cloud data of the study area.

Fig. 12. Visualizations of 3D models in the study area.

processing, it clearly presents the detailed structure of the transmission lines, towers, and surrounding environment. Compared with the raw point cloud data, the 3D model removes noise points and accurately reconstructs key components of transmission lines, such as towers and conductors. In addition, the model also shows the topographic features around the transmission line, providing a complete environmental context. This high-precision 3D model not only outperforms traditional methods in detail richness but also offers accurate data support for the planning and maintenance of power lines.

4.4. Discussion

This study highlights the remarkable advantages of using airborne LiDAR technology for 3D modeling of 500 kV power transmission lines, showcasing its impact on advancing 3D modeling technology and its practical importance in the power industry. Compared to traditional 2D or low-precision 3D models, LiDAR technology provides high-precision point cloud data that significantly improves model accuracy. For instance, Wang et al. (2019) [36] indicated that traditional measurement methods resulted in limited accuracy and detail, particularly in complex terrains and high-detail scenarios, where precision often failed to meet practical needs. In this study, LiDAR technology generates high-resolution, detailed 3D models, enhancing the accuracy of modeling transmission lines and their surrounding environments, thus improving planning, design, and operational efficiency.

In practical applications, LiDAR's efficient data acquisition and processing capabilities provide substantial support to the power industry. Compared to the findings of Wang et al. (2018) [37], LiDAR technology significantly reduces modeling time by approximately 33.33 %, accelerating project progress. This efficiency boost is crucial for time-sensitive projects, particularly in transmission line construction and maintenance, where it markedly increases work efficiency and reduces costs.

Furthermore, LiDAR technology demonstrates notable advantages in risk assessment and safety management. Compared to traditional methods, LiDAR offers more precise structural and environmental data, supporting more effective safety evaluations and risk management. Zhang et al. (2023) [38] noted that traditional methods might affect assessment results due to insufficient data accuracy, whereas LiDAR's high-precision models could more accurately identify potential risk points and safety hazards, ensuring the safe and stable operation of power systems.

In summary, the airborne LiDAR technology used in this study not only demonstrates superior data quality and modeling efficiency but also provides effective technical support in practical applications. The application of this technology has made vital contributions to the modernization and intelligent development of the power industry, especially in improving modeling accuracy, shortening project cycles, reducing costs, and enhancing safety, demonstrating its broad practical significance.

5. Conclusion

This study successfully achieves the accurate reconstruction of 3D models for 500 kV transmission lines and their complex terrain environments by integrating airborne LiDAR technology, point cloud data processing techniques, and CAD technology. Through steps such as noise point removal, terrain feature extraction, geographic coordinate correction and fusion, point cloud vectorization, and final 3D entity construction and optimization, the model's spatial resolution and geometric accuracy are significantly enhanced, demonstrating excellent performance in detail richness and terrain adaptability. The study not only showcases the efficiency of airborne LiDAR technology in complex terrains but also confirms its significant advantages in modeling time and decision-making efficiency. Compared to traditional surveying and aerial imaging techniques, airborne LiDAR technology saves approximately 33.33 % of modeling time, particularly in urgent or time-sensitive transmission line projects. However, despite the improvements in accuracy and usability achieved through point cloud data processing, higher computational costs and processing time requirements remain a challenge, especially when handling large-scale data. This study further validates airborne LiDAR technology's superiority in detail capture and geometric precision but also highlights the resource consumption issues associated with LiDAR technology in big data processing, as noted in similar literature. Future research focuses on developing more efficient point cloud processing algorithms, leveraging advanced ML models like CNNs to optimize point cloud classification and feature extraction. Additionally, upgrading hardware facilities is a key direction for addressing the feasibility of large-scale data processing to further reduce computational costs, shorten processing times, and improve the feasibility of handling large-scale data.

CRediT authorship contribution statement

Jianquan Chen: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Yi Zhuang:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Lihong Lai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization. **Jinhong Chen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization. **Hongde Ma:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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