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Information Extraction Method of DBH of Individual Trees in Artificial Forest Based on UAV Image

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Abstract. The information acquisition of tree height, individual tree crown and diameter at breast height is an important part of forest resources survey. In this study, the UAV images of artificial *Robinia pseudoacacia* forest in Zhangjiatan Town of Yan River Basin were obtained by DJI Phantom 4 UAV platform. The crown width and tree height were obtained by neural network clustering algorithm, visual interpretation and spatial measurement. The relative error between the extracted value and the measured value of individual tree crown width was 5. 98%, and the relative error of tree height was 7. 53%. We used 80% of the data to extract, crown, tree height and diameter at breast height to establish single regression models, exponential function models, logarithmic function models, power function models and binary regression models. Among those established DBH inversion models, the model with the highest fitting accuracy was $y = 4.255a + 0.044b^2 - 0.135a^2 - 2.111$, with a determination coefficient of 0.85, and the average relative error was 4.3% after being verified by using the remaining 20% of the data. The stand factors of the study area can be quickly obtained by using UAV images, and the DBH can be obtained with high precision, which can provide a reference for the realization of precision forestry.

Keywords: UAV, DBH, model fitting, neural network clustering, informatization of forestry

1 Introduction

Artificial forests are an important part of forest resources [1-2]. The results of the Ninth National Forest Resources Inventory In China show that the area of the artificial forest in China exceeds 1/3 of the total forest area [3]. Efficient and accurate monitoring of stand factors is an important prerequisite for efficient utilization of artificial forest resources and sustainable management [4]. The unique topography of the Loess Plateau results in the low distribution density of forest resources [5], which makes it possible to extract stand factors by image analysis in this area. During the forest resource survey, the tree height, crown width, and diameter at breast height (DBH) are the basic factors that determine the distribution of the forest level structure (tree position), which influence the growth status of stands, the relative distance between the trees and their interrelationship [6]. The DBH data acquisition is an important part of the forest resource inspection. The traditional forest resource survey obtains a single wooden DBH through the manual measuring method. When this manual method is applied to large-scale DBH survey, it will show the disadvantage of laborious, time consuming, expensive, and data lags.

In recent years, low altitude remote sensing technology has provided new opportunities and challenges for for-

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est parameter information acquisition [7-8]. Among them, UAV remote sensing technology can effectively make up for the shortcomings of the original methods when obtaining forest parameters [9-11]. Zhang et al. [12] used the UAV data to extract the crown width of individual trees through the plot canopy height model (CHM). Then they fitted the crown width and crown area of individual trees in different density levels to estimate the DBH of individual trees. However, their work only considers the influence factors of crown width, and the model determination coefficient is low. Jia et al. [13] used UAV images to generate digital surface models and digital orthophoto images, obtained crown area values and crown amplitudes. Then they extracted tree height through point cloud data, and then obtained the best DBH inversion model of Ginkgo biloba. Their research area is located on the university campus, which is not applicable to the actual forest resource inventory. Studies in other fields show that the neural network clustering algorithm can realize the information extraction of crown width on the premise of ensuring accuracy [14]. Therefore, due to the differences in research areas and forest resource characteristics, it is necessary to improve the existing methods and continue to develop more universal information methods to meet the needs of forestry information monitoring of different tree species in different regions [15].

In this paper, the data source is the field measured data and UAV images. Based on the neural network clustering algorithm and the visual interpretation, tree height and crown diameter of *R.pseudoacacia* plantation which located in the Yan River of the Loess Plateau were extracted. Then the inversion model of *R.pseudoacacia* DBH was established. The R^2 of the best model is 0.85, which illustrated this model can be used to estimate DBH of *R.pseudoacacia* plantation.

This paper has five chapters: the first chapter is a brief introduction, the basic introduction to the research motive and the main contributions in this paper; the second chapter introduces the data sources; the third chapter is the information methods of this research, including the extraction methods of the crown width, the tree height and the DBH; the fourth chapter is the results and analysis; the last chapter is the conclusion and future prospect.

The main contributions and innovation of this work are as follows.

- In this paper, the extraction of DBH is realized through the information method, which saves a lot of manpower and material resources.
- This paper introduces the neural network clustering algorithm into the extraction process of DBH, which reduces the workload and ensures the extraction accuracy.
- This method can provide reference for UAV forest resource inventory, and solve the problems existing in the current acquisition of DBH data.

2 Data Acquisition

2.1 The Study Area

The study area is located in the Zhangjiatan Town, Yan'an City, Shaanxi Province. Zhangjiatan Town belongs to the Yan River Basin, Yan River out of Xiatongdi Village flows through 7 villages, which flows 43.7 km long in Zhangjiatan Town. The study area belongs to warm temperate arid continental monsoon climate with an annual average temperature of 10.4 °C. There is a large temperature difference between day and night. The annual average precipitation is 564mm, mainly concentrated in July, August and September. Lush vegetation is one of the reasons why we chose this area as the study area. The study area has four distinct seasons in spring, summer, autumn and winter, with obvious cold, warm, dry and wet. Artificial *R.pseudoacacia* forest is mainly planted within the area, and three sample plots were selected from the sunny slope of the forest area in the study area. The UAV images were obtained as shown in Fig. 1 (the location of the sample plot has been marked in the map). Before the field survey, the three sample plots were numbered, and the relevant data of *R.pseudoacacia* in the sample plots were recorded in detail.

2.2 Data Sources

Measured Data. The height of individual tree of *R.pseudoacacia* in the study area was measured by traditional level instrument. The crown width of *R.pseudoacacia* was measured with a tape measure. The distance of the vertical projection of the tree on the ground is recorded as the East-west crown width, and the north-south projection was the North-south crown width. The DBH of individual tree of *R.pseudoacacia* was measured by DBH ruler at 1.3 meters above the ground, and the data of DBH of *R.pseudoacacia* was read directly on the DBH ruler.

UAV Data Acquisition. The UAV field survey was conducted on August 29, 2021, when the vegetation grew luxuriantly, the weather was clear and windless. The natural conditions had little influence on the flight of UAV. The data acquisition platform is DJI Phantom 4 RTK, as shown in Fig. 2. This UAV mainly for low-altitude photogrammetric applications, equipped with centimeter navigation and positioning system and high-performance imaging system. The maximum rising speed is 6m/s, the maximum falling speed is 3m/s, and the maximum horizontal flight speed is up to 58km/h. Under suitable temperature circumstances, the flight altitude is up to 182m. In additional, the maximum single flight time is about half an hour.

The flight altitude of this experiment was 50m. In order to meet the requirements of aerial photogrammetry, the camera orientation was parallel to the main route. At the same time, the longitudinal overlap and lateral overlap of the flight route was set to 85% and 85% respectively before the flight. A total of 451 aerial images were taken during the flight, covering an area of about 80 hectares.

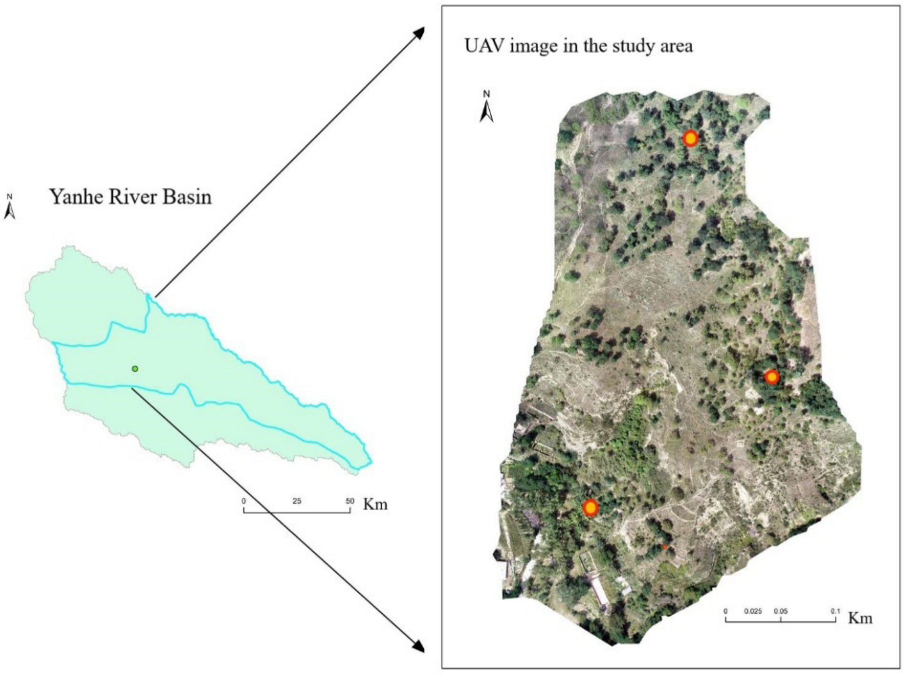


Fig. 1. Location of the study area and sample plots

Fig. 2. DJI Phantom 4RTK 4-rotor UAV

3 Methods

With the support of the UAV remote sensing system and its camera, the UAV image of the study area can be obtained by setting the flight route and flying in the target area [16]. This work used the remote sensing image processing software to model the image. The information and automation of stand factor extraction (including East-west crown width, North-south crown width, crown width and tree height) can be realized by some measurement software [17].

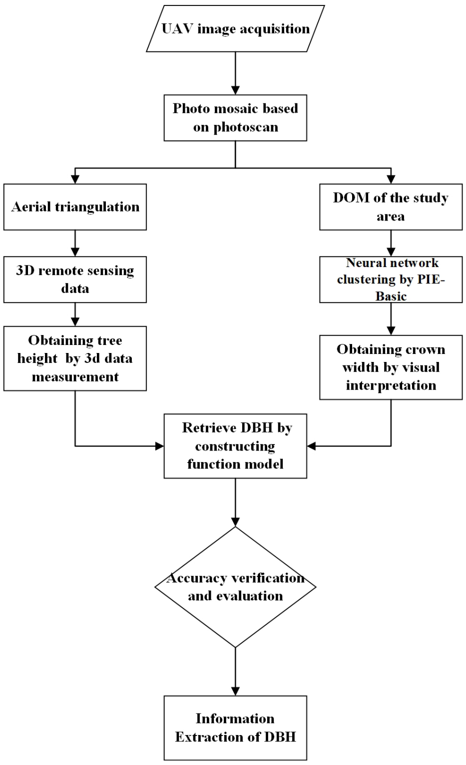
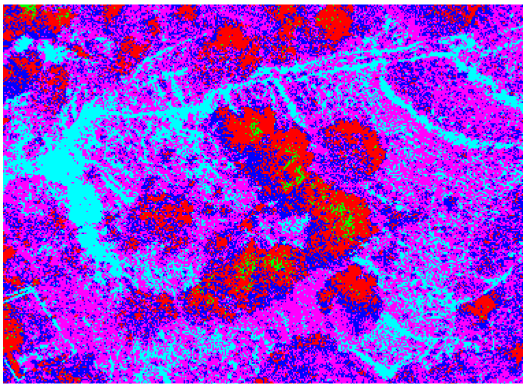


Fig. 3. Extraction process of individual tree DBH of artificial R. pseudoacacia forest

Agisoft Photoscan Pro software was used for the image preprocessing and stitching. PIE-Basic and 3D modeling software Context Capture was used for image processing, because we need obtain the required 3D spatial data model and neural network clustering results. The crown width and tree height of *R.pseudoacacia* were obtained by using three-dimensional measurement tools and visual interpretation method. After obtaining the crown width and tree height in line with the error range of forest resources survey, 80% of the image extraction sample data were used to establish the DBH inversion function model. Then the remaining measured sample data were used for error analysis to verify the accuracy of the DBH inversion model. The specific process is shown in Fig. 3. The method in this study is very suitable for regions with the characteristics of large plant row spacing and less shading such as Yan River Basin [18].

3.1 Crown width Extraction

As the characteristics of low canopy density of artificial forest in northern Shaanxi, the method of visual interpretation was used to extract crown width [19]. In this experiment, the neural network clustering function of PIE-Basic software was used for classification. Clustering algorithm is a widely used unsupervised classification method, and its principle is to classify objects only according to the spectral characteristics of ground objects without adding any prior knowledge [20-21]. That is, based on the changes of different image features and the difference between the magnitude of eigenvalue, images are divided into different types of small images [22]. In the neural network algorithm structure, the transfer of knowledge and information is realized by interconnection of neurons [23]. The non-parametric method is used in the classification, and there is no need to make assumption or estimation of the probability distribution function of the target object [24]. The interactive propagation network has good adaptability and complex mapping ability, why it is suitable for this experiment. To ensure the classification accuracy, the neural network classification number was set to 5 categories. In additional, the classification window size was set to 1: 1, and the number of iterations was determined to be 10000. The automatic classification result is shown in Fig. 4(a).



(a) Neural network clustering classification results

(b) Original UAV image

Fig. 4. Comparison of neural network clustering classification results with the original UAV image

Based on the results of neural network clustering classification, spatial measurement tools were used for visual interpretation. Then calculated the east-west and north-south canopy data of trees in the study area, and the average crown width was calculated as formula (1):

$$W_c = \frac{W_{c1} + W_{c2}}{2}. \quad \textbf{(1)}$$

where, W_c is the average crown width, W_{c1} is the East-West crown width, and W_{c2} is the North-south crown width.

3.2 Tree Height Extraction

Context Capture software was used to generate 3D spatial model from the preprocessed UAV original image. The key step of individual tree height data extraction is the recognition of crown vertices. Acute 3D Viewer software can accurately measure the position, distance, area and volume of 3D spatial model [25]. In this study, the method of visual interpretation was used to identify the crown vertices. Based on the 3D spatial data model and crown vertex data obtained by Acute 3D Viewer software, the distance between the top of the tree and the ground is the individual tree height (H).

3.3 DBH Extraction

Before the construction of DBH inversion model, the correlation between extracted crown width (W_c), extracted tree height (H) and measured DBH (D_{BH}) was analyzed. Because the outlier produced in the actual measurement process will affect the results of correlation analysis, SPSS software was used to deal with the outlier. After the pre-process, Spearman correlation analysis was conducted. Then constructed the extraction tree height-DBH model (H-D_{BH}), the extraction crown width-DBH model ($W_c - D_{BH}$) and the extraction tree height & extraction crown width-DBH model ($H \& W_c - D_{BH}$). A total of 75 groups of extracted crown width, tree height and measured DBH data were obtained in the experiment, which were randomly divided into 2 groups at 4:1. 60 groups of UAV extraction data and measured DBH data were used to establish DBH inversion models, while 15 groups of measured DBH data were used to verify the accuracy of the models. The commonly used DBH inversion models including primary polynomial, power function, logarithmic function, exponential function and quadratic polynomial were selected to establish the inversion model of individual tree DBH.

4 Results and Analysis

4.1 Extraction Accuracy Analysis

When obtaining the field data, only the East-west crown width (W_{c1}) and North-south crown width (W_{c2}) of the tree were obtained, but not the actual crown width (W_c). In order to ensure the rationality of the accuracy evaluation, the comparison between the measured and extracted values of East-west crown width and North-south crown width was added in the evaluation process.

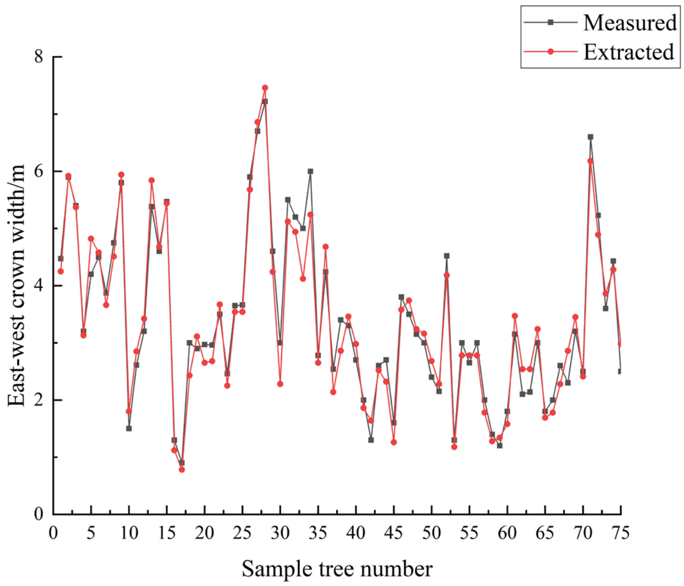
In this study, the relative error was used to analyze the accuracy, and the expression of relative error is shown in formula (2) and formula (3):

$$\varepsilon = x - a \,, \tag{2}$$

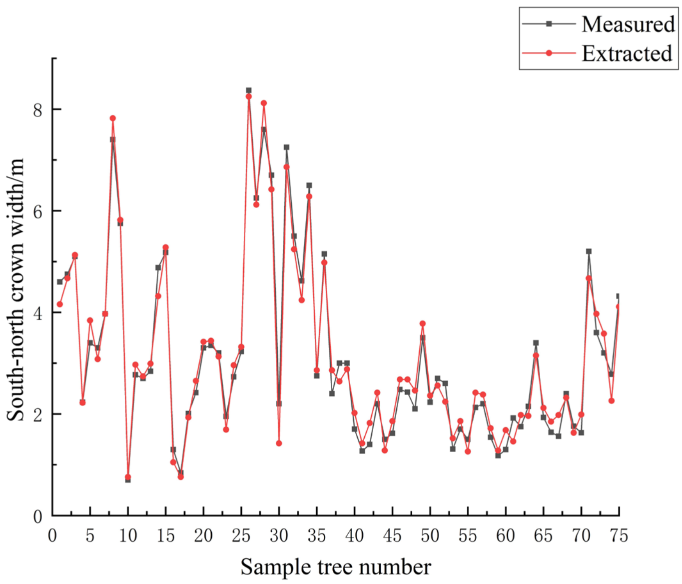
$$\delta = \left(\frac{\varepsilon}{a}\right) \times 100\% \,. \tag{3}$$

where, x is the inversion (extraction) value, a is the measured value, and δ is the relative error rate.

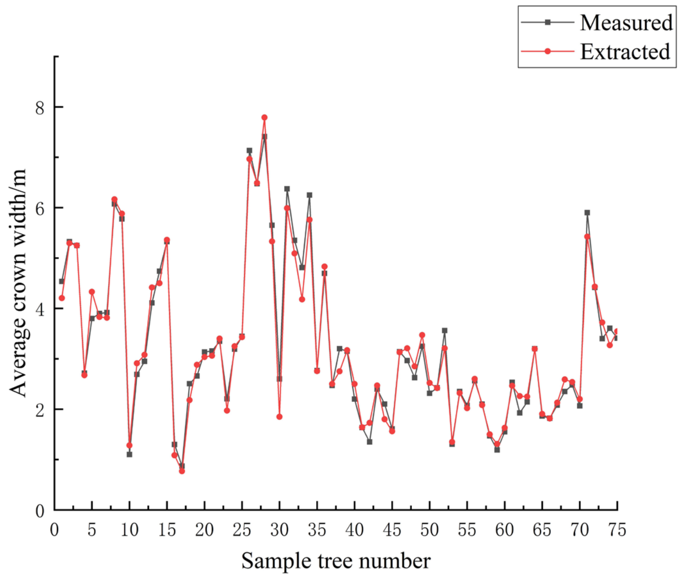
The minimum value of extracted East-west crown is 0.78m, the maximum is 7.46m, and the average is 3.37m; the minimum value of measured East-west crown is 0.9m, the maximum is 7.22m, and the average is 3.42m. The statistical histogram of East-west crown extraction and measured values is shown in Fig. 5(a), and the average relative error is 9.04%. The minimum value of extracted North-south crown width is 0.76m, the maximum value is 8.25m, and the average value is 3.15m; the measured North-south crown width minimum value is 0.7m, the maximum value is 8.37m, and the average value is 3.13m. The statistical histogram of North-south crown width extraction and measured values is shown in Fig. 5(b), and the average relative error is 9.83%. The maximum values of the extracted crown width and the measured data are 7.79m and 7.41m respectively, the minimum values are 0.77m and 0.87m respectively, and the average relative error is 5.98%. The statistical histogram is shown in Fig. 5(c). The error is within a reasonable range, and the extraction result is good. The error is shown in Fig. 6. Compared with the artificial vectorization measurement method used by Wang Yue et al. [26] to obtain crown width data, the method used in this study reduces the time of vectorization but improves the accuracy of crown width extraction.



(a) Comparison and distribution of East–west crown width



(b) Comparison and distribution of South-north crown width



(c) Comparison and distribution of Average crown width

Fig. 5. Comparison and distribution of crown width extracted by UAV and measured manually

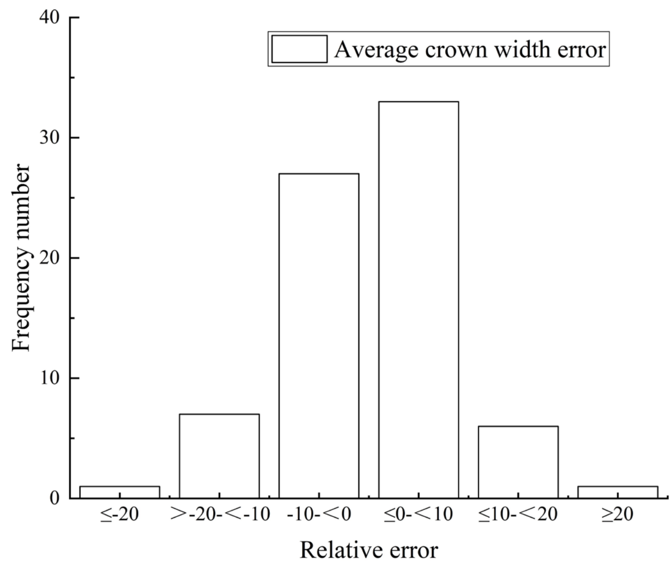


Fig. 6. Average crown width relative error frequency number

The statistical chart of the extracted tree height and the measured tree height is shown in Fig. 7. The average relative error of extracting tree height is 7.53%. Within the prescribed range of error value of tree height factor of 10% in the class B investigation standard stipulated by *The state forestry administration of the People's Republic of China*. Due to the strong subjectivity of visual interpretation, the accuracy will change with subjective factors such as the work experience of internal staff. After statistical analysis, the maximum relative error of tree height extraction is 1.65 and the minimum is 0.06, which shows that the extraction result is good and the error is shown in Fig. 8.

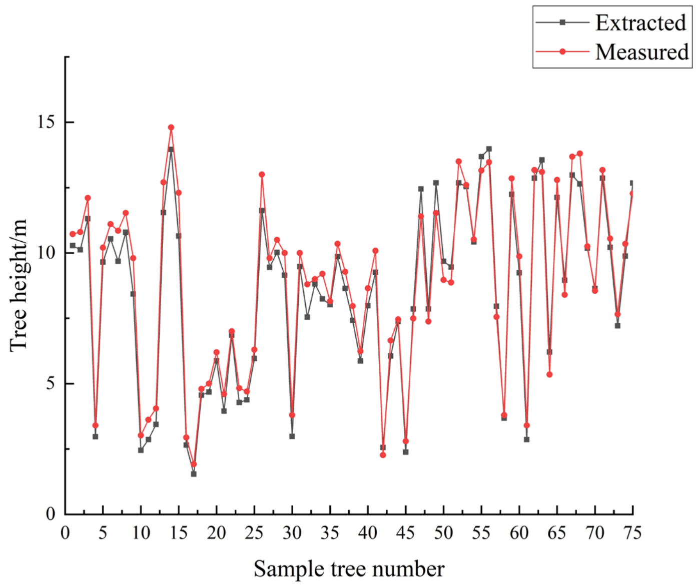


Fig. 7. Comparison and distribution of tree height extracted by UAV and measured manually

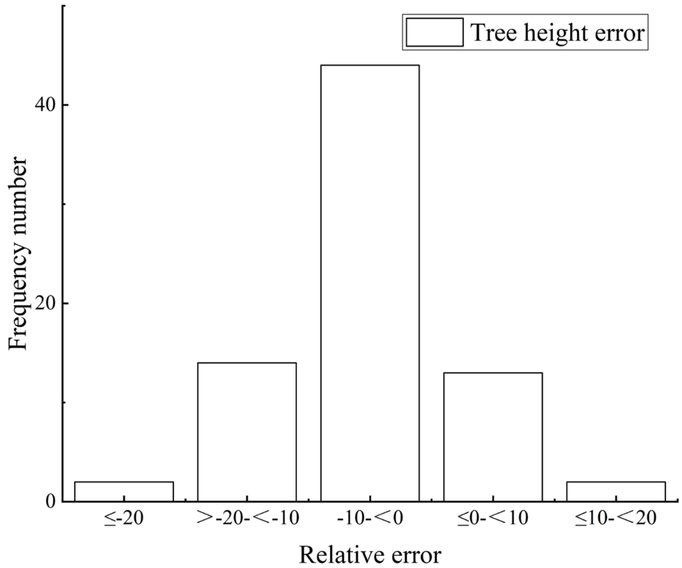


Fig. 8. Tree height relative error frequency number

To sum up, the application of UAV remote sensing technology in forestry can effectively reduce the working time of field work and the difficulty of obtaining stand factors, and reduce the cost of field work.

After statistical analysis with the measured data, the average relative error are 5.98% and 7.93% respectively. The overall technical process of the method used in this study is not complicated, which can provide some reference for the increasingly automated forestry investigation in northern Shaanxi and have the potential conditions for large-scale popularization.

4.2 Correlation between Extracted Crown Width, Tree Height and Measured DBH

Used SPSS26.0 software for Spearman correlation analysis, the data were exported to get the correlation analysis results as shown in Table 1. According to the mathematical principle of correlation analysis, when the repeated value in the analyzed data is 0 and the two variables conform to complete monotone correlation, the corresponding Spearman correlation coefficient is 1 or -1 [27]. The correlation coefficients of extracted crown width, extracted tree height and measured DBH are 0.689 and 0.820 respectively, and the significance test values of double tails are all below 0.01 (Table 1). It shows that there is a significant positive correlation between extracted crown width, extracted tree height and measured DBH, thus the extracted crown width and tree height can be used to construct the DBH inversion model.

4.3 The Fitting Models of DBH

The fitting effect of the model was evaluated by the determination coefficient (R^2), and it was considered that the higher the determination coefficient, the better the fitting effect. The expression of the determination coefficient is shown in Formula (4):

$$R^2 = \frac{\sum (y-\hat{y})^2}{\sum (y-\overline{y})^2} . \tag{4}$$

where, y represents the dependent variable, $\overline{y}$ represents the average value of the dependent variable, and $\hat{y}$ represents the inversion value of the dependent variable.

The function expression and determination coefficient of the mathematical function fitting model were shown in Table 2:

4.4 Accuracy of the DBH Model

As 80% of the measured crown data was used to establish the DBH model, another 20% remaining data was used to evaluate the accuracy of the DBH models. Compared with the actual measured DBH value, minimum and average relative error were obtained as shown in Table 3. In all the models fitted, the maximum value of the average relative error is 32.4% and the minimum value is 4.3% (Table 3). The maximum relative error of univariate model is generally large, and the average relative error is more than 18%. The relative error of DBH inversion model with extracted tree height as independent variable is significantly higher than that of DBH inversion model with extracted crown width as independent variable. This is consistent with the larger correlation coefficient between DBH and extracted crown width in Spearman correlation analysis. The maximum relative error of the unary quadratic model with extracted tree height as independent variable is 91.4%, indicating that the fitting effect of the model is very poor and cannot be applied. With the increase of independent variables, the error of DBH inversion model becomes smaller. Among them, the relative error of the binary model of $H\&W_c - D_{BH}$ is the smallest, and the average relative error of the three binary quadratic models containing extracted crown width data are all less than 5%. It is consistent with the requirement that the DBH error rate is less than 5% in the class A investigation standard stipulated by *The state forestry administration of the People's Republic of China*. This indicated this model has a certain applicability for the determination of individual tree factors of *R. pseudoacacia.* Compared with the DBH inversion model established by Zhang et al. [12], our work not only increases the selection of independent variables, but also made the inversion model significantly higher than their model. The method of constructing DBH model with individual independent variable has the disadvantage of low fitting degree of the model, but the binary model has a good fitting effect. On the whole, the relative error of binary model is obviously lower than that of univariate model, and the relative error of binary model is less than 10%, which can be used as an inversion model to determine the DBH of artificial *R.pseudoacacia*.

Table 1. Results of Spearman correlation analysis

Method	Forest stand factor	D_{BH}	H	W_c
	D_{BH}	1	0.689**	0.820**
Spearman	H		1	0.307**
	W_c			1

Note. **: extremely significant correlation (P < 0.01).

Table 2. Model fitting result

Inversion model	Mathematical expression	Coefficient of determination (R^2)
$W_c - D_{BH}$	$y = 3.682a + 1.309$	0.741
	$y = 1.137 + 11.464\ln a$	0.701
	$y = 5.28a - 0.203a^2 - 1.241$	0.749
	$y = -1.287a + 1.636a^2 - 0.15a^3 + 5.354$	0.766
	$y = 4.318a^{0.932}$	0.751
	$y = 4.678e^{0.279a}$	0.692
H-D_{BH}	$y = 1.331b + 2.924$	0.423
	$y = 8.556\ln b - 3.194$	0.443
	$y = 2.97b - 0.107b^2 - 2.131$	0.454
	$y = -0.166b + 0.337b^2 - 0.018b^3 + 3.802$	0.463
	$y = 2.468b^{0.801}$	0.629
	$y = 4.555e^{0.120b}$	0.553
$H \& W_c - D_{BH}$	$y = 3.053a + 0.721b - 2.338$	0.844
	$y = 3.183a + 0.045b^2 - 0.442$	0.847
	$y = 4.255a + 0.044b^2 - 0.135a^2 - 2.111$	0.850
	$y = 4.275a + 0.046b^2 - 0.137a^2 - 0.029b - 2.053$	0.850
	$y = 0.817b - 0.355a^2 + 2.181$	0.807
	$y = 0.354a^2 + 0.825b - 0.001b^2 + 2.157$	0.807

Note. a is the extraction crown width (m); b is the extraction tree height (m); y is the measured DBH (m).

Table 3. Model accuracy verification (%)

Inversion model	Mathematical expression	Maximum relative error	Minimum relative error	Average relative error
$W_c - D_{BH}$	$y = 3.682a + 1.309$	38.5	3.7	19.5
	$y = 1.137 + 11.464\ln a$	49.1	1.2	18
	$y = 5.28a - 0.203a^2 - 1.241$	38.4	4.8	19.8
	$y = -1.287a + 1.636a^2 - 0.15a^3 + 5.354$	42.1	0.3	20.8
	$y = 4.318a^{0.932}$	41.1	6.5	21.2
	$y = 4.678e^{0.279a}$	43.8	4.3	22.4
$H\text{-}D_{BH}$	$y = 1.331b + 2.924$	78.9	3.6	30.4
	$y = 8.556\ln b - 3.194$	87.5	0.7	29.3
	$y = 2.97b - 0.107b^2 - 2.131$	91.4	0.6	29.4
	$y = -0.166b + 0.337b^2 - 0.018b^3 + 3.802$	97.9	3.1	32.2
	$y = 2.468b^{0.,801}$	72.2	0.4	27.8
	$y = 4.555e^{0.120b}$	68.9	3.2	32.4
$H \& W_c - D_{BH}$	$y = 3.053a + 0.721b - 2.388$	15.8	0.17	5.3
	$y = 3.183a + 0.045b^2 - 0.442$	8.7	0.4	4.3
	$y = 4.255a + 0.044b^2 - 0.135a^2 - 2.111$	9.3	0.7	4.3
	$y = 4.275a + 0.046b^2 - 0.137a^2 - 0.029b - 2.053$	9.3	1.0	4.4
	$y = 0.817b + 0.355a^2 + 2.181$	28.6	0.1	8.1
	$y = 0.825b + 0.354a^2 - 0.001b^2 + 2.157$	28.1	0.5	8.0

Note. a is the extraction crown width (m); b is the extraction tree height (m); y is the measured DBH (m).

5 Conclusion and Prospect

The rapid development of near-surface remote sensing technology makes it possible to realize the informationization and automation of forest resources investigation and forest parameter information acquisition. In this study, two forest stand factors of individual tree crown width and tree height were obtained by using UAV images in Yan River Basin on the Loess Plateau. Then different inversion models of individual tree DBH were established by mathematical function fitting method. the inversion value of DBH of single tree was obtained. However, there had some limitations, including only considers the role of single tree crown width and tree height in the inversion of DBH model; the crowns of most trees will overlap in the non-artificial forest area, and there may be trees covering shrubs.

Work of Future: 1. The visible light near infrared sensor can make it possible to extract the crown information better, so the near infrared band image can be used to improve the crown vertex. 2. More stand factors can be added to the DBH inversion model in the form of independent variables to improve the accuracy of the model. 3. we can also try to establish more inversion models of stand factors that can not be extracted directly from images.

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