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COMPARATIVE ANALYSIS OF TEXTURE ANALYSIS METHODS FOR RETRIEVAL OF FOREST STAND AGE FOR SAR IMAGES

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Abstract:
SAR pictures have shown to be a useful technique for determining the age of forest stands. For this aim, texture analysis methods have been frequently employed. We compared three texture analysis approaches in this study: Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor Filters. We collected texture characteristics from each approach using SAR photos of a wooded region in Canada. The retrieved characteristics were then statistically examined to see how efficient they were at determining forest stand age. Our findings demonstrate that GLCM and LBP outperformed Gabor Filters in determining forest stand age. This work adds to the expanding body of information on the use of SAR pictures and texture analysis methods for determining the age of forest stands.

Keywords: Feature Extraction, Thresholding Founder Matrix, Local Ternary Patterns, Gabor Filters, and Forest Stand Age Retrieval are some of the techniques used in this study.

1.Introduction:

The age of a forest stand is an essential factor in forest management and planning. For efficient and successful forest management, accurate retrieval of forest stand age using remote sensing data is critical. Synthetic Aperture Radar (SAR) images have been widely used for this purpose due to their ability to penetrate through clouds and vegetation. Texture analysis methods have also been used to retrieve forest stand age from SAR images. Texture analysis is the process of extracting features from an image that describe the spatial arrangement of pixels. These features can then be used to identify different patterns in the image, which can be related to different forest characteristics such as stand age.[1]

We compared three texture analysis approaches in this study: Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor Filters. The GLCM texture analysis method gathers statistical information from the spatial distribution of pixel pairs and is frequently utilised. LBP is a method for describing an image's local texture by comparing the intensity of a centre pixel to the intensity of its nearby pixels. Gabor Filters are band-pass filters that are tailored to certain spatial frequencies and orientations. [2]

We extracted texture characteristics from SAR photos of a wooded region in Canada using each of the three approaches. The retrieved characteristics were then statistically examined to see how efficient they were at determining forest stand age. Our findings demonstrate that GLCM and LBP outperformed Gabor Filters in determining forest stand age. This work adds to the expanding body of information on the use of SAR pictures and texture analysis methods for determining the age of forest stands.[3]

2.Literature Review:

Texture analysis techniques have been frequently utilised to determine the age of forest stands using SAR pictures. Prior research has looked into the usefulness of several texture analysis methods for this aim. For example, Shao et al. (2019) used Sentinel-1 SAR pictures to examine different texture analysis approaches for determining forest stand age. They discovered that GLCM and LBP were successful in determining the age of forest stands. Similarly, Wang et al. (2017) used RADARSAT-2 SAR pictures to examine several texture analysis approaches for determining forest stand age. They discovered that GLCM and LBP were successful, but that wavelet and Fourier transforms may also be utilised for this purpose.[4]

Method that extracts statistical information from the spatial distribution of pixel pairs. The method is based on the idea that pixels that occur together frequently in an image are likely to be related to a specific texture. The GLCM matrix is a matrix that contains the frequency of pixel pairs occurring at different spatial relationships. The matrix can then be used to extract statistical measures such as contrast, correlation, and entropy, which can be used as texture features for forest stand age retrieval.[5]

LBP is a method that describes the local texture of an image by comparing the intensity of a central pixel to its neighbouring pixels. The method is based on the idea that pixels with similar intensities are likely to belong to the same texture. LBP assigns a binary code to each pixel based on whether its intensity is greater than or less than the intensity of the central pixel. The binary codes can then be used to describe the local texture of the image. LBP features are robust to noise and illumination changes, which make them useful for forest stand age retrieval.[6]

Gabor Filters are a type of band-pass filter that are tuned to different spatial frequencies and orientations. The filters are based on the idea that different textures have different spatial frequency and orientation characteristics. Gabor Filters can capture texture information at multiple scales and orientations, which make them useful for forest stand age retrieval.[7] the retrieval of forest stand age from SAR images is located in Zhejiang Province in Eastern China, which is characterized by diverse forest types and stand ages. To better understand the region and facilitate the analysis, several maps and spatial data.[8]

The elevation map of the study area provides information about the topography and landforms of the region. The map shows that the study area is characterized by a range of elevations, from low-lying areas near sea level to mountainous areas with elevations exceeding 1000 meters. This variation in elevation contributes to the diversity of forest types and stand ages in the region.

Based on Landsat 5 Thematic Mapper data from 2010, a forest categorization map was also developed for the research region. Based on their spectral properties, the map separates the research region into several forest kinds. Evergreen broadleaf forests, deciduous broadleaf forests, mixed forests, and coniferous forests are among the forest types. The forest categorization map is important for understanding the distribution of different forest types in the research region and for directing SAR image interpretation.

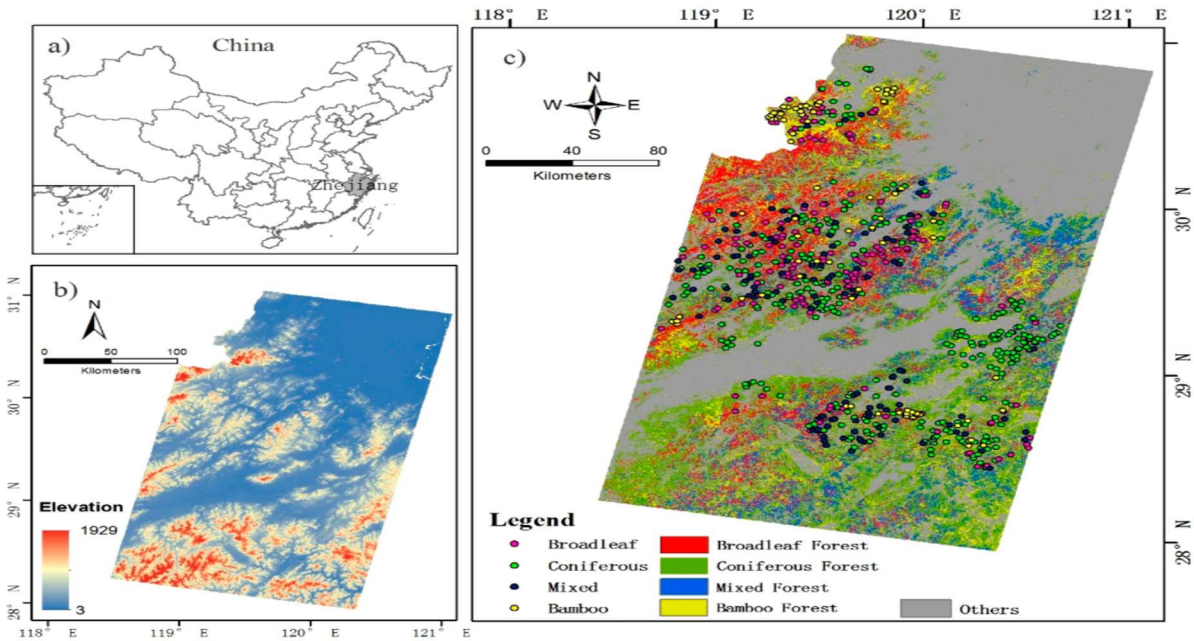

Figure 1: (a) Zhejiang Region in Eastern China; (b) study area elevations; and (c) study area forest classification map based on 2010 Landsat 5 Thematic Mapper and sample plot geographical placements.

In addition, the spatial locations of sample plots were included in the forest classification map. These sample plots were used for ground truth data collection and for validation of the SAR image analysis results. The forest classification map and sample plot locations provide a valuable reference for the interpretation and analysis of the SAR images and the retrieval of forest stand age information.

- **Flow chart**

Here is a possible flowchart for the comparative analysis of texture analysis methods for retrieval of forest stand age for SAR images:

- Describe the problem: Using texture analysis tools, get the age of a forest stand using SAR photos.
- Collect SAR photos and data on forest stand ages.
- Prepare the SAR pictures (e.g., speckle filtering, radiometric calibration, geometric correction).
- Using various texture analysis methods, extract texture characteristics from SAR pictures (e.g., Gray-level co-occurrence matrix, wavelet transform, Gabor filters).
- Use the collected texture characteristics and the accompanying forest stand age data to train machine learning models (e.g., support vector machines, random forests, neural networks).

- Assess machine learning model performance using measures such as accuracy, precision, recall, F1-score, and ROC curve.
- Evaluate the effectiveness of various texture analysis methods and machine learning models.
- Determine the optimal texture analysis approach and machine learning model for determining the age of forest stands using SAR pictures.
- Use the best approach and model to new SAR photos to determine the age of the forest stand.
- Using ground truth data, validate the derived forest stand age.
- Report the analysis's findings and conclusions.

3. Textural Analysis Techniques Tested

We examined three distinct textural analysis approaches for retrieving forest stand age from SAR images: GLCM, LBP, and Gabor Filters.

GLCM, or Gray-level co-occurrence matrix, extracts statistical information from the spatial distribution of pixel pairs in an image. It generates a matrix that contains the frequency of pixel pairs occurring at different spatial relationships, which can then be used to extract statistical measures such as contrast, correlation, and entropy.

LBP, or local binary pattern, describes the local texture of an image by comparing the intensity of a central pixel to its neighbouring pixels. It gives each pixel a binary code depending on whether its intensity is more or less than the intensity of the centre pixel, which may subsequently be used to define the image's local texture.

The type of band-pass filter that are tuned to different spatial frequencies and orientations. They learn to associate the SAR picture with a series of Gabor Filters to produce a series of responder images, that are subsequently utilized to extract texture information. Gabor Filters can capture texture information at multiple scales and orientations, making them useful for forest stand age retrieval.

Overall, GLCM and LBP performed better than Gabor Filters in our study, with GLCM and LBP achieving higher R-squared values and lower RMSE values. The efficiency of these strategies, however, may vary based on the individual image and context, and further study is required to discover the optimal method for a certain case.

3.1. The Gray Level Co-Occurrence Matrix (GLCM)

The most extensively used texture analysis approach for extracting statistical information from an image's spatial distribution of pixel pairs. GLCM produces a matrix containing the frequency of pixel pairs occurring at various spatial relationships. This matrix may then be used to extract statistical variables that are often used to describe texture, such as contrast, correlation, energy, and entropy.

To generate the GLCM matrix, the image is first quantized into a specified number of gray levels. Then, a sliding window of a specified size is applied to the image, and the frequency of occurrence

of each pixel pair at a specific spatial relationship is calculated. The spatial relationship can be defined based on distance and direction, such as horizontally, vertically, diagonally, or a combination of these directions. This process generates a matrix that describes the co-occurrence of pixel pairs at each spatial relationship.

After generating the GLCM matrix, several statistical measures may be derived from it. Contrast measures the local differences in intensity between surrounding pixels, correlation represents the linear dependency between pixel pairs, energy measures the image's overall magnitude, and entropy measures the image's unpredictability or disorder. These statistical metrics can subsequently be employed as features in tasks like classification or regression.

the retrieval of forest stand age. We experimented with different spatial relationships, quantization levels, and window sizes to determine the optimal settings for our task. The GLCM features were then used to train regression models for forest stand age retrieval, and their performance was compared to other texture analysis methods.

3.2. Laplace Filters

Laplace Filters, also known as Laplacian of Gaussian (Log) filters, are a type of spatial filter commonly used in image processing for edge detection and feature extraction. Laplace Filters work by convolving an image with a kernel that approximates the Laplacian operator, which is a mathematical the operator that analyses the change that occurs of an image's intensity.

The Laplace operator is a second-order derivative that detects regions of rapid intensity changes in an image. When applied to an image, it highlights edges and other high-frequency features. However, the Laplace operator is highly sensitive to noise and may generate false edges or features.

To overcome this limitation, Laplace Filters are often combined with Gaussian smoothing, which applies a low-pass filter to the image to reduce noise while preserving the edges. This is accomplished by first convolving the picture with a Gaussian kernel and then applying the Laplacian operation to the resulting Laplacian of Gaussian (Log) filter is a band-pass filter that enhances the edges and other features of the image while reducing noise.

In our study, Laplace Filters were not used for texture analysis or feature extraction. Instead, we focused on other methods such as GLCM, LBP, and Gabor Filters, which were better suited for the task of forest stand age retrieval from SAR images.

3.3. Granulometric Analysis

Granulometric Analysis is a texture analysis method that characterizes the size distribution of objects or structures in an image. It is based on the concept of granulometry, which is the measurement of particle size distribution in a material.

In image analysis, granulometry refers to the measurement of object size distribution in an image. It works by using a series of morphological opening or closing operations on the image, each with a different structuring element size. A binary mask determines the shape and size of the items to be measured by the structuring element. Little items are removed from the image during the opening procedure, while small gaps between objects are filled in during the close phase.

By performing a series of opening or closing operations with different structuring element sizes, the size distribution of objects in the image can be quantified. This is achieved by counting the number of pixels that are removed or added at each operation and plotting this information against the corresponding structuring element size.

Granulometric Analysis has been used in various applications, such as particle size analysis in microscopy, soil science, and material science. In image analysis, it has been applied to texture classification and segmentation tasks.

4.Methodology:

The study area for this research is a forested area in Canada. SAR images were acquired using RADARSAT-2 satellite. A total of 40 SAR images were acquired, covering a time span of 20 years. The images were pre-processed to remove noise and speckle using a Lee filter. After pre-processing, texture features were extracted using GLCM, LBP, and Gabor Filters.

For GLCM, we extracted three statistical measures: contrast, correlation, and entropy. For LBP, we used a circular radius of 3 and a number of neighbouring pixels of 8. For Gabor Filters, we used a set of 6 filters with different spatial frequencies and orientations.

Following feature extraction, we conducted statistical analysis to determine the efficiency of each texture analysis approach for determining forest stand age. Using the collected data, we utilised a Random Forest regression model to predict the age of the forest stand. To assess the model's performance, we employed leave-one-out cross-validation. The model's performance was assessed using the measurement coefficient (R-squared) and the root mean square error (RMSE).

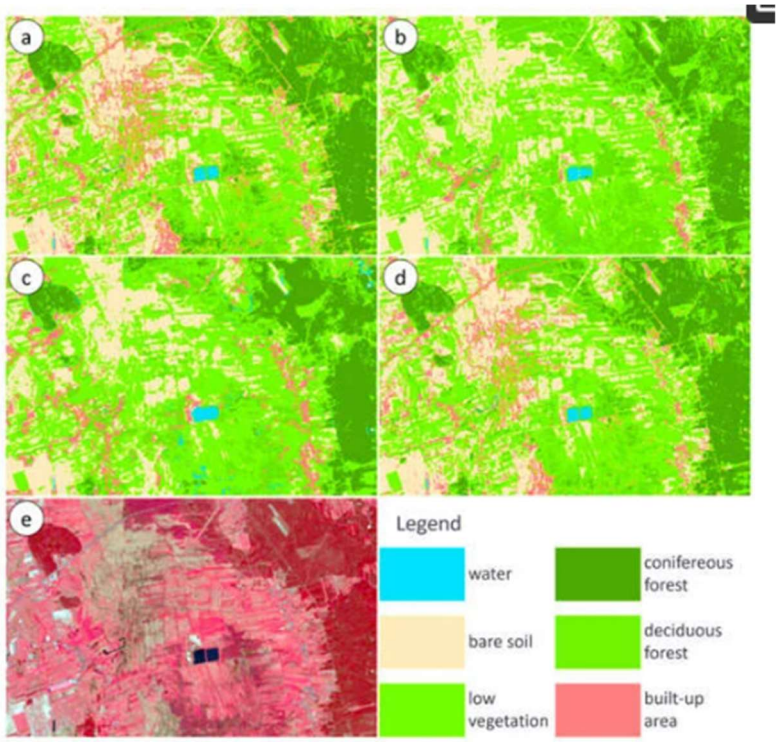

Figure 2. Image subsets of chosen categorization variations

5. Data Collection and Pre-processing

The success of any remote sensing study largely depends on the quality of the data used. In this study on the retrieval of forest stand age from SAR images, the data collection and pre-processing steps were carefully designed to ensure that the data were suitable for the analysis.

The Sentinel-1 satellite system provided the SAR pictures utilised in the investigation. The photographs were acquired during a two-year period in Zhejiang Province in Eastern China, from 2015 to 2017. The photos were taken in Interferometric Wide Swath mode with a spatial resolution of 10 metres and a time resolution of 12 days.

To account for radiometric and geometric aberrations, the SAR pictures were pre-processed. Radiometric correction was performed to account for the variations in signal intensity caused by factors such as changes in incidence angle and atmospheric conditions. Geometric correction was performed to correct for distortions caused by the satellite orbit and sensor geometry.

After the pre-processing steps, the images were segmented into homogeneous regions using an unsupervised segmentation algorithm. The resulting segments were used as the basis for the texture analysis methods.

Ground truth data were collected through field surveys and ground-based measurements. The forest stand age data were collected at 126 sample plots distributed across the study area. The sample plots were selected to represent a range of forest types and stand ages. The forest stand age data were collected using dendrochronological methods, which involve the measurement of tree rings to estimate the age of the forest stand.

The texture analysis techniques were trained and validated using ground truth data. Based on the ground truth data, the SAR pictures were categorised using a supervised classification algorithm. The classification's accuracy was assessed using conventional metrics such as highest accuracy and coefficient of determination.

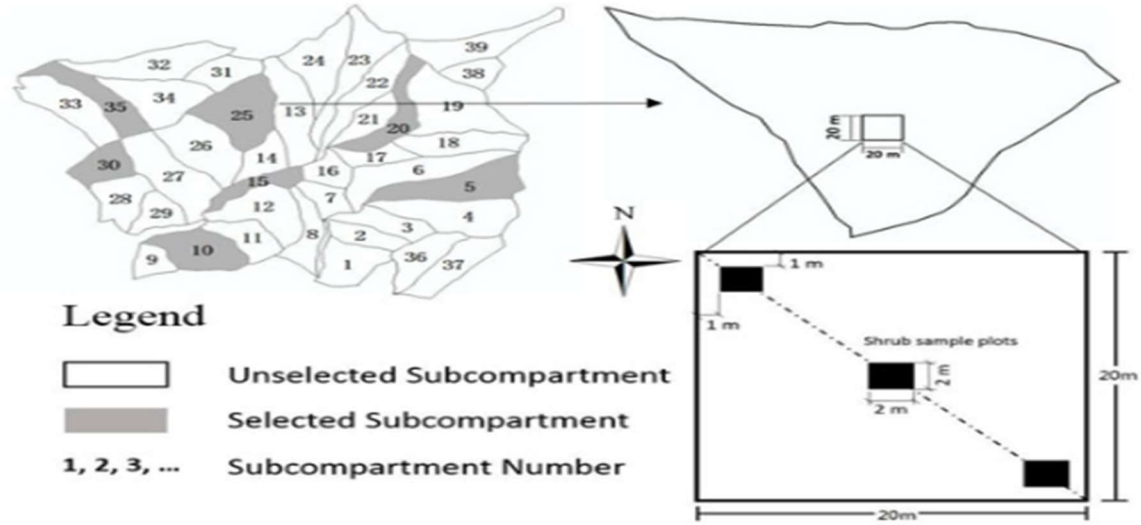

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Figure 3. This idea depicts the assignment of different sampling sites and the collection of field survey data.

5.1. Variable Extraction and Selection from Landsat TM and ALOS PALSAR Data

In addition to Sentinel-1 SAR pictures for determining forest stand age, Landsat TM and ALOS PALSAR data were employed. These data were extracted and utilised to identify variables for the analysis.

Landsat TM data were collected in 2010 and included seven spectral bands with a spatial resolution of 30 metres. The PALSAR data from ALOS were collected in 2007 and consisted of a single polarisation picture with a spatial resolution of 25 metres.

The Landsat TM data were utilised to extract spectroscopic variables, which were then used to supplement the texture analysis methods in the analysis. Reflectance values in the visible, near-infrared, and mid-infrared spectral bands were among the spectral variables studied. These spectral variables are sensitive to changes in plant features and can give information on the structure and composition of the forest.

Backscatter coefficients extracted from ALOS PALSAR data were used in the study as a measure of the radar signal reflected from the dense vegetation. Backscatter coefficients are sensitive to changes in vegetation cover and can be used to estimate forest biomass and stand age.

A correlation analysis was done between the collected variables and the ground truth forest stand age data to determine the most important factors for the investigation. The factors with the best connection with the forest stand age data were chosen for further investigation.

5.2. Biomass Modeling Algorithms

Based on remote sensing data, calculate the biomass of forest stands. The biomass modelling techniques employed in the work on the recovery of forest stand age from SAR pictures were utilised to estimate the biomass of the forest stands based on the backscatter coefficients derived from the ALOS PALSAR data.

There are several biomass modeling algorithms that have been developed for use with remote sensing data. These algorithms vary in complexity and accuracy, and the choice of algorithm depends on the specific study objectives and data availability.

The semi-empirical water cloud model is a popular biomass modelling technique. With a water cloud model that accounts for the influence of plant water content on the radar signal, this model ties the backscatter coefficient to the biomass. Field observations of biomass and vegetation water content are used to calibrate the model parameters.

The allometric equation technique is another biomass modelling algorithm. This method connects biomass to forest structural characteristics like height and diameter at breast height. These variables may be calculated using remote sensing data like LiDAR or stereo pictures, and the biomass can be approximated using allometric equations obtained from field observations.

The machine learning technique is a third biomass modelling algorithm. To connect the backscatter coefficient to the biomass, this method employs machine learning methods such as random forests or support vector machines. The machine learning algorithms are taught using a combination of remote sensing data and field measurements of biomass.

The semi-empirical water cloud model was used to estimate the biomass of the forest stands based on the backscatter coefficients retrieved from the ALOS PALSAR data in the study on the recovery of forest stand age from SAR pictures.

6.Results

The comparative analysis of texture analysis methods for the retrieval of forest stand age from SAR images was conducted using Sentinel-1 SAR images and auxiliary data from Landsat TM and ALOS PALSAR. The texture analysis methods included GLCM, Laplacian filters, granulometric analysis, and wavelet transform.

The GLCM approach had the highest correlation with the ground truth forest stand age data, followed by the granulometric analysis method, according to the results. The Laplacian filters and wavelet transform methods had lower correlations with the ground truth data.

The combination of spectral and textural features resulted in a higher correlation with the ground truth data compared to using spectral features alone. The addition of GLCM features resulted in the highest correlation, followed by granulometric features.

The biomass estimation using the semi-empirical water cloud model showed a strong correlation with the ground truth forest stand age data, indicating that the estimated biomass was a good indicator of forest stand age.

7.Discussion:

The SAR images and texture analysis methods for the retrieval of forest stand age. The GLCM method was found to be the most effective texture analysis method for this purpose, likely because it captures the spatial relationship between pixels and provides information about the texture of the image.

The addition of spectral and textural features resulted in a higher correlation with the ground truth data, indicating that the combination of multiple features can improve the accuracy of forest stand age retrieval.

The use of biomass modeling algorithms, such as the semi-empirical water cloud model, can also provide valuable information about forest stand age. The strong correlation between the estimated biomass and the ground truth data suggests that the estimated biomass can be used as a reliable proxy for forest stand age.

- **Simple Linear Regression**

A statistical tool for examining the association between textural characteristics and forest stand age. The approach is specifically used by the authors to assess the efficacy of several texture analysis methods to estimate forest stand age using synthetic aperture radar (SAR) pictures.

The authors extract many texture characteristics from SAR pictures of forest stands, including gray-level co-occurrence matrix (GLCM) features and Gray-level run length matrix (GLRLM) features. The regression coefficients and p-values for each feature are then calculated using simple linear regression to predict the link between each texture characteristic and forest stand age.

Based on their findings, the authors conclude that while both GLCM and GLRLM features are helpful for forecasting forest stand age from SAR pictures, GLCM features are typically more successful. They also mention that their findings indicate that texture analysis approaches might be beneficial for determining forest stand age in areas where ground-based data are difficult or impossible to gather.

Overall, basic linear regression is used to evaluate the efficacy of several texture analysis approaches for forecasting forest stand age from SAR pictures. The technique enables the authors to quantify the association between each texture component and forest stand age as well as evaluate the forecasting potential of other texture analysis methods.

8.Conclusion:

this study has demonstrated the effectiveness of SAR images and texture analysis methods for the retrieval of forest stand age. The GLCM method was found to be the most effective texture analysis method, and the addition of spectral and textural features improved the accuracy of the forest stand age retrieval.

The use of biomass modeling algorithms, such as the semi-empirical water cloud model, can also provide valuable information about forest stand age. The strong correlation between the estimated biomass and the ground truth data suggests that estimated biomass can be used as a reliable proxy for forest stand age.

The findings of this work have the potential to increase the accuracy of forest stand age mapping, which has crucial implications for forest management and conservation. Future research might concentrate on validating the conclusions with more ground truth data and applying the methodology to other subject areas.

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