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ORIGINAL ARTICLE

Modeling Forest Structure using Voxel

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Abstract: Along with the depopulation and aging in mountainous area, a ruined forest has been increasing. There are various function in forest such as water source cultivation and national land conservation, but the ruined forest lose these. Therefore, a forest must be maintained and managed. Measuring forest structure is important to maintain and manage a forest. Voxel modeling is suitable to represent forest structure because it can give data about various attributes of the leaves and trees. A voxel model is made from 3D point cloud data obtained using a LiDAR sensor. A voxel model can be used to estimate the Leaf Area Index (LAI) of a forest. The point cloud data in a voxel model can be analyzed to measure the 2D area of the leaves. Such measurement requires categorizing each data point as "leaf" or "non-leaf". The classification methods are usually based on the RGB data or the reflection intensity in the LiDAR data. However, the accuracy of such methods is highly dependent on light quality and weather conditions. The classifying methods should be highly robust. In this study, a classification method was developed that extracts leaf data from a LiDAR image. The physical quantities of reflection intensity, normal vector and direction to measurement point were computed from the image. The classification method was based on a decision tree. The rules of decision tree were derived from the observed data. The developed method was applied at 6 points with different conditions. The results had an accuracy of over 88% on these 6 points. In addition, the forest structure was represented by a voxel model, and from this model was computed the LAI, the position of the trees and the space in the forest. However, the accuracy verification of the LAI, tree position, and space in forest was insufficient. As a further verification method, some trees will be actually cut down and their position and LAI will be measured.

Keywords: Forest, LiDAR, Point cloud, Voxel model, Leaf Area Index

1. Introduction

Along with the depopulation and aging in mountainous area, a ruined forest has been increasing. There are various function in forest such as water source cultivation and national land conservation, but the ruined forest lose these. Therefore, a forest must be maintained and managed. Measuring forest structure is important to maintain and manage a forest. Recently, forest structure has often been measured using terrestrial LiDAR (Light Detection And Ranging). LiDAR is a remote sensing technology that uses laser light to measure distance and brightness. A LiDAR sensor measures reflected light from objects. The data generated by a LiDAR sensor is called "point cloud data". Point cloud data has random coordinates on the ground. The spatial density of

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points in the cloud is not uniform. Additionally, it takes time to compute a point cloud because of the huge volume of data. Voxel modeling is suitable to measure and represent the structure of a forest. Point cloud data should be converted to voxel. Spatial density of voxel is uniform.

In order to store the voxel model, it is necessary to detect leaves within the point cloud data. Several detection methods have been suggested using attribute values of point cloud data. Kaneko (2016) tried to classify leaves based on RGB color data. However, the method is affected by condition of a light source. Fujiwara (2017) tried to classify leaves based on reflection intensity. However, Reflection intensity changes with surface reflectance of the tree. For various trees and various light source conditions, a more robust method is needed.

In this study, method of classifying leaves and non-leaves using physical quantities from LiDAR data was developed. Classified point cloud was stored to voxel, and thus, the forest structure could be represented by the voxel model.

2. Creation of forest structure

2.1 Study area

The study area is a forest around Kanamine Shrine located in Nakagonyu district in Kami City, Kochi Prefecture (Figure2.1). The size of the study area is about 350m^2, in which live Cedar (Cryptomeria), cypress (Chamaecyparis obtusa) and bamboo. along with shorter plants, such as Aoki (aucuba) and camellia. The forest is not currently not being maintained.

Figure 2.2 is an aerial photograph of the study area taken by a UAV.

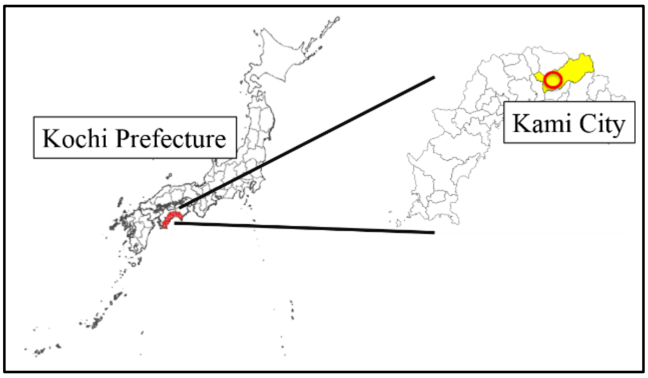


Figure 2.1 Location of Kami city

Figure2.2 UAV picture of the study area

2.2 LiDAR measurement

2.2.1 Specifications of LiDAR

Point cloud data of study area was obtained using a “Terrestrial LiDAR” sensor (Figure 2.3) made by TOPCON Company. The wavelength of its laser light is 1500nm. The point cloud data obtained from this LiDAR device has XYZ coordinates, RGB values, reflection intensity (V) and normal vectors (Nx, Ny, Nz). Table 2.1 shows Specifications of this LiDAR.

Figure2.3 LiDAR

Table 2.1 Specifications of LiDAR device

Products of Laser Scanner	GLS-1500
Effective measurement range	500m
Measurement angle	70 ×360
Ranging accuracy	±4mm (in 150m)
Measurement density	Max 1mm (in 20m)
Max points	100,000,000 points
Measurement principle	Time of Flight
Wavelength of the laser	1535nm

The LiDAR device produces 4 different images, namely (1) the RGB image, (2) the reflection intensity image, (3) the normal vector, and (4) the angle image. The latter 3 of these were used to classify “leaf” and “non-leaf” data points. Compared to the analysis of the 3D point cloud data, the analysis of these images was fast because it contained only 2D data. Figure 2.4 shows a schematic of the LiDAR scan.

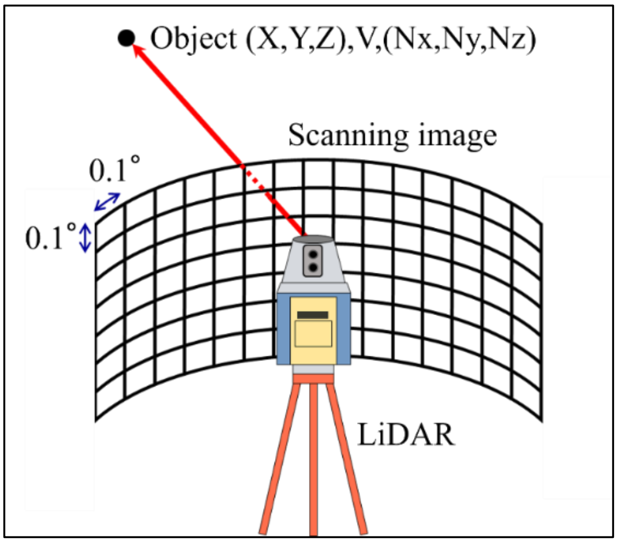


Figure 2.4 Schematic of the scan by LiDAR

Measurements were performed 6 points (P1-P6) to cover the whole study area. The vertical and horizontal step angle at measurement points was 0.1 degrees. Reflectors were used as ground control points for geometric correction. Ground coordinates (X,Y,Z) of reflectors were surveyed by total station. For each LiDAR measurement points, reflectors were measured 5 points. Figure 2.5 shows the scanned image at point P1. Point cloud data is a scanned image expanded into a three-dimensional space. Figure 2.6 shows the point cloud obtained by LiDAR.

Figure 2.5 Scanned image of P1

Figure 2.6 Point cloud obtained by LiDAR

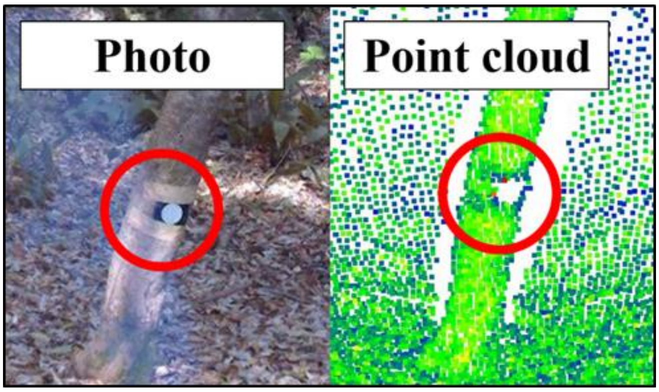


Figure 2.7 Reflector

Figure 2.7 shows a sample of a reflector and the corresponding point cloud. Figure 2.8 shows the measurement points and the reflectors.

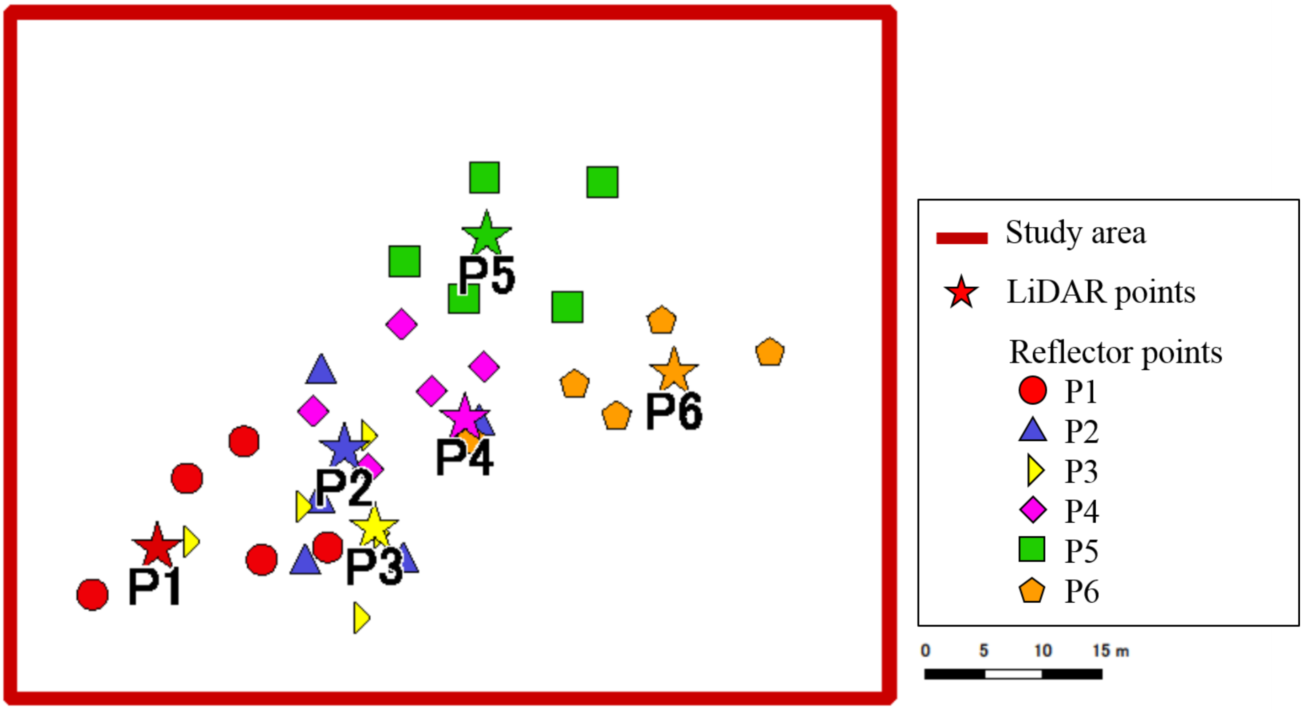


Figure 2.8 Measurement and reflectors position

2.2.2 Geometric correction using ground control points

Equation 1 was used for geometric correction. The point cloud data was converted from local coordinates to ground coordinates using 5 ground control points. However, P6 was converted using 4 ground control points because one of the ground control points had low accuracy. Table 2.2 shows the root mean square error around the ground control points. The maximum mean squared error overall was 0.0712m in P1.

$$\begin{pmatrix} X_i \\ Y_i \\ Z_i \end{pmatrix} = \begin{pmatrix} p_0 & p_1 & p_2 \\ p_3 & p_4 & p_5 \\ p_6 & p_7 & p_8 \end{pmatrix} \begin{pmatrix} u_i \\ v_i \\ w_i \end{pmatrix} + \begin{pmatrix} X_0 \\ Y_0 \\ Z_0 \end{pmatrix} \quad \text{Eq.1}$$

(X_i, Y_i, Z_i) : Ground coordinate
(u_i, v_i, w_i) : Local coordinate
$(p_0 \sim p_8)$: Transformation coefficient
(X_0, Y_0, Z_0) : Ground coordinate of LiDAR

Table 2.2 Root mean squared error

Measured Point	Reflectors used	Root mean squared error(m)
P1	5	0.0712
P2	5	0.0676
P3	5	0.0448
P4	5	0.0702
P5	5	0.0696
P6	4	0.0271

3 Extraction of leaves from measured point cloud

3.1 Characteristics of reflection intensity

The reflection intensity is the signal intensity of the laser reflected light from an object. Figure 3.1 shows a scanned image of the reflection intensity. The reflection intensity is affected by the material of an object, distance, incident angle of the laser, and weather conditions. Therefore, the distribution of the reflection intensity of leaves and tree trunks is different. Leaf reflection intensity tends to be low and tree trunk reflection intensity high. Figure 3.2 shows a histogram of the reflection intensity of both leaves and tree trunks. According to the histogram, when the reflection intensity is more than 200, the data points represented only the tree trunks, and when the reflection intensity is less than 150, the majority of the data points represents leaves.

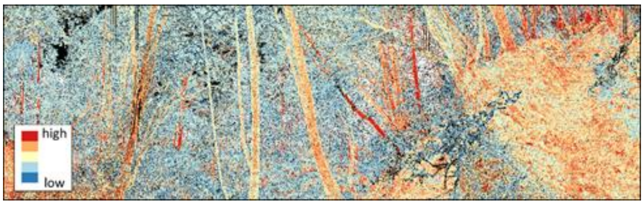


Figure 3.1 Reflection intensity image

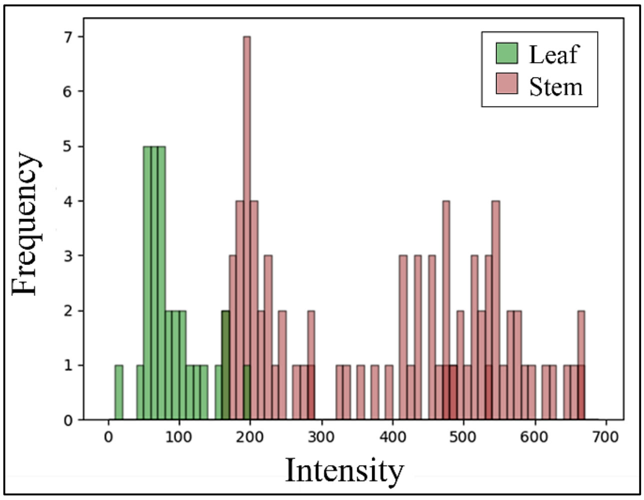


Figure 3.2 Reflection intensity

3.2 Characteristics of Nz

The Z element of a normal vector (Nz) can also be used to classify leaves and tree trunks. The normal vector is a parameter that represents the direction of the surface. The point cloud data includes Nx, Ny, Nz as attribute values. Figure 3.3 shows the normal vector assumption of leaves and tree trunks. Leaves have a high Z element because they are upward and face the sky. On the other hand, tree trunks have a high XY element because of their cylindrical shape. Figure 3.4 shows a scanned image of Nz and Figure 3.5 shows a histogram of Nz. According to the histogram, when the Nz value is less than -0.2, most of the data points represented leaves.

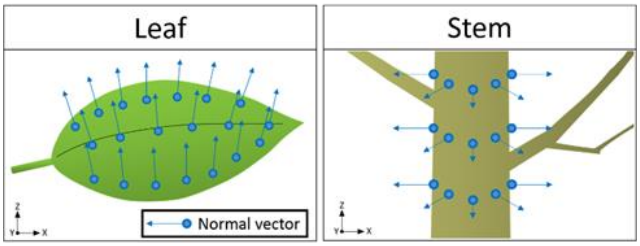


Figure 3.3 Assumption of normal vector

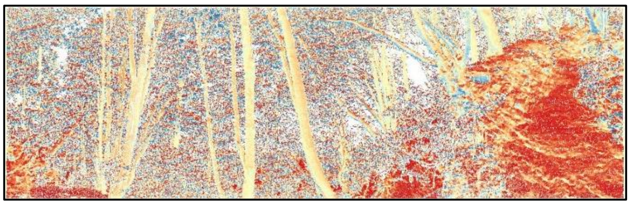


Figure 3.4 Scanned image of Nz

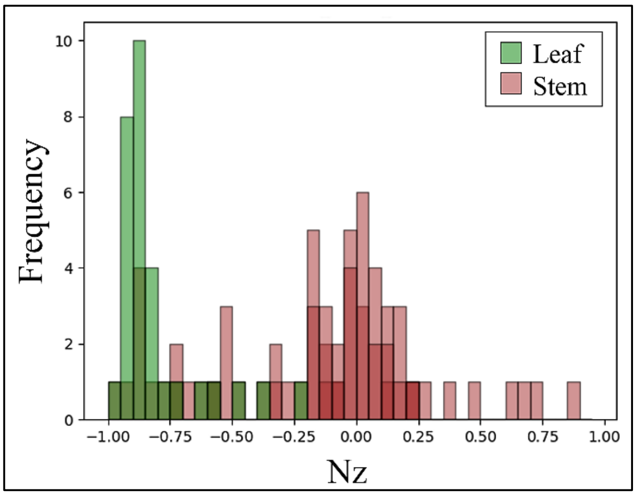


Figure 3.5 Z element of normal vector

3.3 Characteristics of the Angle between laser direction and normal vector

The angle (θ) between the laser direction from LiDAR and the normal vector can also be used to distinguish between leaves and non-leaves. Figure 3.6 shows the assumption of θ. Leaves have a large θ, and tree trunks have a small θ. Figure 3.7 shows a scanned image of cosθ and figure 3.8 shows a histogram of cosθ. According to the histogram, when the cosθ value is less than 0.2, most of the data points represented leaves.

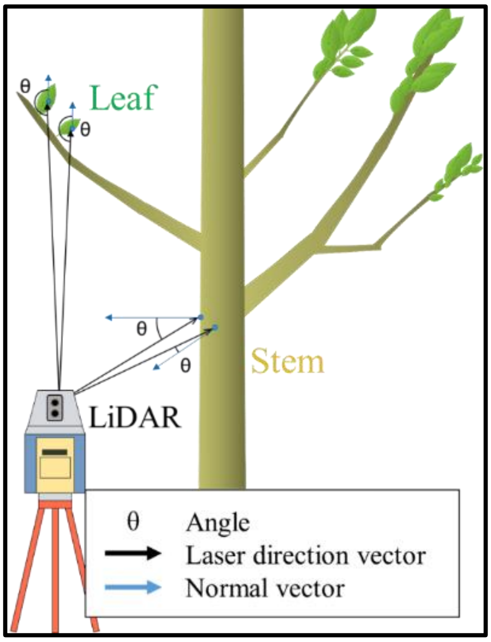


Figure 3.6 assumption of θ

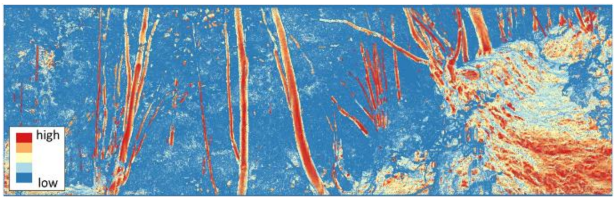


Figure 3.7 Scanned image of cosθ

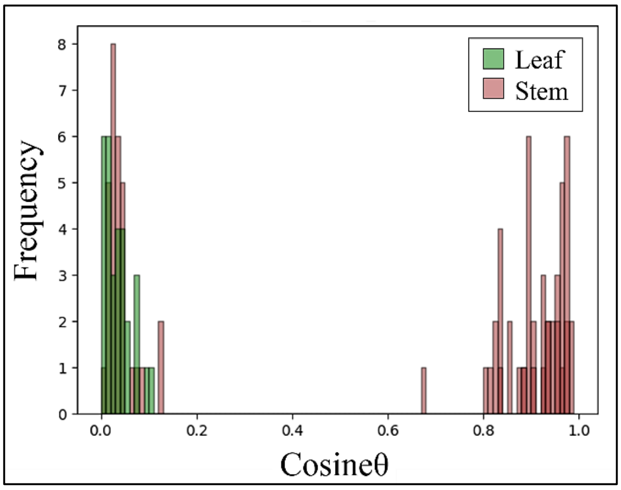


Figure 3.8 Cosθ

3.4 Classification by decision tree

A decision tree was used to extract leaf data from the point cloud. Pixels with a reflection intensity of 200 or more were classified as non-leaves and 150 or less were classified as leaves. This condition is very clear in order to extract leaves. On the other hand, pixels with a reflection intensity between 150 to 200 must be classified using other items such as cosθ and Nz. Pixels with a cosθ value of less than 0.2 were classified as leaves, and 0.2 or more values were classified based on Nz. Pixels with a Nz value of less than -0.2 were classified leaves, and -0.2 or more values were classified non-leaves. Figure 3.9 shows the created decision tree.

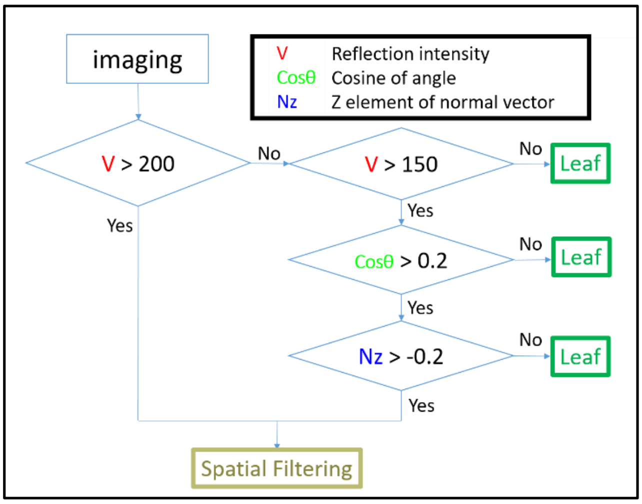


Figure 3.9 Decision tree

The classified non-leaf points generated by the decision tree still contained some leaves. Therefore, these leaves were extracted by spatial filtering using a scanned image. Firstly, a binary image was created with only non-leaf values (Figure 3.10). The center pixel and the 3*3 neighboring pixels are used for classification. If the center pixel has a non-leaf value and is less than one pixel in size, then there is a non-leaf value in the neighboring pixel, and it is extracted as leaf data (Figure 3.11).

Figure 3.10 image of classified non-leaf

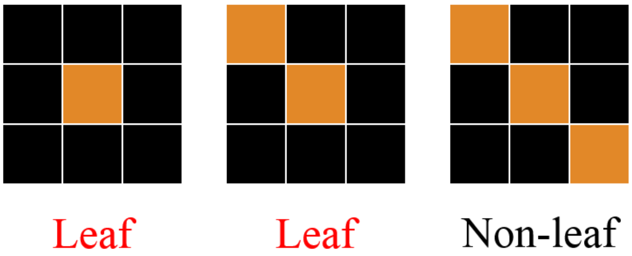
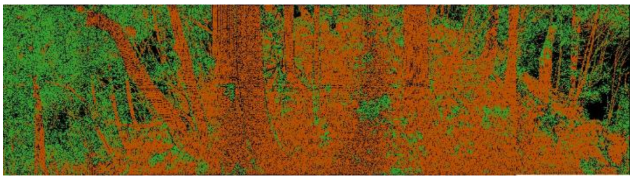
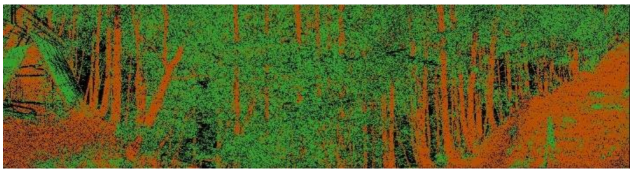


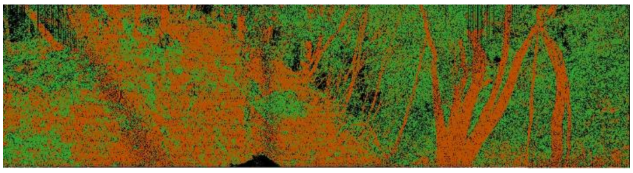
Figure 3.11 Extraction of leaves by spatial filtering

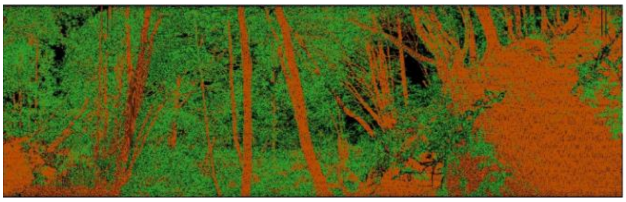
3.5 Extraction result and accuracy verification

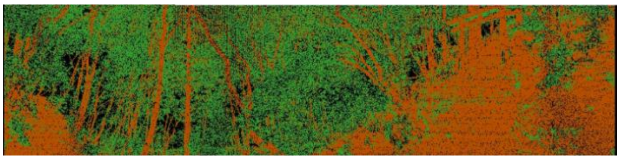
The decision tree from the data at P1 was applied to all data. Figure 3.12 shows the classification results of leaves and non-leaves. The accuracy was verified by visual interpretation on the point cloud image. Table 3.1 shows the result of accuracy verification at all points. In the results, the highest accuracy was 95%, obtained at point P2. The lowest accuracy was 88%, which was obtained at points P3 and P4. According to these results, the same method was used to detect the presence or absence of leaves in measurement data with different measurement conditions.











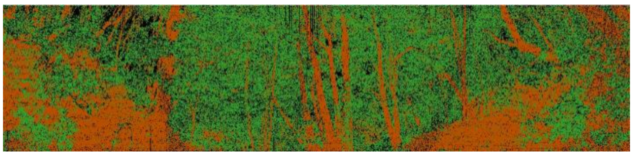


Figure 3.12 Classification results at P1-P6

Table 3.1 Result of accuracy verification

Point	Verification		Classification result		Accuracy (%)	
			Leaves	Leaves		
P1	Leaves	50	45	5	90	90
	Others	50	5	45	90	
P2	Leaves	50	47	3	94	95
	Others	50	2	48	96	
P3	Leaves	50	44	6	88	88
	Others	50	6	44	88	
P4	Leaves	50	44	6	88	88
	Others	50	6	44	88	
P5	Leaves	50	44	6	88	91.1
	Others	50	3	47	94	
P6	Leaves	50	45	5	90	90
	Others	50	5	45	90	

4 Voxel modeling of forest structure

A voxel model is a data model that divides three-dimensional space into small cubes, about which many attributes can be stored. A voxel model can be called homogenized point cloud data. The largest spacial distance of points in the cloud data from the

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LiDAR was 3.5cm. Therefore, the voxel size was set at 5cm. Figure 4.1 shows an outline of the voxelization process. The number of the points (k) in each voxel is counted. When the number of points is less than 3, it was considered to be noise and was not used. The attribute data was categorized as "leaf", "non-leaf" or "mixed".

The ground height is the distance between the voxel center coordinates and the elevation data. The ground height is an important attribute to represent forest structure. The elevation data was created by point cloud. Firstly, the point cloud data was separated into with 2D grid of 1m squares. Secondly, the lowest point in the grid was extracted. Finally, the lowest point was interpolated with a 10cm grid by triangle division interpolation. Figure 4.2 shows the elevation data.

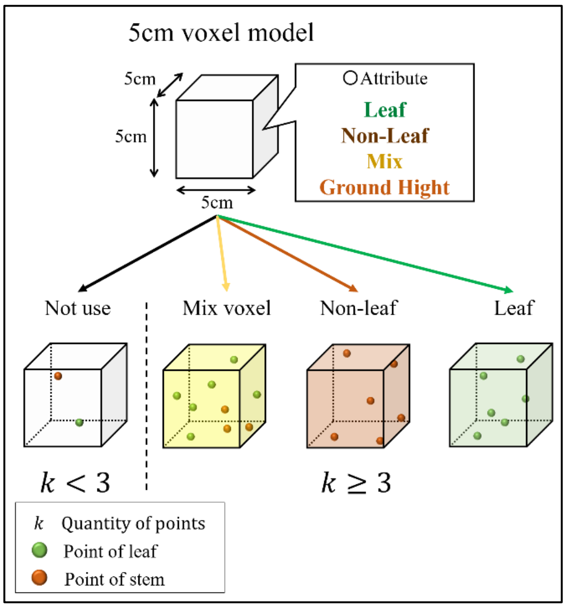

Figure 4.1 Overview of 5cm voxel

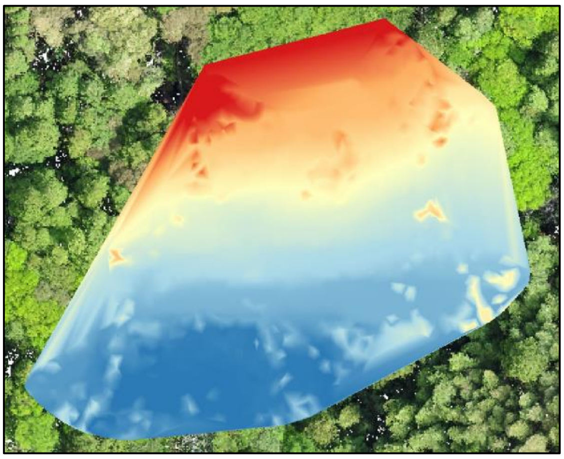

Figure 4.2 Elevation data

5 Products from voxel model

An application to analyze the forest structure, tree position, space inside the forest, and LAI was derived from the voxel model.

5.1 Method and results of tree position estimation

The tree position at any height was estimated using voxel model. Figure 4.3 shows flow chart of tree position estimation. Firstly, the voxels of non-leaf and mixed categories were extracted from the voxel model. When, the number of connected pixels on the XY plane had more than 3 pixels, these were categorized as being a tree. Finally, the tree position was determined by calculating the centroid of the pixels. Figure 4.4 shows estimation result of tree position.

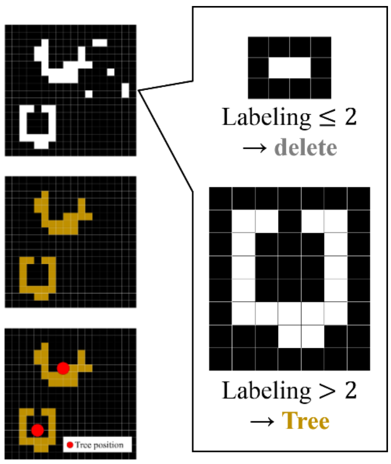

Figure 4.3 Flow chart of tree position estimation

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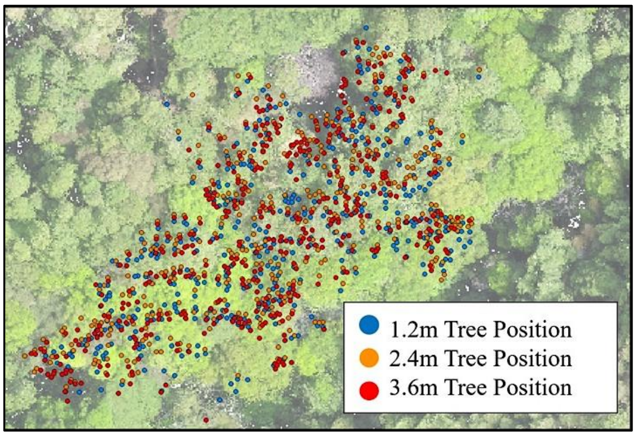

Figure 4.4 Estimation result of tree position

5.2 Method and results of estimation of space inside the forest

Using voxel model, the space inside the forest to was estimated using a 1m Grid. Figure 4.5 shows the results of this estimation of the space, from the ground to a height of 20m.

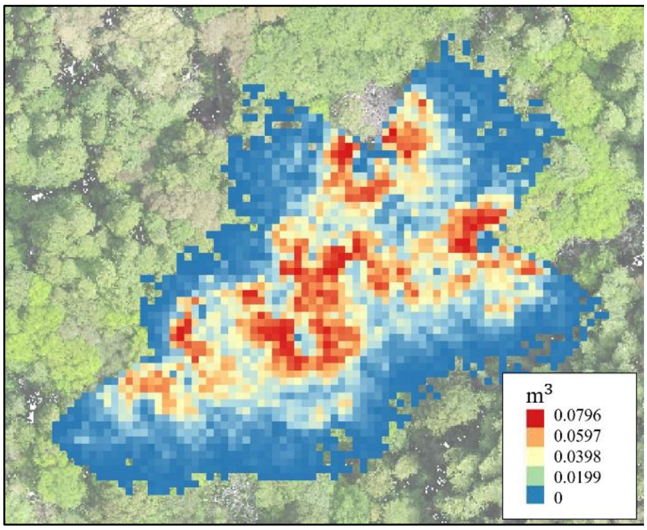

Figure 4.5 Estimation result of space in forest

5.3 Method and results of LAI estimation

LAI is an important parameter for understanding the ecological and physical characteristics of the plant community. LAI means the total leaf area per $1m^2$ on the ground. The total leaf area per unit area can be computed by summing the leaf voxels.

In this study, the leaf area per $1m^2$ was calculated using 5cm voxel model. Equation 2 was used to calculate leaf area of each voxel. Firstly, the leaves and mixed voxels per $1m^2$ were counted. Secondly, leaves voxel were multiplied by $25.0cm^2$ and mixed voxel were multiplied by $12.5cm^2$ to calculate the total leaf area. Figure 4.6 shows estimation result of LAI.

$$\text{Leaf Area} = 25.0 \times Pv + 12.5 \times Mv \qquad \text{Eq.2}$$

25.0(cm²): Leaf area of pure voxel of leaf
12.5(cm²): Leaf area of mix voxel
Pv：Number of pure voxel of leaf in 1m Grid
Mv：Number of mix voxel in 1m Grid

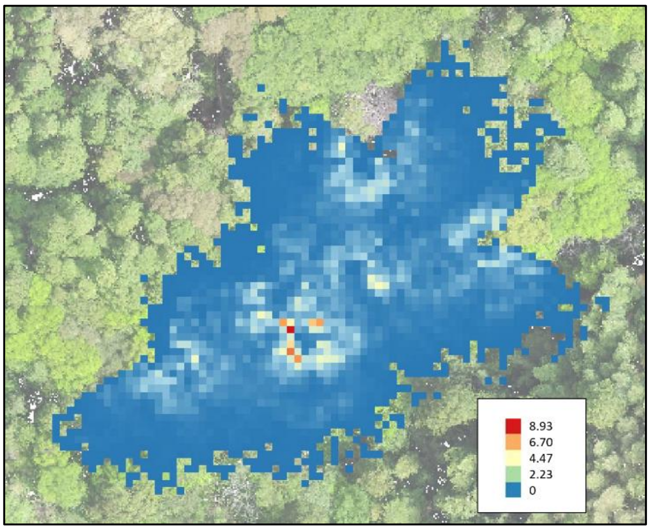

Figure 4.6 Estimation result of LAI

6 Conclusions

In this study, data on the presence or absence of leaves was extracted by scanned the image from a LiDAR using reflection intensity, cosθ and Z element of normal vector. Thus, the forest structure was estimated using a classified voxel model.

To extracting this leaf data, a decision tree was applied to the data with different observation conditions. The highest extraction accuracy was 95%, whereas the lowest extraction accuracy was 88%. The method was highly robust what was not dependant on solar radiation at the time of observation.

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Inside the forest, the space, tree position at any height and LAI can be estimated using a voxel model. However, the accuracy verification of LAI, tree position, and space is insufficient. As a verification method, some trees will be actually cut down and their LAI, tree position, and material volume was measured.

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