Development of forest prediction model using Individual Tree Crown method and Gray theory in an old –growth *Chamaecyparis obtusa* stand, in the Akazawa Forest Reserve, central Japan

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Contents

Abstract

In this paper, a prediction model was developed for forest management, including the detection system and prediction system. The detection system can obtain accurate data based on satellite image and aerial data, and the prediction system can forecast the condition of forests in the future. In this study, the high resolution aerial photographs, long-term investigated data and satellite images were analyzed by individual tree crown approach and gray theory model. The Individual Tree Crown method provides a good solution for detecting remotely sensed data over vast areas, and it can delineate trees at the individual level using aerial data and/or satellite images with high resolution of less than 1m. The Gray thoery, defined as Gray derivative and differential equation with correlation analysis and smooth discrete function, can forecast forest growth at individual tree level based on the long-term tracking investigation without environment data. Akazawa Reserve Forest in kiso town, Nagano Prefecture, central Japan is a precious forest for research and is well protected since its establishment. In 1988, a permanent plot with an area of 4 ha was established in the old-growth *Chamaecyparis obtusa* forest with an age of over 300 years, and the surveys were been periodically conducted by each 5 years in the following 20 years. The objectives of this thesis, using high resolution aerial data, long-term investigation and satellite images, were first developing a systematic prediction system of tree individuals, which was used to analyze the change pattern of forest structure and development process. This study then attempted to provide a new detection method and forecast theory, and offer some recommendation for management of modern forest.

Firstly, from detection system, the individual tree crown method can provide accurate method for obtaining accurate data based on high resolution aerial data and satellite images. For the accurate measurement of forest biomass in the Akazawa Forest Reserve, this study analyzed texture measures derived from GeoEye-1 satellite data using the individual tree crown (ITC) method. In this basis, canopy area, tree tops and tree species of individual trees were delineated. Tree crowns of 282 and tree tops of 352 were extracted. Canopy area was used to calculate the DBH of trees in canopy layer based on canopy-DBH curve in this stand. In the estimation models, between

DBH and height, and between canopy area and DBH were developed by linear regression using forest survey data. Then, according to the interpreted results of satellite data, the biomass of each tree was calculated by biomass expansion factor (BEF). This method was verified against the survey data from old–growth *Chamaecyparis obtusa* stand composed of various cover types. For *Chamaecyparis obtusa*, the accuracy of biomass estimation was higher than 84%. However, the accuracy of *Chamaecyparis pisifera* was less than 60%, because the canopy area of *Chamaecyparis pisifera* was underestimated in the high-density stand. For *Thujopsis dolabrata*, the accuracy ranged from 22.4 % to 78.9%, and from 63.4% to 84.6% for broad-leaved trees, because many of them were in understory. On this basis, for improving the precision of tree detection, this paper analyzed texture measures derived from multispectral airborne digital data and LiDAR data. Canopy area was used to calculate the DBH of trees in canopy layer based on canopy-DBH curve in this stand. LiDAR data can be used to create DCHM data with 50-cm high resolution, and the height of all trees could be estimated from the DCHM data with the tree tops of all trees which were registered in the forest database using ArcGIS 10. For *Chamaecyparis obtusa*, the accuracy of biomass estimation was higher than 87%. The accuracy of *Chamaecyparis pisifera* was less than 60%, because the canopy area of *Chamaecyparis pisifera* was underestimated in the high-density stand. For *Thujopsis dolabrata*, the accuracy ranged from 22.4 % to 78.9%, and from 63.4% to 84.6% for broad-leaved trees, because many of them were in understory. These results indicated that this approach is useful for forest detection whether it is used to calculate biomass of individual tree or forest.

Secondly, from prediction system, gray theory can provide a method for forecast forest growth with high prediction accuracy at individual tree level based on long term survey data. In this paper, with the gray theory of mathematics, this research developed a program of calculating tree growth by using the data of the stand surveyed in 1988, 1998, 2003 and 2008. By this program, a prediction has been completed for the growth of the tree stand in 2018, 2028 and 2038, respectively. In the understory, the average forecast error of *Chamaecyparis obtusa* was 23.8% in 1998, 18.6% in 2003 and 11.9%

in 2008. For *Thujopsis dolabrata*, it was 15.8%, 13.6% and 9.7%, respectively, in the three years. And broad-leaved trees' error was 17.6%, 12.9% and 10.7% in 1998, 2003 and 2008. In middle layer, *Chamaecyparis obtusa*'s errors were 22.8%, 16.8% and 8.9% respectively, while they were 16.5%, 18.5% and 11.3% for *Thujopsis dolabrata*, and 14.9%, 11.9% and 8.7% for broad-leaved trees. In the dominant layer, they were 22.4%, 13.6% and 6.8% for *Chamaecyparis obtusa*, 9.8%, 13.5% and 17.9% for *Thujopsis dolabrata*, and 15.6%, 12.8% and 8.9% for broad-leaved trees in the specified years respectively. The further development in the prediction, a stand prediction model of suitable sites for tree growth attempted to be presented in the old-growth *Chamaecyparis obtusa* forest. Survey results indicated that the total number of recruited tree of *Thujopsis dolabrata* was increased from 1998 to 2008, while the total number of recruited trees of *Chamaecyparis obtusa* was decreased in this period. Furthermore, the number of recruited trees of *Thujopsis dolabrata* will be increased and the number of recruited trees of *Chamaecyparis obtusa* will be decreased in the future. The prediction errors for the number of recruited *Chamaecyparis obtusa* trees ranged from 10.5% to 31.5%, and for recruited *Thujopsis dolabrata* trees, the prediction errors ranged from 10.2% to 28.7% in different layers. In addition, the suitable sites for tree's growth in the future have been predicted by every 10 years from 1998 to 2008 and compared with survey data. The prediction errors for suitable sites of tree growth of *Chamaecyparis obtusa* ranged from 21.3% to 40.3% in different layers. And the prediction errors for suitable sites of tree growth of *Thujopsis dolabrata* ranged from 14.2% to 53.1% in different layers. Finally, the suitable sites for tree's growth in the future have been predicted by per 10 years from 2018 to 2038, where the relationship between tree growth and its suitable habitat was suggested well.

Introduction

1.1 Background

Pure for economic development and neglect of environmental protection, global environment was led to worsen. Global environmental issues were not only partial destruction of environmental pollution and ecological balance. And some global environmental crisis have imperiled the survival and development of humankind, such as global warming, destruction of the ozone layer, acid rain, species extinction, reduction of biodiversity, soil erosion, and forest reduction. The international community has established extensive cooperation to combat global environmental crisis. Forests are significant global ecosystems, having some adjustment function for global environment, such as regulation circulation of air and water, inhibition of desertification and soil erosion and so on. Forest are dominating over 30 percent of the terrestrial landscape and providing habitat for many species of plant, animals, invertebrates and micro-organisms and numerous goods, services and benefits to people (FAO 2011). Forests are also a major part of the global carbon cycle, containing significant stocks of carbon and emitting carbon to the atmosphere during and following disturbances such as fire, storms or landslides or human disturbances such as timber harvesting or clearing for agriculture. Forests remove carbon from the atmosphere in periods of growth and recovery following these disturbances. Forests have been identified as a potential mechanism to human-induced climate change. Many governments and non-governmental organizations directly engage in programs of a forestation and to create forests, increase carbon capture and sequestration, and help to anthropogenic ally improve biodiversity. In some places, forests need help to reestablish themselves because of environmental factors. After large area of global reforestation program, sustainable forest management has gradually become the focus, broad social, economic and environmental goals. The "Forest Principles" adopted at The United Nations Conference on Environment and Development (UNCED) in Rio de Janeiro in 1992 captured the general international understanding of sustainable forest management. In 2007, the United Nations General Assembly adopted the Non-Legally bindinginstrument on all types of forests. The instrument was the first of its kind, and reflected the strong international commitment to promote implementation of sustainable forest management through a new approach that brings all stakeholders together.

Forest management is a branch of forestry concerning with the overall administrative, economic, legal and social aspects and with the essentially scientific and technical aspects, especially silviculture, protection, and forest regulation. This includes management for biodiversity, Landscape aesthetics, wood products, forest genetic resources and other forest resource values. Management can be based on conservation, economics, or a mixture of the two. Techniques include timber extraction, planting and replanting of various species, cutting roads and pathways through forests, and preventing fire. Sustainable forest management is the management of forests according to the principles of sustainable development.

Forest management is based on forest inventory and forest informatics. Forest inventory is the systematic collection of data and forest information for assessment or analysis. The aim of the statistical forest inventory is to provide comprehensive information about the state and dynamics of forests for strategic and management planning. Forest informatics is the combined science of Forestry and Informatics, with a special emphasis on collection, management, and processing of data, information and knowledge, and the incorporation of informatics concepts and theories specific to enrich forest management and forest science; it has a similar relationship to library science and information science. Forest informatics is an interdisciplinary science primarily concerned with the collection, classification, manipulation, storage, retrieval and dissemination of information. As in management science, forest informatics uses decision support systems, mathematical modeling, statistics, and algorithms from engineering, operations research, computer science, and artificial intelligence to support decision-making activities.

Some parameters of forest, such as species composition, density, diameter and height structure, basal area and volume, were always adopted to describe forest structure and constitute information source of forest management in traditional forestry science. But these parameters can not meet the three-dimensional forest management because of lacking spatial information. Now, stand spatial structure defined to the management of the forest using remote sensing and geographic information systems and precise global positioning system has gradually been introduced into forest structure and three-dimensional forest management research. Remote sensing is the use of aerial sensor technologies to detect and classify objects on earth (both on the surface, and in the atmosphere and oceans) by means of propagated signals without making physical contact with the object. Remote sensing is divided into main two main types of remote sensing: passive remote sensing and active remote sensing. Passive sensors detect natural radiation that is emitted or reflected by the object or surrounding areas. Reflected sunlight is the most common source of radiation measured by passive sensors such as film photography, infrared, charge-coupled devices, and radiometers. Active remote sensing emits energy in order to scan objects and areas whereupon a sensor then detects and measures the radiation that is reflected or backscattered from the target such as Radar and LiDAR. Remote sensing makes it possible to collect data on dangerous or inaccessible areas. Remote sensing applications of forestry include forest resource inventory, monitoring growth and deforestation and forest disaster. With its ability to directly measure forest structure, including canopy height and crown dimensions, remote sensing is increasingly used for forest inventories at individual tree level. Previous studies have shown that remote sensing data can be used to estimate a variety of forest inventory attributes including tree, plot and stand level estimates for tree height, biomass (Edson and Wing 2011), volume, basal area (Leckie et al., 2003) and tree species (Katoh et al., 2009). Forest environment depends on the geographical environment, which in turn acts on the surrounding geographical environment. Geographic information system can analyze the effect of forest environment and geographical environment, and lead to decisions regarding for forest management. Geographic information system (GIS) is a system designed to capture, store, manipulate, analyze, manage, and present all types of geographical data. Geographical information science refers to the academic discipline with geographic information systems and is a large domain within the broader academic discipline of geoinformatics.

Remote sensing and geographic information science are used to gain a better understanding of how the underlying spatial patterns of vegetation, forest and natural features are related, ultimately leading to more-informed decisions regarding the sustainable use of resources.

In recent years, how to predict growth of forest was paid more and more attention (FFPRI, 2012). But now it seems that traditional prediction methods can not meet completely the need of modern forest with more emphasis on ecological protective function. Recently in Japan the long rotation management process of conifer plantation is being popular, and through predicting growth of forest plays a very important role for the long rotation management process of conifer plantation. In the traditional forest growth prediction, forest growth prediction systems need consider some factors such as environmental, geography and climate impact on tree growth. The calculation including impact of these factors is complex and difficult for tree growth prediction. Furthermore, how to determine and analyze the affect of these factors is a problem for tree growth prediction. Gray system, which defined gray derivative and differential equation with correlation analysis and smooth discrete function, need not consider the affect of environmental, geography and climate, and may resolve the above shortcomings in predicting forest growth. Because the impact of environment, geography and climate are consider incomplete information, and these impacts were reflected in the basic data of tree in gray theory. Gray system means that a system in which part of information is known and part of information is unknown. With this definition, information quantity and quality form a continuum from a total lack of information to complete information - from black through gray to white. Since uncertainty always exists, one is always somewhere in the middle, somewhere between the extremes, somewhere in the gray area. It defines situations with no information as black, and those with perfect information as white. Gray System Theory is a mathematics theory which can analyze the relevance of clear portion and not clear portion of information. Gray models predict the future values of a time series based only on a set of the most recent data depending on the window size of the predictor. Gray system theory is an interdisciplinary scientific area that was first introduced in early 1980s by Deng (1982). Since then, the theory has become quite popular with its ability to deal with the systems that have partially unknown parameters. As a superiority to conventional statistical models, gray models require only a limited amount of data to estimate the behavior of unknown systems (Deng, 1989). During the last decades, the gray system theory has been developed rapidly and caught the attention of many researchers. It has been widely and successfully applied to various systems such as economic (Wang, 2002), scientific and technological (Lee et al,. 2008), agriculture, industrial, transportation (Guo et al., 2005), mechanical, meteorological, ecological, hydrological, geological, medical, etc., systems. In these studies and the others, it is seen that grey system theory-based approaches can achieve good performance characteristics when applied to real-time systems, since grey predictors adapt their parameters to new conditions as new outputs become available. Because of this reason, grey predictors are more robust with respect to noise and lack of modeling information when compared to conventional methods.

1.2 Objective

Forest resource information, such as species composition, height and DBH, is the basis of sustainable forest management. Traditional field surveys for forest resource management include the number of trees, species and measurements of DBH and tree height in sample plots. One of objectives of this study is to estimate the accurate forest basic data at individual tree level (species, DBH, height, crown area) in the old–growth *Chamaecyparis obtusa* stand which is fixed amount of tree growth stand, based on new remote sensing method and high resolution remote sensing data.

The development of forest growth models can help to formulate management plans for sustainable development, protect forest reserve, and predict yields within the sustainable capacity of the forest, by providing quantitative data which will be made available to forest managers and land use planners. Informed decisions can then be made in regards to silvicultural alternatives. Access to better quantitative information through growth models will lead to increased levels of sustainable timber management. One of the most common and important tree characteristics used in forest management decision-making is tree diameter at breast height (DBH). This variable has numerous beneficial attributes. It is easy to measure and have strong correlations with other tree characteristics. The distribution of trees by DBH class allows foresters and ecologists to understand stand structure, stand dynamics, and future forest diversification. This study also attempted to authenticate the feasibility of tree growth prediction at individual tree level based on estimation data which were estimated from high resolution remote sensing data. Based on forecast data of DBH, forest manager can grasp the change of forest timely, and formulate appropriate management plans for management objective.

The third objective of this study is to develop one systematic system including a accurate forest data estimation system, tree growth prediction system and prediction system for suitable sites of tree growth at individual tree level. Making the system can work efficiently from estimation of forest information to the prediction calculation.

Chapter 2 Study area and survey data

2.1 Overview of plot

Study area and vegetation

The study area is situated in the Akasawa Forest Reserve with an area of about 1046 ha, Kiso town of Nagano Prefecture, central Japan (35°43'57''N, 137°37'50''E) (Figure 1), which was the birthplace of forest bathing and known as one of three most beautiful forests in Japan (NRFO, 1985). The altitude ranges from 1080 to 1558 m above sea level. Annual precipitation is about 2500 mm, and snow accumulation is 50~100 cm per year. The reserve is on an elevated peneplain with a gentle slope. The geology is dominated by acidic igneous rocks such as granitite, granitite porphyry, and rhyolite. Soils are mainly dry and wet podzolic soils, although brown forest soils appear on hillsides and along mountain streams (NRFO, 1985).

Chamaecyparis obtusa generally dominates the canopy layer within the reserve, with occasional associates of *Thujopsis dolabrata* and some hardwoods, while on lower slopes or along mountain streams, *Chamaecyparis pisifera* frequently occurs and dominates in some stands. Old-growth *Chamaecyparis obtusa* stands on this reserve, like other *Chamaecyparis obtusa* forests in the Kiso District, might have been established after the severe cutting during the years 1688-1703 (NRFO, 1985). Since that period most stands have been protected from clear-cutting, although selection cuttings have been made for purposes of forest management.

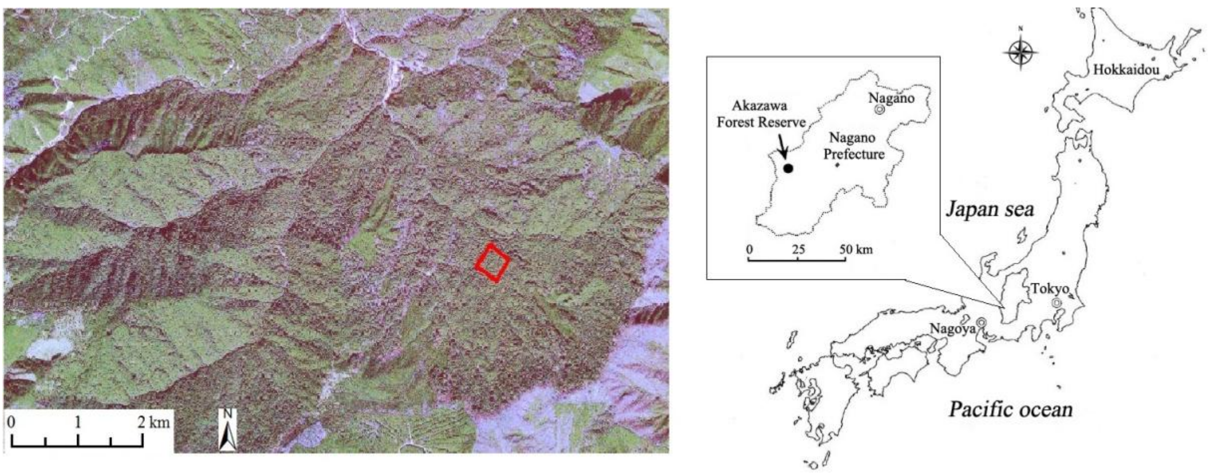

Figure 2-1 The location of Akazawa Forest Reserve

2.2 Basic characteristics of the forest

In 1988, one permanent plot with size of 200 × 200 m was established in an old-growth *Chamaecyparis obtusa* stand with clear-cutting in 350 years ago and selective-cutting in 60 years ago. Field data were collected from 1988 to 2008 of every five years except 1993. All of trees whose DBH was larger than 5 cm were surveyed, including species, DBH, height, crown size, clear bole height and coordinate in 1988, 1998, 2003 and 2008 (Hoshino et al., 2002; Hoshino et al., 2003; Yamamoto, 1993) (Figure 2). The location of plot was confirmed by a handheld GPS device in 2012. Additional Survey was held in 2012. 15 trees of each species were surveyed in different layers, including DBH, height and crown size. And the data was used for regression analysis. Additionally, trees of DBH≥ 5 cm had been confirmed as live or dead and all of live trees were selected to biomass estimation in this study. The positions of all trees in forest from the field survey were registered in the forest database using ArcGIS 10.

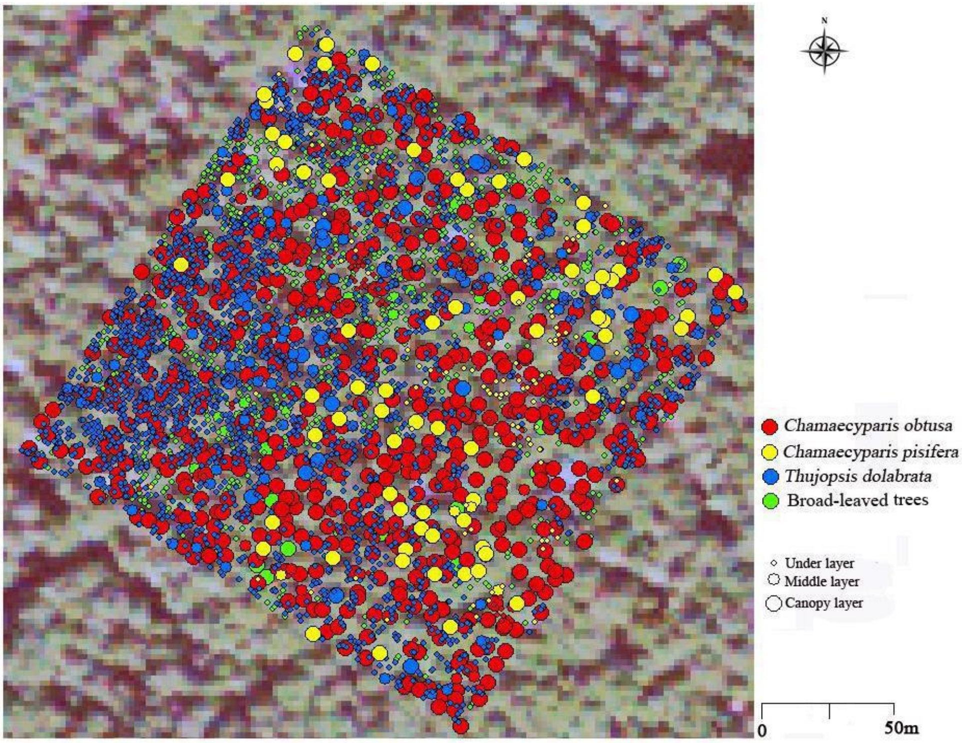

Figure 2-2 Tree stand map with stratum from field-survey data

Total numbers of live trees of the stand in study area was 4811 stems in 2008.

Chamaecyparis obtusa was 702, accounted for about 14.6%. *Chamaecyparis pisifera* was 179, accounted for about 3.7%. *Thujopsis dolabrata* and broad-leaved trees were 2605 and 1325, accounted for about 54.1% and 27.6% respectively (Figure 3).

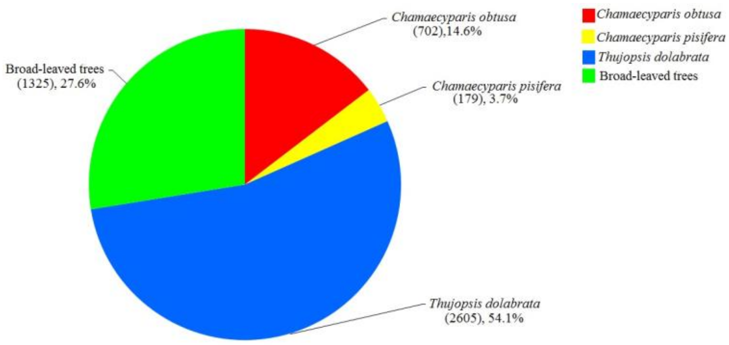

Figure 2-3 Stand Overview

From DBH structure, the stand was dominated by *Chamaecyparis obtusa* in DBH or basal area. Other species dominated in some area where *Chamaecyparis obtusa* did not distributed, such as *Chamaecyparis pisifera*, *Thujopsis dolabrata* and broad-leaved trees. On the other hand, *Thujopsis dolabrata* was absolutely dominant in middle layer and understory (Figure 4). And they were distributed in the under layer of forest together with broad-leaved trees. The DBH structure of *Chamaecyparis obtuse*, the majority of *Chamaecyparis obtuse* are upper layer, accounted for about 82.6%. The DBH structure of *Thujopsis dolabrata* and broad-leaved tree, the majority of them are under growth layer, accounted for about 91.6% and 97.9% respectively (Figure 5). Because in order to promote the recruitment of *Chamaecyparis obtusa*, most individuals of *Thujopsis dolabrata* and broad-leaved tree with large size were cut by clear-cutting in 350 years ago and by selective-cutting in 60 years ago.

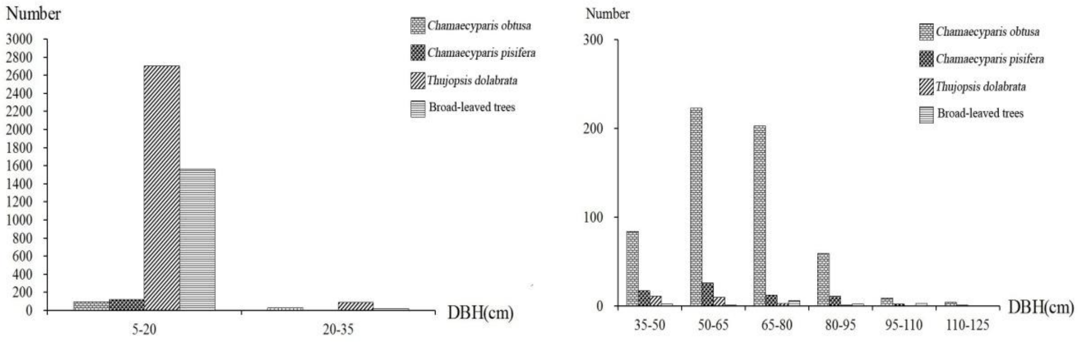

Figure 2-4 DBH distribution by species

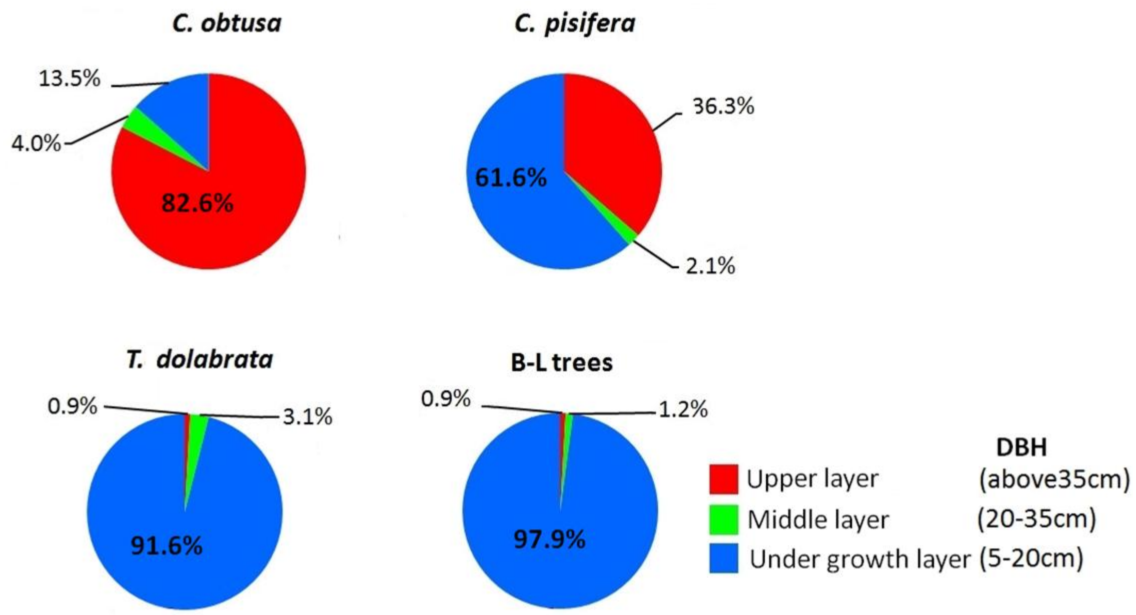

Figure 2-5 Class distributions by DBH

Height-diameter curve

Height-diameter curve explains the relationship of height and DBH which were measured in the same stand and time. Some sample trees of each diameter class were used to determine height curve based on DBH and height. Change of height-diameter curve is small and stable during tree growth in natural forest (Oosumi, 1987). Tree height can be used to estimate DBH with height-diameter curve. In order to generate regressions for the height-diameter equations, height and DBH of 20 trees were collected respectively distrnguishing species *Chamaecyparis obtusa*, *Chamaecyparis pisifera*, *Thujopsis dolabrata* and broadleaved trees. The data were used to carry out regression analysis in Excel 2007(Figure 6), and then height-diameter equations were obtained respectively as follows:

$$H_{C.o} = 1.9243 D_{C.o}^{0.6511}$$

Hc.o is height of *Chamaecyparis obtusa*, $D_{C.o}$ is DBH of *Chamaecyparis obtusa*, and correlation coefficient R^2 is 0.8921.

$$H_{C.p} = 16.079 e^{0.0082 D_{C.p}}$$

$H_{C.p}$ is height of *Chamaecyparis pisifera*, $D_{C.p}$ is DBH of *Chamaecyparis pisifera*, e is constant 2.7183, and correlation coefficient R^2 is 0.7594.

$$H_T = 0.412D_T + 5.3159$$

H_T is height of *Thujopsis dolabrata*, D_T is DBH of *Thujopsis dolabrata*, and correlation coefficient R^2 is 0.9045.

$$H_B = 0.2665D_B + 10.309$$

H_B is height of broadleaved trees, D_B is DBH of broadleaved trees, and correlation coefficient R^2 is 0.9241.

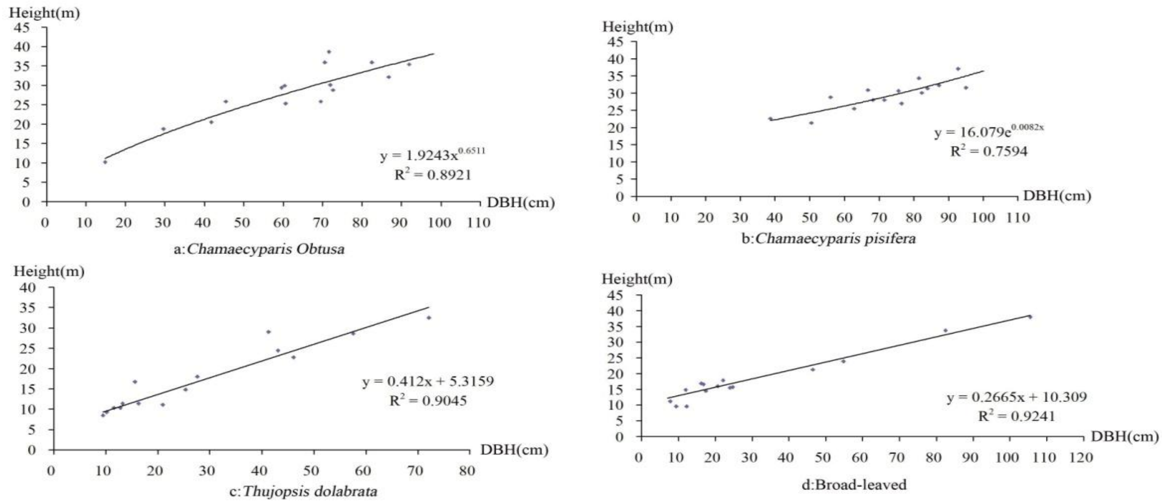

Figure 2-6 Height-diameter curves

Canopy area-diameter curves

Canopy area-diameter curves

The canopy is the main part for tree photosynthesis. The crown development directly affect the growth of trees, which related significance the most to the DBH. Crown radius was measured from four directions of east, south, west and north. And the average crown radius was calculated by the formula:

$$R_a = \frac{(R_e + R_s + R_w + R_n)}{4}$$

R_a is average crown size, R_e, R_s, R_w and R_n were crown radius which were measured in four directions. Then crown projection area can calculate by the formula:

$$S = \pi R_a^2$$

S is crown projection area, π is constant 3.14, R_a is average crown radius.

Regression analysis for crown and DBH was generated with Excel 2007 (Figure 7), and crown size-diameter equations of tree species were obtained respectively as follows:

$$S_{C.o} = 0.1298 D_{C.o}^{1.4386}$$

Sc.o is canopy area of *Chamaecyparis obtusa*, $D_{C.o}$ is DBH of *Chamaecyparis obtusa*, and correlation coefficient R^2 is 0.8834.

$$S_{C.p} = 155.4 D_{C.p}^{0.4724}$$

$S_{C.p}$ is canopy area of *Chamaecyparis pisifera*, $D_{C.p}$ is DBH of *Chamaecyparis pisifera*, and correlation coefficient R^2 is 0.107.

$$S_T = 43.748 \ln(D_T) \quad 95.471$$

S_T is canopy area of *Thujopsis dolabrata*, D_T is DBH of *Thujopsis dolabrata*, and correlation coefficient R^2 is 0.83.08.

$$S_B = 0.451 D_B + 1.3069$$

S_B is canopy area of broadleaved, D_B is DBH of broadleaved, and correlation coefficient R^2 is 0.6949.

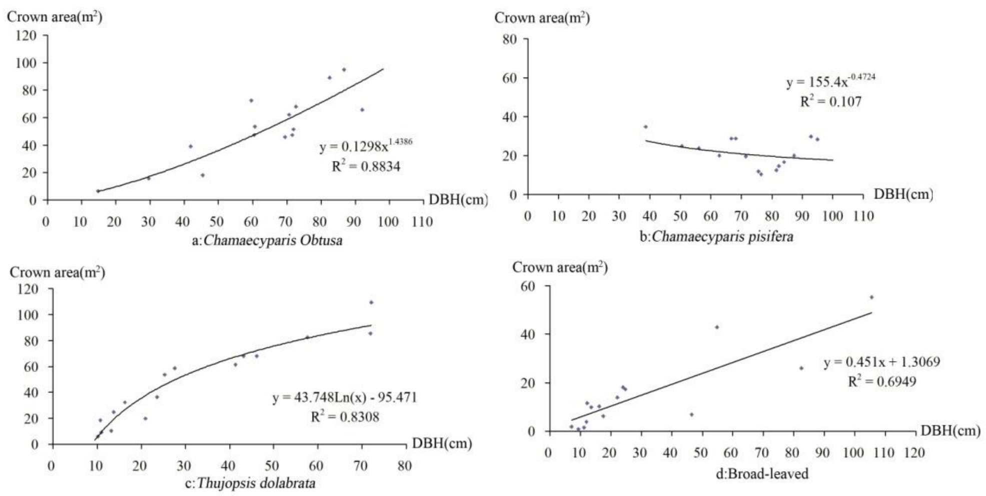

Figure 2-7 Canopy area-diameter curves using survey data

2.3 Biomass estimation method

The measurement of forest aboveground biomass involves extensive field surveys. The destructive weighting method is conducted by removing the leave and branches from trees step by step, and then weighting the cut-off materials successively. This direct measurement means is accurate, but it can obtain only single tree in general, and it is not suitable for research on the spatial distribution of biomass and changes. Moreover, destructive weighting biomass is forbidden in most environments. Biomass expanding coefficient method is small error, but laborious and expensive. Through regression analysis, numerical relationships of height-DBH and crown size-DBH curve were obtained, which would be used to calculate tree height and crown projection area of each tree. In addition, volume can be calculated with formulas of stem volume table (Forestry Agency Planning Division, 1970).

According to the estimation data of DBH and height, the biomass of each tree can be calculated with expanding coefficient method:

$$B = V \times BEF \times D$$

B is biomass, V is volume of tree, BEF is biomass expanding coefficient and D is bulk density.

Estimation error for the four levels: all trees, the trees with DBH ≥35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm distinguishing species, may be calculated by the formula as follows:

$$\varphi = (X - M) \div X \times 100$$

where φ is estimation error, X is the biomass of trees calculated by survey data, and M is estimated biomass.

Chapter 3 Estimation for forest information using ITC method and satellite data at individual tree level

Some parameters, such as species composition, density, diameter and height structure, basal area and volume, were always adopted to describe forest structure in traditional forestry science, and they were classical and essential in forest research. But these indices lacked detailed spatial information, which led to that we did not know how to choose the objective trees in selection cutting and were difficult to evaluate the effect of management. Traditional approach of forest survey could not meet the need of modern forest management completely. In addition, traditional approach of forest survey is time-consuming, laborious and expensive, and it cannot be used for observation on large regional scales, although it is small error. Now stand spatial structure defined to management of the forest using remote sensing and Geographic information systems and other advanced technologies has gradually become the focus in forest structure research.

3.1 Individual Tree Crown (ITC) Method

Individual Tree Crown (ITC) method was developed by Gougeon in 1995. This method is a new method of digital remote sensing data analysis with the purpose of extracting individual tree crown based forestry parameters as automatically as possible, such as individual tree species and canopy area, crown and tree top extraction, stem density, crown closure and gap distribution. The method and its variants have shown good results in conifer stands, especially moderately dense stands (Andrew et al., 1999; Leckie et al., 1999). It is based on the assumption that on spectral imagery, trees are represented by bright pixels surrounded by lower intensity pixels in shaded areas or less illuminated parts of the crown. It is treating the intensity image like a topographic surface, thus it is a well-suited algorithm for isolating trees on satellite data or multi-color data as well.

3.2 Estimation forest information using satellite data

Satellite data and processing

The optical satellite sensor GeoEye-1 was launched in 6 September, 2008. Image data were acquired on 27 October 2011 during clear weather conditions. The sensor provides panchromatic image at a geometric resolution of 0.41 m and 1.65m multi-spectral image in 15.2 km swaths. The spectral ranges of the four bands are 0.45–0.51 μm (band 1, coastal blue), 0.51–0.58 μm (band 2, green), 0.655–0.69 μm, (band 3, red), 0.78–0.92 μm (band 4, near-infrared), stored as 16-bit data. The spacecraft is intended for a sun-synchronous orbit at an altitude of 681 km and an inclination of 98 degrees, with equator crossing time. GeoEye-1 can image up to 60 degrees off nadir. The original images with sensor orientation, topographic relief displacement, and systematic errors were rectified by ortho-correction based on X, Y, and Z values for sensor positions derived from a GPS system and the principal points and focal length of the sensor. The geographic projection was converted to WGS84 north Zone 54. The ground resolution of the multi-image was 2 m， and the ground resolution of panchromatic image was 50 cm after correction.

The geographic projection was converted to WGS84 north Zone 54, and study area was extracted from the multi-image and panchromatic-image respectively with GPS data and software ERDAS IMAGINE 8.6. Pixels classification on the extraction image was used to species classification. The training areas with *Chamaecyparis obtusa*, *Chamaecyparis pisifera*, *Thujopsis dolabrata* and broadleaved trees were selected from the field survey.

On the other hand, ITC (Individual Tree Crown) method was used for tree tops, tree-crown delineations and species classifictiion of delineated tree-crown. ITC method is a new method of digital remote sensing data analysis with the purpose of extracting individual tree crown based forestry parameters as automatically as possible, such as individual tree species and canopy area, crown and tree top extraction, stem density, crown closure and gap distribution. GeoEye-1panchromatic image was used to delineate forest area and non-forest area based on THR (thresholding Image to bitmap) method. This method creates the boundary of each segment based on the spectral values which was specified range of non-forest area. It was important to separate non-forest regions in the image, such as roads and gap of crown. On this basis, the valley-following method from the NIR band of GeoEye-1 multi-color image was used to delineate tree crown (Gougeon 1995). This method compares the spectral values of each pixel, and then it treats the spectral values of the imagery as topography with shaded and darker areas representing valleys and bright pixels of the tree crowns. It produces a bitmap of segments of valley and crown materials. A rule-based system follows the boundary of each segment of crown material to create isolations, which are taken to represent tree crowns. The ITC image was classified into species using a supervised classification process of multi bands based on comparing crown signatures (Katoh 2009). Tree top detection method was used to detect tree tops of canopy tree and count their numbers automatically. Bitmap of tree tops was created based on the highest spectral values of pixels within delineated crown. It confirmed the number of canopy trees. Canopy area can be used to calculate the DBH using the result of image analysis and crown size-DBH regression equation. Then, projection results of DBH can be used to calculate the height based on height-diameter equations. Finally, the volume and biomass can be calculated based on volume formula and expanding coefficient method respectively.

Panchromatic image was necessary to do smoothing based on their own ranges in the illumination image before crown extraction, which was done twice to smooth using an averaging filter of 3× 3 pixels (1.5 by 1.5 m). And the non-forest mask was established after the smoothing process. Typically, it smoothed the small tree areas with a 3x3 average filter, and the big tree areas with a 5x5 filter on top of the 7x7 smoothing. However smoothing process was done by 3x3 average filters, although it is 350 years old-growth forest. Because tree crown growth was affected by high canopy density in this old-growth forest, and the diameter of the tree crowns ranged from 3 to 5 m, a filter size of 3 × 3 pixels was more suitable than 5×5 or 7× 7 pixels. The process was used to mask non-forest areas of the image, such as road and gap between crowns. The ITC isolation image was formalized the outlines of tree crowns and tree clusters partially delineated using valley-following approach producing an output bitmap representing lines and areas of shaded material between tree crowns depending on the non-forest mask. This is done by the valleys of shaded material (dark) between brighter tree crowns. Processing on details can be conducted aiming at some special areas, and the unnecessary or erroneous points can be revised or deleted (Figure 8).

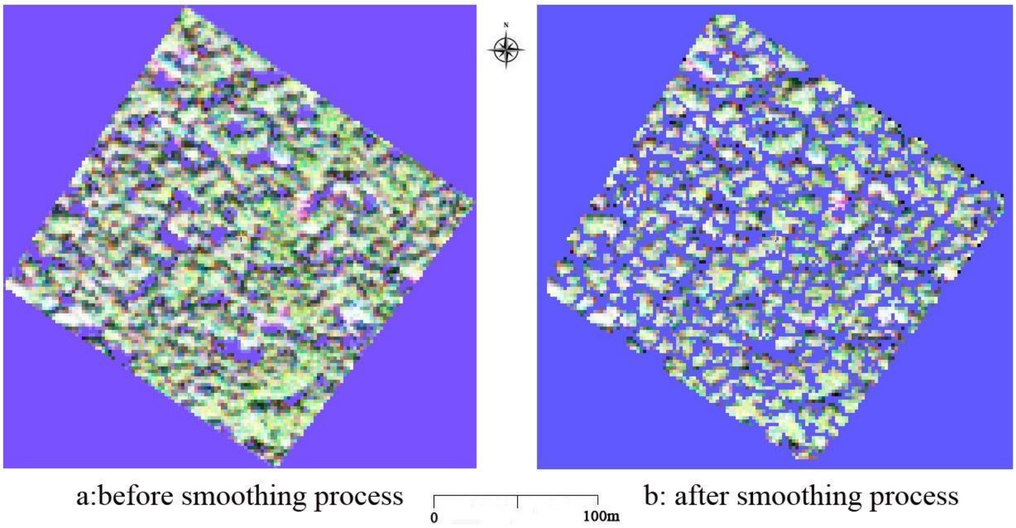

Figure 3-1 Distinction of forest and non-forest

3.3 Results

Estimation for tree information

Some errors were generated from the automatic extraction in the tree crown delineation image, such as tree crown cross and split. The crown delineation processes may have difficulties with these trees which crowns were split up or merged. But this has little influence on this study, as the total number of trees is concerned for biomass estimation. Furthermore, tree tops extraction was used to detect number of these delineated crowns in medium to densely populated areas where some crowns had not been extracted yet apparently visible trees. This program moves a window of a given size on ITC isolation image and detects the local “centered” Gray-level maximum of each window's instance. Delineated crowns in the images corresponded well to dominant trees in the high-density field. In this study, 282 of tree crowns and 352 of tree tops were extracted (Figure 9). The number of crowns from the image analysis was fewer than the stems from the field survey, primarily because some trees in the image were misidentified as one large tree crown rather than a cluster of trees. In order to examine the accuracy of estimated the count of the number of trees using the new method, the number of estimation had been compared with field survey at four levels, including all trees, the trees with DBH ≥35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm distinguishing species (Table 1). The errors for all trees, DBH ≥ 35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm of *Chamaecyparis Obtusa* were 63.39%, 55.84%, 48.39%, and 6.55% respectively. For *Chamaecyparis pisifera*, they ranged from -46.15% to 78.77%. The error for tree number of *Thujopsis dolabrata* ranged from -500% to 99.08%, and these of broad-leaved trees ranged from -200% to 97.28%.

The results indicated that tree number estimation of *Chamaecyparis pisifera* was inferior to *Chamaecyparis Obtusa* owing to their large crowns and same spectrum characteristics resulted in one crown being sometimes misidentified as a cluster of crowns. The tree number estimation error for *Thujopsis dolabrata* and broad-leaved trees *were* relatively large, because *Thujopsis dolabrata* was absent in the large classes, while occurred in the small classes. And multilayered stands have some intermediate or understory trees that are difficult to be extracted using image analysis.

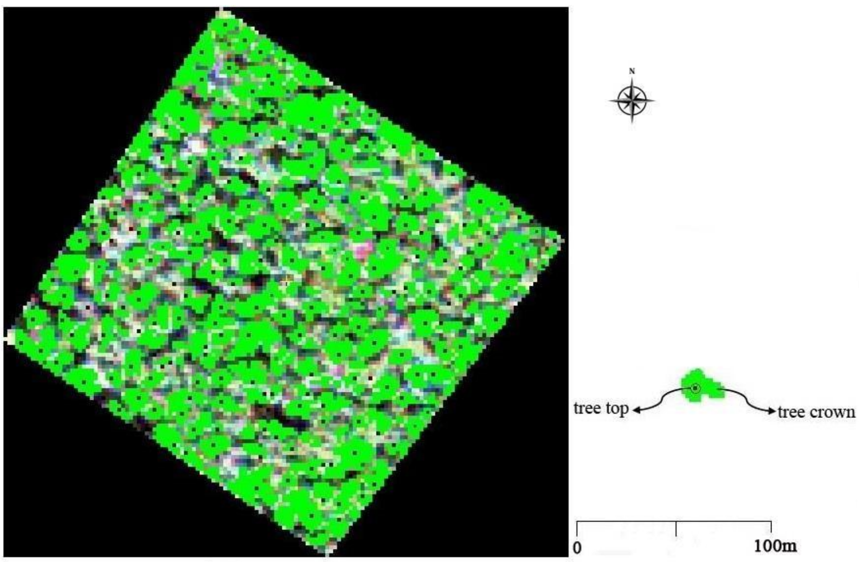

Figure 3-2 Crown and tree tops extraction

Table 3-1 Accuracy of tree number estimation

Species	Field survey data				Estimated data	Error(%)			
	All Stems	DBH≥ 35cm	DBH ≥50cm	DBH ≥65cm		All Stems	DBH ≥35cm	DBH ≥50cm	DBH ≥65cm
Chamaecyparis obtusa	702	582	498	275	257	0.63	0.56	0.48	0.07
Chamaecyparis pisifera	179	69	52	26	38	0.79	0.45	0.27	-0.46
Thujopsis dolabrata	2605	25	14	4	24	0.99	0.04	-0.71	-5.00
Broad-leaved trees	1325	16	14	12	36	0.97	-1.25	-1.57	-2.00

Estimation for forest biomass by species at individual tree level

There are numerous approaches to estimate aboveground dry biomass from satellite data. Regression analysis is the most common modeling approach, using most studies relating vegetation indices based on red and near-infrared (NIR) wavelengths with their field measurements. However, apart from the enhanced vegetation index (EVI), which was proved to be sensitive to canopy variations, and have achieved moderate success in old-growth forest, where biomass levels are high and forest canopy is closed with multiple layers. The method can capable of producing data at large areas, but it is just a rough estimate, for individual tree level the related accuracies generally are not satisfactory.

Therefore, this study focuses on the concrete methods for acquiring biomass. For accurate measurement of forest biomass in the Akazawa Forest Reserve, this study analyzed texture measures derived from GeoEye-1 satellite data using the new remote sensing method. The goal is to develop improved biomass estimation models whether analysis objects is individual tree or large areas of forest, and evaluating both spectral and textural information.

Two methods were used to classify tree species as *Chamaecyparis obtusa*, *Chamaecyparis pisifera*, *Thujopsis dolabrata* and broadleaved trees. Firstly, pixel based classification of the extraction image from multi-spectral images was fed into a supervised classification process, with training some areas of *Chamaecyparis obtusa*, *Chamaecyparis pisifera*, *Thujopsis dolabrata*, broadleaved trees and gaps based on the field survey (Figure 10). According to the results of the pixel based classification, the accuracy of *Chamaecyparis obtusa* was higher than other species, and the *Chamaecyparis pisifera* had a lowest accuracy (Table 2). Because *Chamaecyparis obtusa* dominated in this field. On the other hand, *Chamaecyparis obtusa* and *Chamaecyparis pisifera* belong to the same cupressaceae, and they have similar spectrum characteristics and are difficult to be distinguished in the multi-spectral images. Therefore, some pixels of *Chamaecyparis pisifera* might be misclassified into *Chamaecyparis obtusa* mutually in the classification process. Additionally, some *Thujopsis dolabrata* were misclassified into gaps, because small *Thujopsis dolabrata* distributed in these gaps.

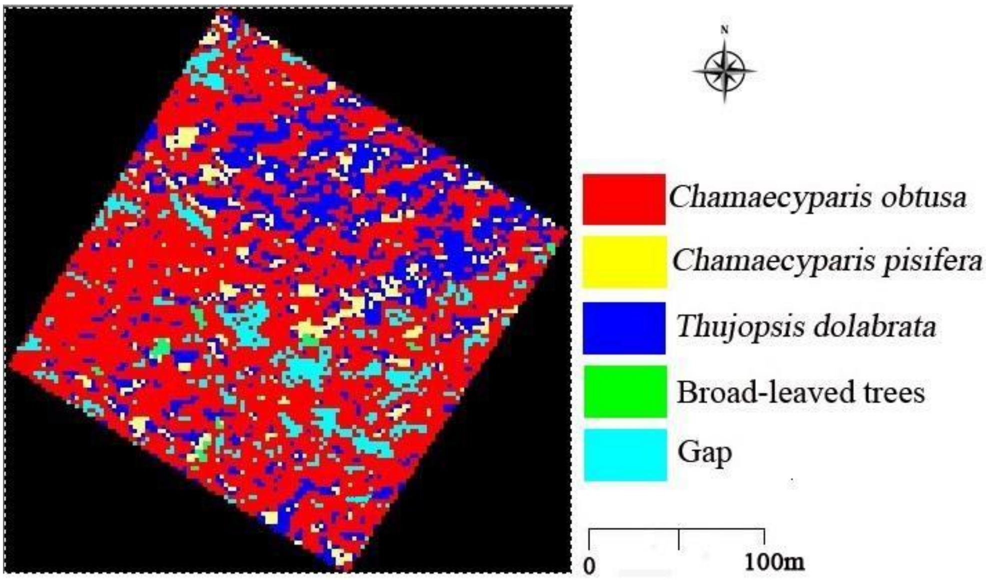

Figure 3-3 Tree species classification with pixel

Table 3-2 Accuracy of tree species classification by pixel

Class name	Class NO.	1	2	3	4	5	Producter's accuracy(%)
Chamaecyparis obtusa	1	64	1	1	1	0	95.5
Chamaecyparis pisifera	2	16	15	0	2	0	45.5
Thujopsis dolabrata	3	4	0	34	0	3	82.9
Broad-leaved trees	4	1	1	0	9	0	81.8
Gap	5	1	0	2	0	24	88.9
User's accuracy(%)		74.4	88.2	91.9	75.0	88.9	

Secondly, the ITC isolation image and multi-spectral images were fed into a supervised classification process with training areas as the same classes as above (Figure 11). Results of indicated that *Chamaecyparis obtusa* had highest accuracy of classification, while that of broad-leaved trees was lowest (Table 3). Because crown size of broad-leaved trees is small in the high-density forest. Biomass estimation is necessary to confirm the species of crown. In the supervised classification, the ITC isolation mask and multispectral images were used to identify species for each crown (Figure 11). The results of crown classification shows tree crown species, size, density, and position. A comparison of the locations of canopy trees identified using the tree crown extraction method within the stand with those mapped through field survey indicated a close correspondence. Three counts of trees were compared against the field data; tree tops identified using local maxima filtering within the smoothed image, crowns identified using the ITC delineation and both treetops and crowns identified using pixel classification and crown classification. The number of crown was 282, tree tops was 352. These results showed that the number of trees by species determined by the new tree top method were less accurate than the total number of trees using the new method. This may be due to the underestimation of *Chamaecyparis Obtusa*, *Chamaecyparis.Pisifera* and *Thujopsis dolabrata*. Thus, the method can be used effectively to extract the number of stems of upper and intermediate canopy trees in pure conifer plantations when multiple layers or high densities are not involved.

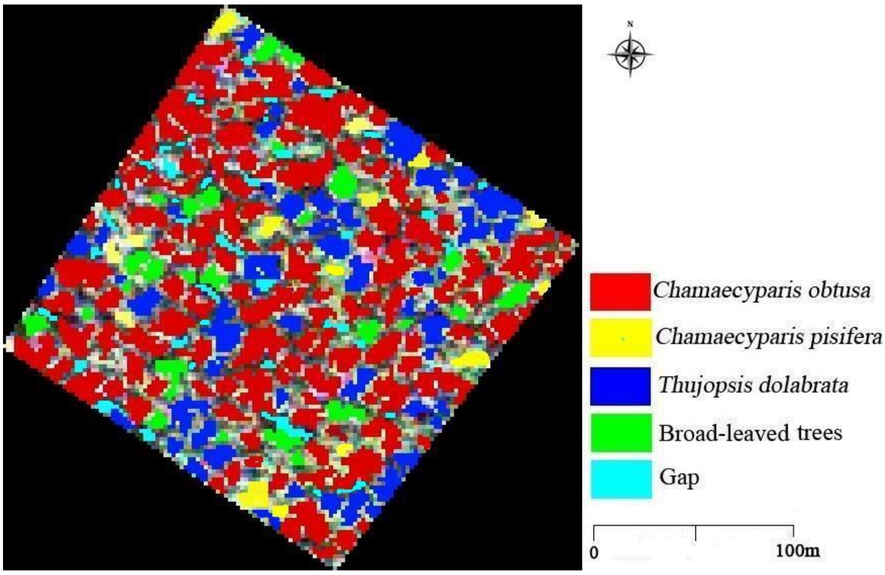

Figure 3-4 Classification of tree crown by species

Table 3-3 Accuracy of classification of tree crown by species

Class name	Class NO.	1	2	3	4	5	Producer's Accuracy (%)
Chamaecyparis obtusa	2	12	86	0	2	0	86.8
Chamaecyparis pisifera	1	32	6	0	0	0	84.2
Thujopsis dolabrata	3	0	2	56	0	4	90.3
Broad-leaved trees	4	0	0	2	20	0	91
Gap	5	0	0	6	0	36	85.7
User's accuracy(%)		72.7	91.5	87.5	91	90	

In order to examine the accuracy of estimated biomass using the new method, the biomass of estimation had been compared with field survey at four levels, including all trees, the trees with DBH ≥35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm distinguishing species (Table 4). The errors for all trees, DBH ≥ 35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm of *Chamaecyparis Obtusa* were 16.1%, 11.94%, 12.36%, and -12.63% respectively. For *Chamaecyparis pisifera*, they ranged from-7.69% to 41.67%. The error for biomass estimation of *Thujopsis dolabrata* ranged from -370.58% to 78.67%, and these of broad-leaved trees ranged from -36.36% to 34.78%. The results indicated that biomass estimation of *Chamaecyparis pisifera* was inferior to *Chamaecyparis Obtusa* owing to their large crowns and same spectrum characteristics resulted in one crown being sometimes misidentified as a cluster of crowns. Furthermore, *Chamaecyparis pisifera* and broad-leaved trees were disadvantage of competition with *Chamaecyparis Obtusa*, which makes canopy area of *Chamaecyparis pisifera* smaller. Therefore, a large error of estimated DBH were produced using DBH-crown curve. The biomass estimation error for total of *Thujopsis dolabrata was* relatively large, because *Thujopsis dolabrata* was absent in the large classes, while occurred in the small classes. And multilayered stands have some intermediate or understory trees that are difficult to be extracted using image analysis.

Table 3-4 Accuracy of biomass estimation

Species	Field survey data (t/ha)				Estimated data (t/ha)		Error (%)		
	All trees	DBH≥ 35cm	DBH≥ 50cm	DBH≥ 65cm		All trees	DBH≥ 35cm	DBH≥ 50cm	DBH≥ 65cm
Chamaecyparis Obtusa	103.31	10.22	9.87	7.68	8.65	16.10	11.94	12.36	-12.63
Chamaecyparis Pisifera	0.24	0.22	0.2	0.13	0.14	41.67	36.36	30.00	-7.69
Thujopsis dolabrata	0.75	0.13	0.085	0.034	0.16	78.67	-21.21	-88.24	-370.59
Broad-leaved trees	0.23	0.13	0.12	0.11	0.15	34.78	-15.38	-25	-36.36

In this chapter, a new remote sensing method was used to explore the potential of GeoEye-1 data for estimation of tree counting and biomass estimation of old-growth forest. The new method might be workable for the biomass estimation whether research object is individual tree or forest in canopy layer. Three kinds of errors were generated from estimation of tree counting and biomass estimation. Firstly, tree height is necessary to calculate volume and biomass. Height-diameter curve was used to estimate each tree height based on survey, and error was generated in this estimation process. LIDAR (Light Detection and Ranging, Laser Imaging Detection and Ranging) data may resolve shortcomings in tree height estimation, which had been demonstrated potentially in measuring forest biomass. Secondly, the error was emerged in step of crown extraction. These errors because of the crown cross and split up, it was caused in canopy area calculation. In order to reduce the error, separation processing or connection was done manually by delineating crowns on the screen using the image editor of the Geomatica software. For the crown which can not be divided, canopy area was calculated as one crown. But this has little influence on this study, as the total number is concerned for biomass estimation. Because the DBH will change with the canopy area. Additionally, the crown of some trees couldn't be extracted in middle layer or under layer such as *Thujopsis dolabrata*. Because multilayered stands have some intermediate or understory trees that are difficult to extract using image analysis. Thirdly, the pixel based classification and object based classification produced errors in species classification and tree crown identification. Because *Chamaecyparis obtusa* and *Chamaecyparis pisifera* have similar spectrum characteristics, which led to one crown was sometimes misidentified as a cluster of crowns.

The precision of biomass estimation for some species is not satisfied, and the main reasons are the poor precision of some species in satellite image and canopy area estimation. New instruments of higher resolutions in spatial, temporal and spectrum are devised for determining reliable forest aboveground biomass. With the development and improvement of the theories and models for biomass estimation by using of remote sensing data, great progress will be taken in the research of forest biomass on large scales.

Some improved approaches for biomass estimation by species could attain high accuracy by combining with these methods. The next research subjects will include further application and testing extend larger areas, multiple scenes, varied topographies and different forest conditions using some other remote sensing data. Detailed comparisons with field survey results will be required to better ascertain the ultimate accuracy of this new method.

Chapter 4 Improved estimation for forest information at the individual tree level using multispectral airborne data and LiDAR data

An integrated airborne measuring system offers high resolution multispectral data and LiDAR data for rapid tree species classification, estimating tree heights, timber volume, and forest biomass over designation areas. The airborne sensor can provide higher resolution data than satellite, and it helps to improve the classification accuracy of tree species, extract crowns of the under growth layer and estimate biomass. The LiDAR-based methods are less weather-dependent and capable of producing data from large areas with high temporal resolutions.

4.1 Multispectral Airborne Data and processing

The airborne sensor measure system was used in an aircraft developed by Asia Air Survey and contained a digital measurement camera (DMC). The image data have good color reproduction which was acquired by DMC. In addition, multi-color (Multi) data, panchromatic image and near-infrared image can be shot at one time without changing lens. Lens focal length of DMC is 120 mm. The image data were acquired on 30 September 2010 during good weather and clear skies. Full-size images had multi-color (Multi) data consisting of four bands (visible blue, green, red, and near-infrared (NIR)) for 7680 lines × 13824 pixels at nadir with 16-bit data stored. The original images with sensor orientation, topographic relief displacement, and systematic errors were rectified by ortho-correction based on X, Y, and Z values for sensor positions derived from a GPS system and principal points and focal length of the sensor. The geometric projection was converted to WGS84 north Zone 54. The ground resolution of the Multi image was 20 cm after correction. Image processing and analysis were performed using ortho-correction processing in ERDAS IMAGINE 8.6 (ERDAS, 2012) and a tree-based stand map of field data was processed in ArcGIS 10. Tree-top detection and tree-crown delineations were performed using the Individual Tree Crown (ITC)-Suite (Gougeon and Leckie, 2003) in Geomatica 9.1(Geomatica 9, 2005).

Airborne multispectral data offers exhaustive information of forest including forest edge and gaps. Some small trees located in the forest edge and gaps, and much of them are in understory layer. Near-infrared band of image was necessary to do smoothing based on their own ranges in the illumination image before crown extraction, which was done twice to smooth using two averaging filter of 3× 3 (0.6 by 0.6 m) pixels and 7×7(1.4 by 1.4 m) pixels. Typically, it smoothed the undergrowth layer areas with a 3x3 average filter, and the large crown areas with the 7×7 smoothing. However, the mask of non-forest areas, small crown areas and large crown areas can not be established well with smoothing processes were done by 3×3 or 7×7 average filters separately. Therefore, firstly, the non-forest mask was created based on luminance the pixel value of the image, which was used to distinguish forest area and non-forest area. Then, small crown area mask and large crown area mask were created based on the range of luminance values in the image. Among the two areas, one area was come under smoothing processing when another area was covered. Because smoothing processes is too big for under growth trees by windows size 7×7, it caused that small tree crowns were often merged in high-density stands or cannot be delineated. On the other hand, smoothing processes is too small for canopy trees by windows size 3×3 or windows size 5×5, it caused that the larger crowns were often split up. Therefore, the image was divided into three regions: larger crown areas, small crown areas and gaps based on the spectral values of Near-infrared band of the image. The smoothing processes of large crown areas was done by window size 7×7 based on concealing other areas which were designated as non forest mask and small crown areas mask. Similarly, the smoothing processes of small crown areas were done by window size 3×3 based on concealing other areas which were designated as non forest mask and large crown areas. The ITC isolation image was formalized the outlines of tree crowns and tree clusters partially delineated using valley-following approach producing an output bitmap representing lines and areas of shaded material between tree crowns depending on the non-forest mask. This is done by the valleys of shaded material (dark) between brighter tree crowns. Processing on details can be conducted aiming at some special areas, and the unnecessary or erroneous points can be revised or deleted (Figure 12). This done improved the accuracy of forest information estimation, although some errors were generated from the automatic extraction in the tree crown delineation image, such as tree crown cross and split. The crown delineation processes may have difficulties with these trees which crowns were split up or merged. But this has little influence on this study, as the total number of trees is concerned for biomass estimation. Furthermore, tree tops extraction was used to detect the number of these delineated crowns in medium to densely populated areas where some crowns had not been extracted yet apparently visible trees. This program moves a window of a given size on ITC isolation image and detects the local “centered” Gray-level maximum of each window's instance. Delineated crowns in the images corresponded well to dominant trees in the high-density field. In this study, 673 of tree crowns and 953 of tree tops were extracted in the large crown areas, and 1408 of tree crowns and 1452 of tree tops were extracted in the small crown areas. The number of crowns from the image analysis was fewer than the stems from the field survey, primarily because some trees in the image were misidentified as one large tree crown rather than a cluster of trees.

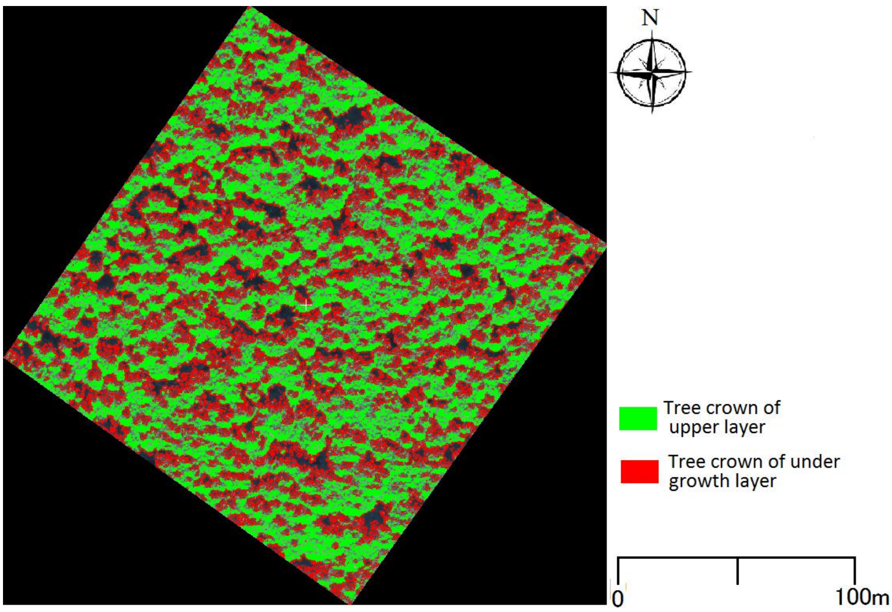

Figure 4-1 Large crowns and Small crowns extraction

4.2 LiDAR data and processing

Lidar is a remote sensing technology that measures distance by illuminating a target with a laser and analyzing the reflected light. The term "lidar" comes from combining the words light and radar. Lidar is popularly used as a technology to make high resolution maps, with applications in geomatics, archaeology, geography, geology, geomorphology, seismology, forestry, remote sensing, atmospheric physics, airborne laser swath mapping (ALSM), laser altimetry, and contour mapping. Lidar combined laser’s focused imaging with radar’s ability to calculate distances by measuring the time for the signal to return. Airborne lidar sensors are used by companies in the remote sensing field. It can be used to create DTM (Digital Terrain Models) and DEM (Digital Elevation Models), which is a common practice for larger areas as a plane can take in a 1 km wide swath in one flyover. An airborne lidar sensor is able to obtain the height of the canopy as well as the ground elevation. A reference point is needed to link the data with the WGS (World Geodetic System). In this study, LiDAR data was acquired on 26 September 2010 from a helicopter. Average density was about 5/m^2. The LiDAR data were geometrically corrected by software ENVI LIDAR3.2 using the DGPS-derived aircraft locations and INS data. And digital elevation model (DEM) data and digital surface model (DSM) data were created with 50cm high resolution using software ENVI LIDAR3.2 at the same time. Then, digital canopy height model (DCHM) data were created with the same resolution by subtracting DSM from the composite DEM using software ArcGIS 10. The Pixel value of DCHM data is tree height, which could be estimated from the DCHM data with the positions of tree tops using ArcGIS 10 (Figure 13).

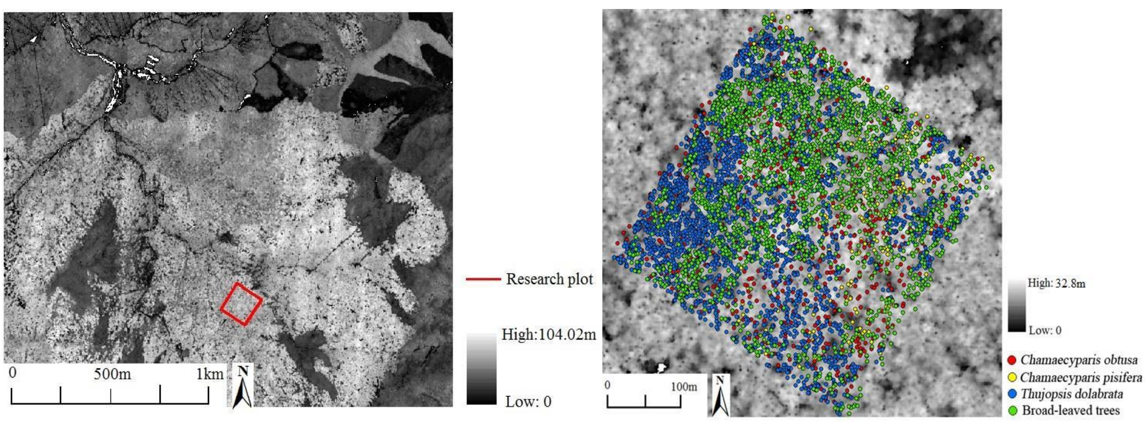

Figure 4-2 Estimation for tree height by tree species using DCHM data

4.3 Biomass estimation method

Biomass calculation needs to calculate volume, and volume calculation needs DBH and tree height. According to estimation crown area, regression analysis for crown diameter-DBH curves was generated within Excel 2007 (Figure 14), the DBH can be calculated by crown size-diameter equations of tree species as follows:

$$S_{C.o} = 2.7345e^{0.0154D_{C.o}}$$

Sc.o is canopy area of *Chamaecyparis obtusa*, $D_{C.o}$ is DBH of *Chamaecyparis obtusa*, and the determination coefficient R^2 is 0.7864.

$$S_{C.p} = 42.408e^{-0.004D_{C.p}}$$

$S_{C.p}$ is canopy area of *Chamaecyparis pisifera*, $D_{C.p}$ is DBH of *Chamaecyparis pisifera*, and the determination coefficient R^2 is 0.1716.

$$S_{T.d} = 1.6381D_{T.d} - 1.0767$$

$S_{T.d}$ is canopy area of *Thujopsis dolabrata*, $D_{T.d}$ is DBH of *Thujopsis dolabrata*, and the determination coefficient R^2 is 0.8354.

$$S_B = 0.4959D_B + 2.2679$$

S_B is canopy area of broadleaved trees, D_B is DBH of broadleaved trees, and the determination coefficient R^2 is 0.6752.

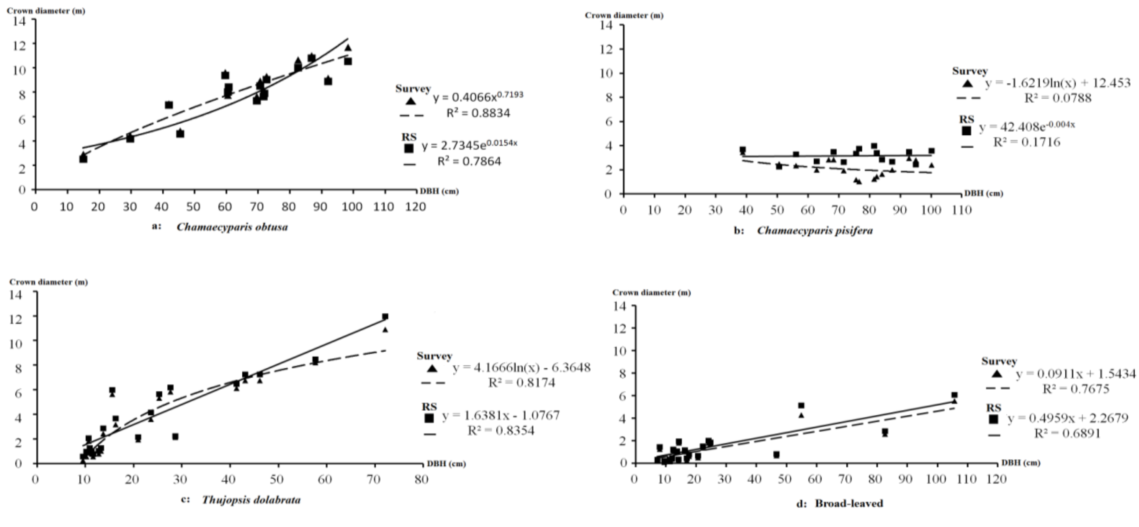

Figure 4-3 Crown diameter-DBH curves by estimation data

Based on crown diameter-DBH curves, the estimation accuracy of biomass for

Thujopsis dolabrata was increased, and the estimation accuracy of biomass for *Chamaecyparis obtusa* was decreased. Because high resolution multispectral airborne data can be used to increase crown extraction of *Thujopsis dolabrata*, but it resulted that the large crown of *Chamaecyparis obtusa* was divided in the crown extraction process.

According to the estimation results of DBH and height, the biomass of each tree can be calculated with expanding coefficient method:

$$B = V \times BEF \times D$$

B is biomass, V is volume of tree, BEF is biomass expanding coefficient and D is bulk density.

Estimation error for the four levels: all trees, the trees with DBH ≥35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm distinguishing species, may be calculated by the formula as follows:

$$\varphi = (X - M) \div X \times 100$$

where φ is estimation error, X is the biomass of trees calculated by survey data, and M is estimated biomass.

4.4 Results

Tree species classification

Airborne multispectral data offer higher resolution than satellite data. This helps to improve the estimation accuracy of forest information. Object-based supervised classification was used to classify tree species into *Chamaecyparis obtusa*, *Chamaecyparis pisifera*, *Thujopsis dolabrata* and broadleaved trees. The ITC isolation image and multi-spectral images were fed into a supervised classification process with training areas as the same classes as classified by GeoEye-1 (Figure 15). The kappa coefficient indicates a classification accuracy of 93.6%. Results indicated that *Chamaecyparis obtusa* had the highest accuracy of classification, while that of broad-leaved trees was lowest (Table 5). This is because *Chamaecyparis obtusa* dominate in this field. On the other hand, *Chamaecyparis obtusa* and *Chamaecyparis pisifera* belong to the same cupressaceae, and they have similar spectrum characteristics and are difficult to be distinguished in the multi-spectral images. Therefore, some pixels of *Chamaecyparis pisifera* might be mutually misclassified into *Chamaecyparis obtusa* in the classification process. Additionally, some *Thujopsis dolabrata* were misclassified into gaps and shadow, because small *Thujopsis dolabrata* distributed in these gaps and forest edge.

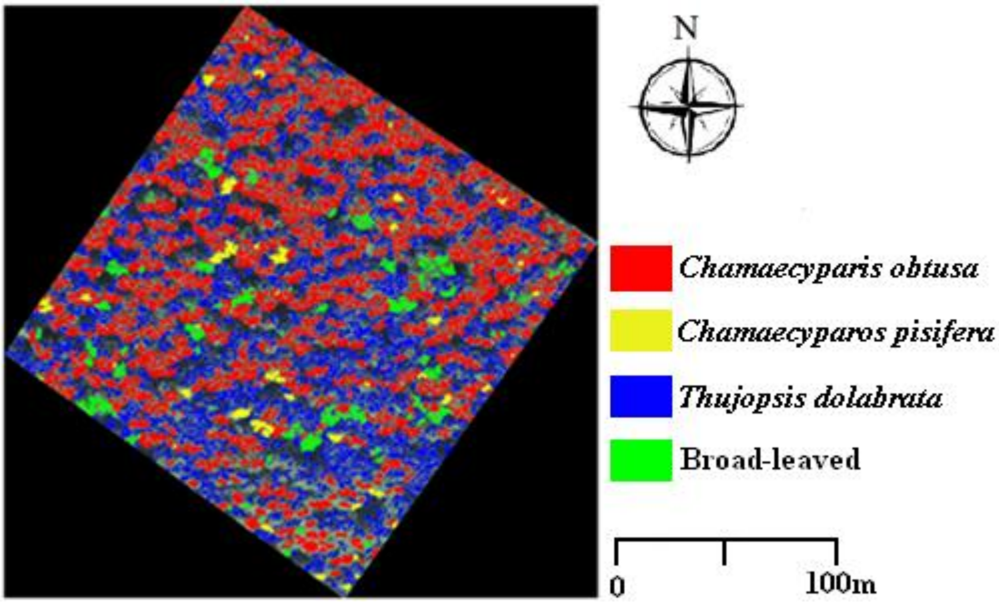

Figure 4-4 Object classification of tree crown by species

Table 4-1 Accuracy of object classification of tree crown by species

Class name	Class NO.	1	2	3	4	5	Producer's accuracy(%)
Chamaecyparis obtusa	1	102	8	0	0	0	92.7
Chamaecyparis pisifera	2	13	52	0	0	0	80
Thujopsis dolabrata	3	0	5	134	7	12	84.8
Broad-leaved trees	4	0	0	11	56	6	67.5
Gap	5	0	0	13	2	38	71.6
User's accuracy(%)		88.6	80	84.8	86.1	67.8	

Crown of species identification

The location image of tree tops, object-based classification of tree crown image and location map were used for localization processing to identify species. A comparison of the locations of canopy trees identified using the tree crown extraction method within the stand with those maps through field survey indicated a close correspondence. Three counts of trees were compared against the field data; tree tops identified using local maxima filtering within the smoothed image, crowns identified using the ITC delineation and both treetops and crowns identified using pixel classification and crown classification. The results of crown classification show tree crown species, size, density, and position. The number of tree crowns and tops was 673 and 953, respectively, in the large crown areas, and 1408 of tree crowns and 1452 of tree tops were extracted in the small crown areas. These results showed that the number of trees by species determined by the new tree top method were less than the total number of trees using the new method. This may be due to the underestimation of *Chamaecyparis Obtusa*, *Chamaecyparis.Pisifera* and *Thujopsis dolabrata*. Thus, the method can effectively be used to extract the stems of upper and intermediate canopy trees in pure conifer plantations when multiple layers or high densities are not involved.

Biomass estimation accuracy

In order to examine the accuracy of estimated biomass using the new method, the biomass of estimation was compared with field survey at four levels, including all trees, the trees with DBH ≥35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm distinguishing species as the same classes as biomass estimation by GeoEye-1 data (Table 6). The errors for all trees, DBH ≥ 35 cm, DBH ≥ 50 cm and DBH ≥ 65 cm of *Chamaecyparis Obtusa* were 13.39%, 12.62%, 9.52%, and -16.28%, respectively. For *Chamaecyparis pisifera*, they ranged from -20.0% to 35.0%. The error of *Thujopsis dolabrata* ranged from -1464.71% to 29.07%, and that of broad-leaved trees ranged from -48.33% to 22.61%. The results indicated that biomass estimation of *Chamaecyparis pisifera* was inferior to *Chamaecyparis Obtusa* owing to their large crowns and same spectrum characteristics resulted in one crown being sometimes misidentified as a cluster of crowns. Furthermore, *Chamaecyparis pisifera* and broad-leaved trees were disadvantage of competition with *Chamaecyparis Obtusa*, which makes canopy area of *Chamaecyparis pisifera* smaller. Therefore, a large error of estimated DBH was produced using DBH-crown curve. The biomass estimation error for total of *Thujopsis dolabrata* was reduced significantly, because multispectral airborne data provide high resolution, which helps to extract crown of the undergrowth layer. *Thujopsis dolabrata* was absent in the large classes, while it occurred in the small classes. Though high resolution multispectral airborne data resulted in the high crown extraction error, this did not effect on biomass estimation.

Table 4-2 Accuracy of biomass estimation using Multispectral Airborne Data

Species	Field survey data (t/ha)				Estimation data (t/ha)	Error(%)			
	All trees	DBH above 35cm	DBH above 50cm	DBH above 65cm		All trees	DBH above 35cm	DBH above 50cm	DBH above 65cm
Chamaecyparis.obtusa	10.31	10.22	9.87	7.68	8.93	13.39	12.62	9.52	-16.28
Chamaecyparis.pisifera	0.24	0.22	0.2	0.13	0.156	35.00	29.09	22.00	-20.00
Thujopsis.dolabrata	0.75	0.132	0.085	0.034	0.532	29.07	-303.03	-525.88	-1464.71
Broad-leaved	0.23	0.13	0.12	0.11	0.178	22.61	-36.92	-48.33	-61.82

In this chapter, we proposed a method for improving forest biomass estimation. One object coverage model was used for improving biomass estimation of under growth layer in multispectral airborne images. The object coverage model was slightly better than the commonly used filters in terms of preserving details in forestry areas. The results showed the biomass estimation accuracy was significantly improved when object coverage model was used in comparison to estimating the biomass in multistoried forest.

Chapter 5 Development tree growth prediction model with Gray theory

Forests offer many different kinds of services, for example: wood production, environment protection, provision of scenic beauty and recreation, and so on (Forest Agency, 2006). However, they are effected easily in short term by all kinds of human disturbances, including harvesting, over-harvesting and degradation, fire control, and also impacted evidently by many natural causes such as large-scale occurrence of wildfires, strong winds, pest and disease outbreaks, snow damage， and especially climate change of long term (Morisawa, 1999). Studies on the change of forest in the past are to understand its development in the future, then provide some commendation for forest management and improve its function. In recent years, how to predict growth of forest was paid more and more attention (FFPRI, 2012). But now it seems that traditional prediction methods cannot meet completely the need of modern forest with more emphasis on ecological protective function. Recently in Japan the long rotation management process of conifer plantation is being popular， and through predict growth of forest plays a very important role for the long rotation management process of conifer plantation.

Analysis on stand structure characteristics and reasonable forecast results were the important departments of forest management. The diameter at breast height (DBH) of tree describes the growth process of tree, and DBH has relationship with geographic factors and environmental factors (Minowa, 1995). So the diameter at breast height (DBH) of tree, a basic and very important parameter in forest research, was essential for calculation of tree volume and describing forest structure. Even though a great of forest forecast systems had been developed (Ando, 1968; Kikukawa, 1981; Matumoto, 2005; Shiraishi, 2005), most of them couldn't predict DBH of tree individuals, and they needed environmental and geographical factors in forecasting growth of total stand. Gray theory, which defined Gray derivative and differential equation with correlation analysis and smooth discrete function, needn't environment data and may resolve the above shortcomings in predicting forest growth (Deng, 1990).

Although collected data can be used to do some simple prediction by simple line regression, the objective of this study, based on the survey of tree DBH in the past 20 years, attempted to firstly develop a precise tool for forecasting DBH growth of tree individuals by mathematics. And then it was used to analyze the change law of forest structure and development process by every ten years. This paper might provide a new forecast theory and offer some recommendation for management of modern forest.

5.1 Gray theory

Gray theory developed by Julong Deng in 1982 is a subject of applied mathematics, which might be used to research the systems that include some known and also unknown information at same time (Deng, 1990). Both Gray theory and regression analysis are major tools in the field of prediction. In this theory, the completely known information was defined as white system, and completely unknown information was defined as black system, while incomplete information was defined as Gray system. And it defined Gray derivative and differential equation with correlation analysis and smooth discrete function. A differential equation model called GM (Gray Model) would be established when the known data set met the principle convergence of relevance (Usuki and Kitaoka, 2001). For example, GM (1, N) is a 1-order differential equation based grew model, which had N variables and might be expressed by the formula as follows:

$$\frac{dX_1}{dt} + aX_1 = b_1X_2 + b_2X_3 + \cdots + b_{N-1}X_N$$

And when the number of known variable is one, the above model became GM (1, 1) and might be represented by the formula as follow:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u$$

5.2 Calculation process

Tree growth was mainly decided by its gene and also influenced by a lot of factors such as site condition and climatic environment. However, it was difficult to express the information of tree’s gene and effect of environment using numerical value directly. DBH, one of basic parameters of forest structure, might be measured accurately and used to reflect the interaction of all of impact factors. It is completely known information in forest system. Therefore, Gray Model can be used to predict growth of trees well without local environment information. In this study, DBH of trees in the stand surveyed in 1988, 1998, 2003 and 2008 was as the completely known information and GM (1, 1) was adopted to establish derivative equation to forecast the growth of every tree individual. For prediction, time series data with even-interval such as 5 or 10 years is necessary. Because of lacking the survey data in 1993, the average growth of every tree from 1988 to 2008 was used to assess its DBH in 1993. Then the time series data in 1988, 1993, 1998, 2003 and 2008 was used to establish one-order matrix by the formula as follows:

$$X_{(n+5)}^{(m)} = \left\{X_{(1988)}^{(m)}, X_{(1993)}^{(m)}, X_{(1998)}^{(m)}, X_{(2003)}^{(m)}, X_{(2008)}^{(m)}, \ldots\right\}$$

Where *X*(*m*)(*n*) is predictive value of tree DBH, *m* is tree No. marked in survey, and *n* is survey year. The differential equation of GM (1, 1) might be expresses as follows:

$$\widehat{X}_{(K+1)}^{(m)} = (X_{(1)}^{(m)} - \frac{u}{a})e^{-ak} + \frac{u}{a}$$

Where *a* is development parameter of the numerical sequence, *u* is the control parameter on *a*, and *e* is natural logarithm. The parameter *a* related with *u* as follows:

$$\hat{a} = [a, u]^T$$

And $\hat{a}$ might be calculated by the formula:

$$\hat{a} = (B^T B)^{-1} BY$$

In the above equation, in order to explain the process of calculation easily, here Y was a code with no real meaning, and also for B. And BT is the transposed matrix of B. They might be expressed by the next matrixes as follows:

$$Y = \begin{vmatrix} X_{(1993)}^{(m)} \\ X_{(1998)}^{(m)} \\ X_{(2003)}^{(m)} \\ X_{(2008)}^{(m)} \end{vmatrix}$$

$$B = \begin{vmatrix} -\frac{(X_{(1988)}^{(m)}+X_{(1993)}^{(m)})}{2} & 1 \\ -\frac{(X_{(1993)}^{(m)}+X_{(1998)}^{(m)})}{2} & 1 \\ -\frac{(X_{(1998)}^{(m)}+X_{(2003)}^{(m)})}{2} & 1 \\ -\frac{(X_{(2003)}^{(m)}+X_{(2008)}^{(m)})}{2} & 1 \end{vmatrix}$$

$$B^T = \begin{vmatrix} -\frac{(X_{(1988)}^{(m)}+X_{(1993)}^{(m)})}{2} & -\frac{(X_{(1993)}^{(m)}+X_{(1998)}^{(m)})}{2} & -\frac{(X_{(1998)}^{(m)}+X_{(2003)}^{(m)})}{2} & -\frac{(X_{(2003)}^{(m)}+X_{(2008)}^{(m)})}{2} \\ 1 & 1 & 1 & 1 \end{vmatrix}$$

Finally, a program for the above calculation process was written by using the Visual Basic of Microsoft Corporation. By this program, the growths of tree individuals can be forecasted with every 5-year and we only have calculated the DBH of every tree in 2018, 2028 and 2038 in this study.

Prediction accuracy

Forecast error may be calculated by the formula:

$$\Phi = (X - M) \div X \times 100$$

Φ is forecast error, *X* is survey data and *M* is calculated by Gray program in same year.

5.3 Results

Prediction for *Chamaecyparis obtusa* growth

The DBH distribution can be used to explain the change of forest dynamics. But finding the change of DBH distribution of old-growth forest needed much time and survey data. Using Gray theory of mathematics, this research developed a program of calculating tree growth by using the data of the stand surveyed in year 1988, 1998, 2003, 2008 and the presumed data of 1993 by average growth method. By this program, the growth of every *Chamaecyparis obtusa* individual was predicted in 2018, 2028 and 2038 respectively (Figure 16). According to survey data, average DBH increment of *Chamaecyparis obtusa* was only 0.5-1.5 cm in every 5 years, the DBH distribution had no significant change. In order to improve forecast accuracy and grasp the changes of forest dynamics, the DBH of every tree was grouped by 2 cm intervals, and all of trees were classified as under layer, middle layer or dominant layer based on their DBH. In this study, the DBH range of understory layer was 5cm to 24cm, middle layer was 24cm to 58cm, and dominant layer was 58cm to 80cm. Results of prediction indicated that the DBH distribution of *Chamaecyparis obtusa* ≤ 24cm had no obvious change except the classes from 5 cm to 10 cm in the next 30 years (Figure 16). This is because sufficient light is necessary for the growth of *Chamaecyparis obtusa*, but in understory of the stand, illuminance was no enough due to the closed canopy, which led to the slow growth of *Chamaecyparis obtusa* trees in understory. Another season is a frost disturbance in 1998 may be a large part of a cause of mortality for stems in smaller size classes (Morisawa, 1999). In addition, a number of trees with DBH from 5 cm to 10 cm may increase markedly in the next 30 years, because these saplings mainly distributed in the canopy gaps between in big trees. The canopy gaps may provide good light environment for the growth of *Chamaecyparis obtusa*. Furthermore, the forest floor was cleaned up in the clear-cutting in 350 years ago and selective-cutting in 60 years ago, thence *Chamaecyparis obtusa* seed can germinate on the forest floor, and these saplings can regenerate well.

In middle layer of the forest, the number of *Chamaecyparis obtusa* trees from 36 cm to 42 cm may be decreases with time. However, the number of trees from 52 cm to 58 cm may be increases. This illustrated that the *Chamaecyparis obtusa* in middle layer would have good growth and be in advantage in the competition with other species, because most of big *Thujopsis dolabrata* and Broad-leaved trees were cut in the selective-cutting of 60 years ago (Hoshino et al., 2002). In the dominant layer, the number of old-growth *Chamaecyparis obtusa* individuals would have no significant change. Even though some trees in middle layer will come into dominant layer, some old trees will die with natural succession and old-growth *Chamaecyparis obtusa* grow very slowly.

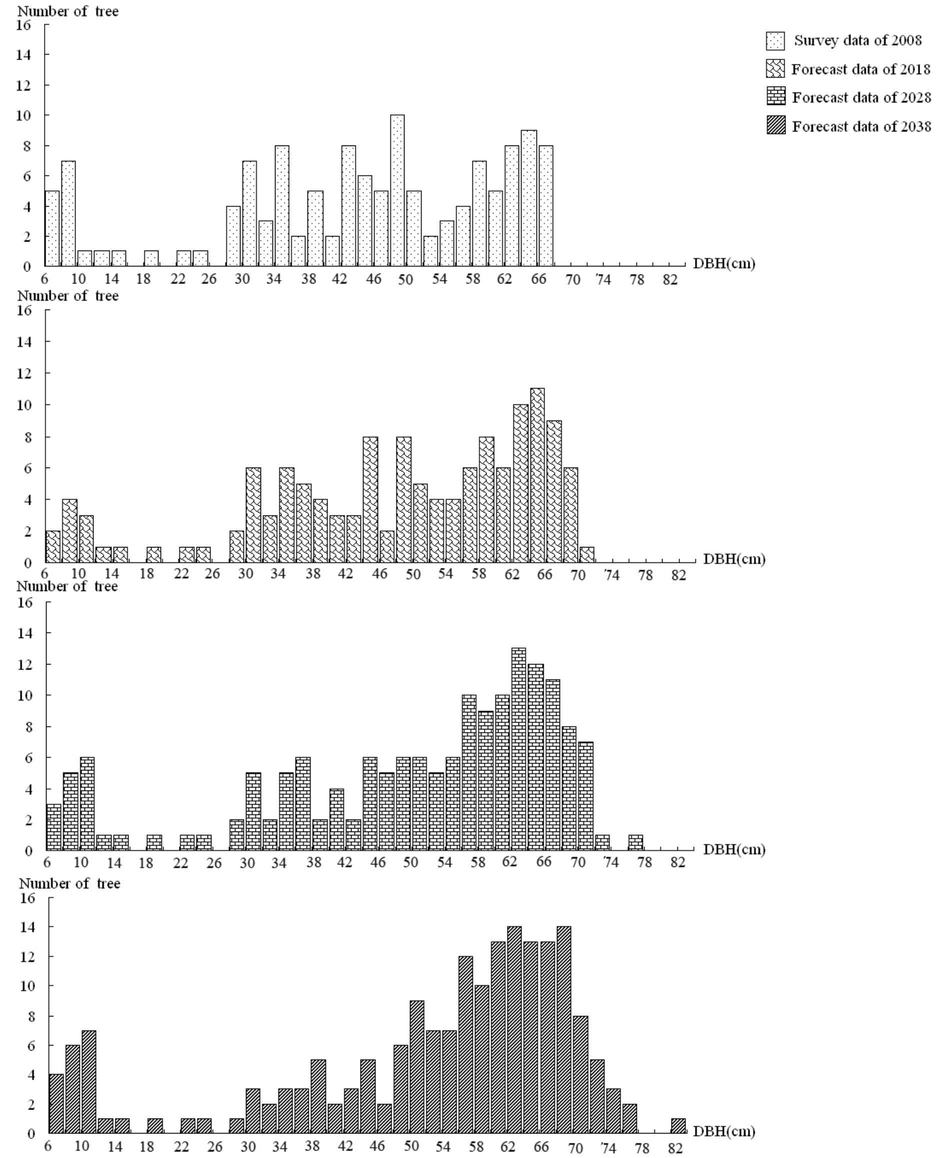

Figure 5-1 Forecast of changes in DBH distribution of *Chamaecyparis obtusa*

Prediction for *Thujopsis dolabrata* growth

In this study, the species of *Thujopsis dolabrata* with DBH from 5cm to 14cm was classified as under layer to middle layer from 14cm to 27cm, and middle layer to dominant layer from 27cm to 48cm. *Thujopsis dolabrata* was absent in the larger classes, but more trees occurred in the smaller classes. The DBH distribution of *Thujopsis dolabrata* was characterized by L-shape, the features of natural regeneration, which showed an inverse pattern with *Chamaecyparis obtusa* (Figure 5-2). Saplings of

Thujopsis dolabrata predominated understory of the stand with a mixture of broad-leaved trees. Forecast result showed that in the future 30 years, the number of *Thujopsis dolabrata* individuals with DBH from 5cm to 8 cm would decrease with time, while the trees with DBH from 8cm to 14cm would be increased (Figure 5-2). Because of vigorous growth of understory plants, it indicated that intra-species competition between saplings will become more and more severe and existing small trees will advance to higher-order DBH class with high-speed growth.

The trees in middle layer will be increased significantly with time, which mainly result from fast growth of the trees distributed in the understory now. Closed canopy formed by big *Chamaecyparis obtusa* and *Thujopsis dolabrata* provided a suitable environment for the growth of regenerated *Thujopsis dolabrata* trees. On the other hand, the total number of trees in the dominant layer will be not changed in the next 30 years, because of the lack of trees distributed in middle layer now.

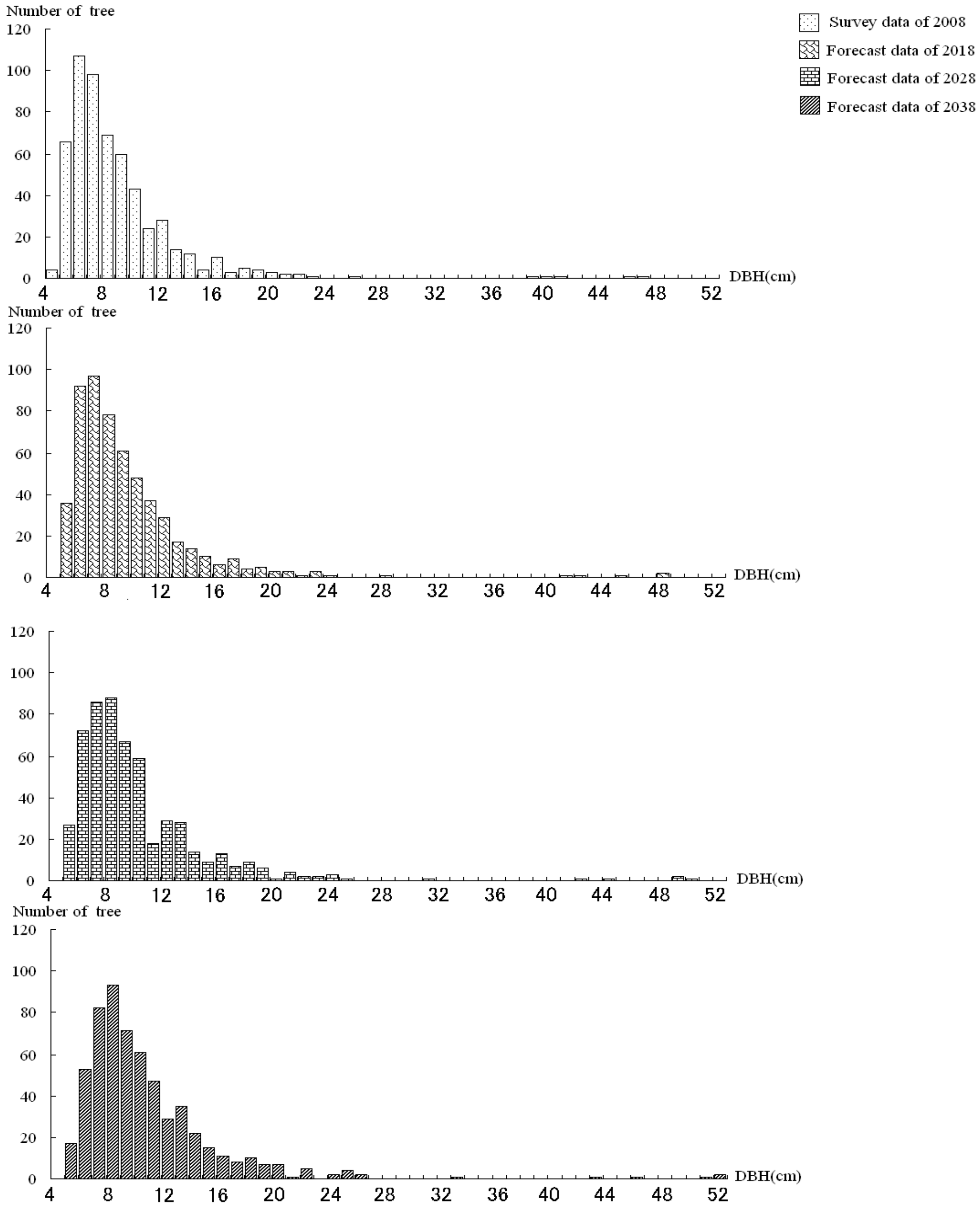

Figure 5-2 Forecast of changes in DBH distribution of *Thujopsis dolabrata*

Prediction accuracy of tree growth

In the understory, the average forecast error of *Chamaecyparis obtusa* was 23.8% in 1998, 18.6% in 2003 and 11.9% in 2008. For *Thujopsis dolabrata*, it was 15.8% 13.6% and 9.7% respectively in the three years. And broad-leaved trees' error was 17.6%, 12.9% and 10.7% in 1998, 2003 and 2008. In middle layer, *Chamaecyparis obtusa*'s errors were 22.8%, 16.8% and 8.9% respectively, while they were 16.5%, 18.5% and 11.3% for *Thujopsis dolabrata*, and 14.9%, 11.9%, 8.7% for broad-leaved trees. In the dominant layer, they were 22.4%, 13.6%, 6.8% for *Chamaecyparis obtusa*, 9.8%, 13.5%, 17.9% for *Thujopsis dolabrata*, and 15.6%, 12.8%, 8.9% for broad-leaved trees in the three years respectively (Table 5-1). From the total stand, forecast error was highest in 1998, because snow and ice damage occurred in that time. Additionally, results of forecast indicated that prediction accuracy increased with the increment of DBH, because anti-interference ability of dominant trees is higher than the trees in middle layer and saplings when natural disturbance occurred.

Table 5-1 Prediction accuracy validation

Species	Year	Average prediction error (%)		
		Understory layer	Middle layer	Dominant layer
Chamaecyparis obtusa	1998	23.8	22.8	22.4
	2003	11.9	12.5	13.6
	2008	9.6	8.9	6.8
Thujops dolabrata	1998	25.8	23.5	23.5
	2003	13.6	14.9	13.8
	2008	9.7	11.3	10.9
broad-leaved	1998	26.7	25.6	23.9
	2003	12.9	13.2	15.6
	2008	10.7	8.7	8.9

In the 20 years, *Chamaecyparis obtusa* dominated canopy layer and *Thujopsis dolabrata* generally dominated understory and middle layer in the plot of this old-growth forest. However, the demographic parameters showed that *Chamaecyparis obtusa* is the least species. *Chamaecyparis obtusa* dominant species in the canopy layer has resulted in the dark forest floor environment except some places of canopy gap. The low light environment of forest floor may lead to the regeneration barriers of *Chamaecyparis obtusa*. Therefore, this species will decrease in importance in the canopy layer and will decline in the proportion of tree number in the future, although its bimodal DBH indicates presence of relatively abundant small or young stems. *Chamaecyparis obtusa* Saplings did not grow in the place around *Thujopsis dolabrata*, but some saplings were found in canopy gaps together with small broad-leaved trees. On the other hand, we can found that abundant young stems of *Thujopsis dolabrata* in understory and middle layer of the plot, which had very few canopy stems, probably due to its high shade tolerance and vegetative reproduction. It also indicates that such environment is appropriate for *Thujopsis dolabrata*'s growth, and it will increase in the canopy layer. Furthermore, a lot of *Thujopsis dolabrata* saplings will appear around *Chamaecyparis obtusa* saplings in the future, suggesting *Thujopsis dolabrata* will interfere with the growth of young *Chamaecyparis obtusa* and its natural regeneration will become more and more difficult. However, the forest will be dominated by *Chamaecyparis obtusa* in the canopy layer at long term if no major disturbance. But, if no some measurement for promoting regeneration of *Chamaecyparis obtusa* saplings in the canopy layer of this forest, *Chamaecyparis obtusa* will become less important and the more shade-tolerant species, *Thujopsis dolabrata*, will become more important(Hoshino et al., 2003), and the forest will be dominated by *Thujopsis dolabrata* finally after senescence and wilt of old-growth *Chamaecyparis obtusa*. This prediction is maintained from the results of this study. Accidental factors cause a decline in forecast accuracy, such as disaster, plant diseases and insect pests. Because Gray theory can not take into accidental factors. But the disturbance of accidental factors decrease the long forecast period. Therefore, Gray theory is suitable for Long-term forecasts of forest growth.

Prediction for broad-leaved trees

All of broad-leaved trees were divided into three layers: under layer is the trees with DBH from 5cm to 14cm, middle layer is from 14cm to 34cm, and dominant layer is from 34cm to 82cm. most of broad-leaved trees are mainly in under layer with DBH≤12 cm (Figure 18). The DBH distribution is also characterized by L-shape, showed the features of natural regeneration. Few broad-leaved trees with the DBH size over 54 cm survived in the plot because of the selective-cutting in 60 years ago. According to the survey, the understory is characterized by a dense coverage of *Thujopsis dolabrata* and broad-leaved saplings, so the growth of small trees in understory was mainly effected by the competition between *Thujopsis dolabrata* and broad-leaved trees. In the understory layer, the number of broad-leaved trees with DBH ≤ 6 cm will be decreased evidently in the future 30 years. However, the trees with DBH from 6cm to 14cm will be increased. It indicated that inter-species competition between *Thujopsis dolabrata* and broad-leaved trees will become more and more severe and existing small broad-leaved trees will advance to higher-order DBH class with fast growth. In middle layer, the broad-leaved trees with DBH from 14 cm to 20 cm will be increased with time, which mainly derived from the increase of trees in the understory. Additionally, the total number of trees in the dominant layer will be not changed in the next 30 years, because there are few trees distributed in middle layer growing into big individuals now.

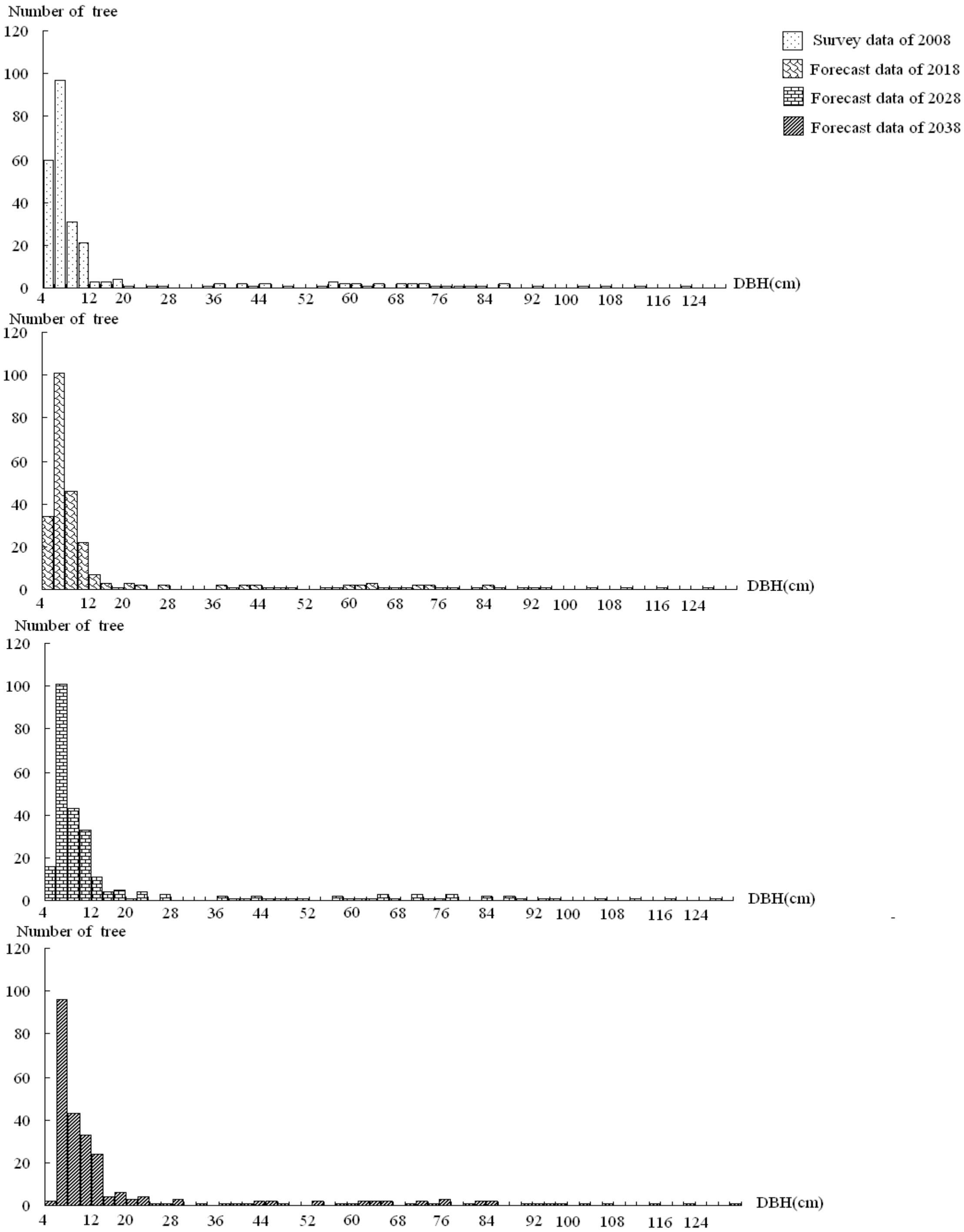

Figure 5-3 Forecast of changes in DBH distribution of broad-leaved trees

Chapter 6 Prediction model for suitable sites of tree growth

Old-growth forests have been studied partly because they represent the best fit of the vegetation to the long term climate, soils, and physiography of an area. This information is available on natural vegetation of forest. However, many factors influence the success of tree regeneration in managed old-growth forests, such as disaster, pest and disease outbreaks, and specially climate change of long term. Studies on the change of forest in the past are to understand its development in the future, then provide some commendation for forest management and improve its function. Analysis on stand structure characteristics and reasonable forecast results are the important departments of forest management. And forecast is an ecosystem-based, stand-level, forest growth simulator. Therefore, sophisticated computer models for forest growth have been imported into forest management and have become important forest management tools. In recent years, how to predict growth of forest was paid more and more attention (FFPRI, 2012). But now it seems that traditional prediction methods can't meet completely the need of modern forest with more emphasis on ecological protective function. Recently in Japan the long rotation management process of conifer plantation is being popular, and predicts growth of forest plays a very important role for it. The survey data describes the growth process of tree, and has relationship with growth factors such as geographic factors and environmental factors (Minowa, 1995).

Despite the abundant literature discussing the problems with using remnant or reconstructed old-growth to predict future forest composition and structure this process is still used to develop management guidelines in many forest types. However, most of them couldn't predict growth of tree individuals, and they needed environmental and geographical factors in forecasting growth of total stand. Gray theory, which defined Gray derivative and differential equation with correlation analysis and smooth discrete function, needn't environment data and may resolve the above shortcomings in predicting forest growth (Deng, 1990).

In this study, the future structure of forest can be predicted based on the abiotic site characteristics of old-growth forest. Although collected data can be used to do some simple prediction by simple line regression, the objective of this study, based on the survey of recruited trees in the past 20 years, attempted to firstly develop a precise tool for forecasting suitable sites of tree growth as similar as possible by mathematics. And then it was used to analyze the change law of forest structure and development process by every ten years. This paper might provide a new forecast theory and offer some recommendation for management of modern forest.

6.1 Calculation process

Tree growth was mainly decided by its gene and also influenced by a lot of factors such as site condition and climatic environment. However, it was difficult to express the information of tree's gene and effect of environment using numerical value directly. The location of recruited trees in the stand, one of basic parameters of forest structure, might be measured accurately and used to reflect the interaction of all of impact factors from site condition and climatic environment. It is completely known information in forest system. Therefore, Gray Model can be used to predict suitable sites of trees growth well without local environment information. In this study, coordinate of recruited trees in the stand surveyed in 1988, 1998, 2003 and 2008 was as the completely known information and GM (1, 1) was adopted to establish derivative equation to forecast the growth of every tree individual. For prediction, time series data with even-interval such as 5 or 10 years is necessary. Because of lacking the survey data in 1993, the average growth of every tree from 1988 to 2008 was used to assess its DBH in 1993. The recruited trees were selected based on the survey and assess data, and the coordinate of recruited trees were accomplished as time series data for prediction.

Survey plot was equally divided into 11 rectangular areas, and named these areas from A1 to A11 respectively (Figure 19). These vertices were designated as its area reference point, and named these reference points from P1 to P12. These boundary lines of each rectangular area were desingated as reference lines and named these reference lines from L1 to L12 from northwest. The distances are from recruited tree to the two reference points within one rectangular area were used to establish one-order matrixes in 1993, 1998, 2003, and 2008 respectively by the formula as follows:

$$P^{(m)}_{(n=5)} = \left\{P^{(m)}_{(1993),}P^{(m)}_{(1998),}P^{(m)}_{(2003),}P^{(m)}_{(2008),}\ldots\ldots P^{(m)}_{(n),}\right\}$$

Where $P^{(m)}_{(n)}$ is predictive value of distances which are from recruited tree to the two reference points within one rectangular area, *m* is reference point No. marked in survey, and *n* is survey year. The differential equation of GM (1, 1) might be expresses as follows:

$$\hat{P}^{(m)}_{(k+1)} = (P^{(m)}_{(1)} - \frac{u_{P(m)}}{a_{P(m)}})e^{-ak} + \frac{u_{P(m)}}{a_{P(m)}}$$

Where $a_{P(m)}$ is development parameter of the numerical sequence, $u_{P(m)}$ is the control parameter on $a_{P(m)}$, and *e* is natural logarithm. The parameter $a_{P(m)}$ related with $u_{P(m)}$ as follows:

$$\hat{a}_{P(m)} = [a_{P(m)}, u_{P(m)}]$$

And $\hat{a}_{P(m)}$ might be calculated by the formula:

$$\hat{a}_{P(m)} = (B_{P(m)}{}^{T} B_{P(m)})^{-1} B_{P(m)} Y_{P(m)}$$

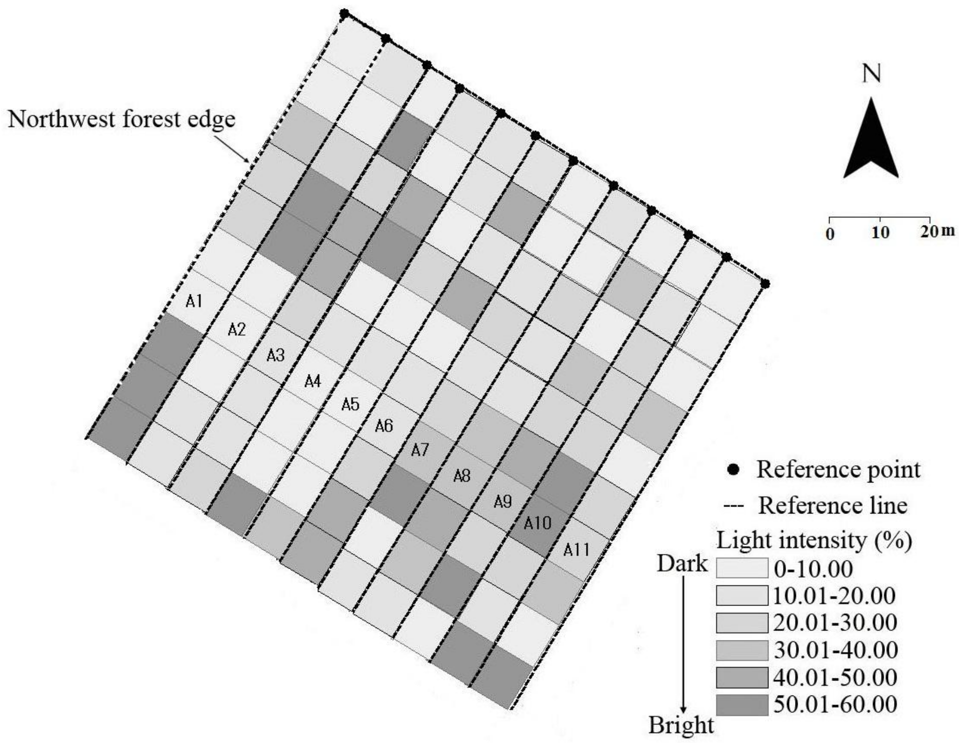

Figure 6-1 Rectangular area and light intensity

In the above equation, in order to explain the process of calculation easily, here $Y_{P(m)}$ was a code with no real meaning, and also for $B_{P(m)}$. $B_{P(m)}{}^{T}$ is the transposed matrix of B. They might be expressed by the next matrixes as follows:

$$Y_{p(m)} = \begin{vmatrix} P_{(1998)}^{(m)} \\ P_{(2003)}^{(m)} \\ P_{(2008)}^{(m)} \end{vmatrix}$$

$$B_{p(m)} = \begin{vmatrix} -\frac{(P_{(1993)}^{(m)} + P_{(1998)}^{(m)})}{2} & 1 \\ -\frac{(P_{(1998)}^{(m)} + P_{(2003)}^{(m)})}{2} & 1 \\ -\frac{(P_{(2003)}^{(m)} + P_{(2008)}^{(m)})}{2} & 1 \end{vmatrix}$$

$$B_{p(m)}{}^{T} = \begin{vmatrix} -\frac{(P_{(1993)}^{(m)} + P_{(1998)}^{(m)})}{2} & -\frac{(P_{(1998)}^{(m)} + P_{(2003)}^{(m)})}{2} & -\frac{(P_{(2003)}^{(m)} + P_{(2008)}^{(m)})}{2} \\ 1 & 1 & 1 \end{vmatrix}$$

A program for the above calculation process was written by using the Visual Basic of Microsoft Corporation. By this program, the distance is from recruited tree to the reference point can be forecasted by every 5-year and we only calculated the distance in 2018, 2028 and 2038 in this study.

On the other hand, the distances which are from recruited tree to the two reference lines within one rectangular area were used to establish one-order matrixes in 1993, 1998, 2003 and 2008 respectively by the formula as follows:

$$L_{(n+5)}^{(m)} = \left\{L_{(1993)}^{(m)}, L_{(1998)}^{(m)}, L_{(2003)}^{(m)}, L_{(2008)}^{(m)}, \ldots\ldots L_{(n)}^{(m)},\right\}$$

Where $L^{(m)}{}_{(n)}$ is predictive value of distances which are from recruited tree to the two reference lines within one rectangular area, *m* is reference line No. marked in survey, and *n* is survey year. The differential equation of GM (1, 1) might be expressed as follows:

$$\hat{L}^{(m)}_{(k+1)} = (L^{(m)}_{(1)} - \frac{u_{L(m)}}{a_{L(m)}})e^{-ak} + \frac{u_{L(m)}}{a_{L(m)}}$$

Where $a_{L(m)}$ is development parameter of the numerical sequence, $u_{L(m)}$ is the control parameter on *a*, and *e* is natural logarithm. The parameter *a* related with *u* as follows:

$$\hat{a}_{L(m)} = [a_{L(m)}, u_{L(m)}]$$

And $\hat{a}_{L(m)}$ might be calculated by the formula:

$$\hat{a}_{L(m)} = (B_{L(m)}{}^{T} B_{L(m)})^{-1} B_{L(m)} Y_{L(m)}$$

In the above equation, in order to explain the process of calculation easily, here $Y_{L(m)}$ was a code with no real meaning, and also for $B_{L(m)}$. $B_{L(m)}{}^{T}$ is the transposed matrix of $B_{L(m)}$. They might be expressed by the next matrixes as follows:

$$Y_{L(m)} = \begin{vmatrix} L^{(m)}_{(1998)} \\ L^{(m)}_{(2003)} \\ L^{(m)}_{(2008)} \end{vmatrix}$$

$$B_{L(m)} = \begin{vmatrix} -\frac{(L^{(m)}_{(1993)} + L^{(m)}_{(1998)})}{2} & 1 \\ -\frac{(L^{(m)}_{(1998)} + L^{(m)}_{(2003)})}{2} & 1 \\ -\frac{(L^{(m)}_{(2003)} + L^{(m)}_{(2008)})}{2} & 1 \end{vmatrix}$$

$$B_{L(m)}{}^{T} = \begin{vmatrix} -\frac{(L^{(m)}_{(1993)} + P^{(m)}_{(1998)})}{2} & -\frac{(L^{(m)}_{(1998)} + L^{(m)}_{(2003)})}{2} & -\frac{(L^{(m)}_{(2003)} + L^{(m)}_{(2008)})}{2} \\ 1 & 1 & 1 \end{vmatrix}$$

By the prediction program, the distance from recruited tree to the reference line within one rectangular area can be forecasted with every 5-year but we only calculated the distance in 2018, 2028 and 2038 in this study.

The prediction distances data from recruited tree to the reference points and lines were used to create the buffer based on prediction distance data in 2018, 2028 and 2038 respectively by ArcGIS 10 software. The overlapping portions of these buffers were considered as suitable sites of tree growth.

Prediction accuracy of prediction model for suitable sites of tree growth

Forecast error of suitable sites may be examined by three steps in this study. Firstly, the number of recruited trees was used to calculate the forecast error from 1993 to 2008 within suitable sites in same year. Forecast error may be calculated by the formula:

$$\varphi = (X - M) \div X \times 100$$

φ is forecast error, X is the number of recruited trees of survey data and M is predicted number by Gray program in same year within same rectangular area.

φ is forecast error, X is the number of recruited trees of survey data and M is predicted number by Gray program in same year within same rectangular area.

Secondly, in another paper of the author, the growths of tree individuals have been forecasted by every 5-year and have calculated the DBH of every tree in 2018, 2028 and 2038 (Nan Wang et al., 2012). The predicted DBH might be used to determine the recruited trees and confirmed the location of the recruited trees within suitable sites of the plot in 2018, 2028 and 2038. Based on the prediction data, the number of recruited tree were counted within the suitable sites and forecast error may be calculated by the formula as follow:

$$\theta = (T_i - T_a) \div T_a \times 100$$

è is forecast error, T_i is the number of recruited trees of survey data within the suitable sites and T_a is the numbers of all the recruited trees in the same rectangular area which were calculated by Gray program in same year.

All forest organisms ultimately depend on photosynthesis for their energy requirements. In this study, light intensity may be calculated by the formula:

$$\mu = L_i \div L_o \times 100$$

ì is relative light intensity, L_i is light intensity in the forest and L_o is light intensity outside the forest measured in same time. Finally, we analyzed the relationship between relative light intensity and the predicted suitable sites for tree growth.

6.2 Results

Basic characteristics of the forest

Results of survey and assessment data indicated that the recruited trees of *Chamaecyparis obtusa* were 48 stems/ha, 27 stems/ha, and 25 stems/ha in 1998, 2003 and 2008 respectively (Table 8). The total number of recruited trees of *Chamaecyparis obtusa* decreased significantly in the 10 years. This is because in understory of the stand, illuminance was not enough due to the closed canopy, which led to the slow growth of *Chamaecyparis obtusa* trees in understory. Besides, a frost disturbance was happened in 1998 explained the mortality of stems with small size classes (Morisawa, 1999). The densities of recruited *Thujopsis dolabrata* trees were 317 stems/ha, 324 stems/ha, and 391 stems/ha in 1998, 2003 and 2008 respectively (Table 8). The total number of recruited trees of *Thujopsis dolabrata* increased in the 20 years but had no obvious change from 1998 to 2003. Additionally, by counting the recruited trees within rectangular areas and analyzing the relationship between the position of recruited trees and the light intensity, we found that the recruited trees of *Chamaecyparis obtuse* was occurred infrequently in the understory and dominant layer, but most of them occurred in the middle layer (Table 8). This is because sufficient light is necessary for the growth of *Chamaecyparis obtusa*, but in understory of the stand, illuminance was not enough due to the closed canopy, which led to the slow growth of *Chamaecyparis obtusa* trees in understory. Contrary, the recruited trees of *Thujopsis dolabrata* was absent in the dominant layer, while many individuals occurred in the understory (Table 8). This is probably due to its high shade tolerance.

Table 6-1 Distribution of recruited tree based on survey data

Species	Layer / Year	Understory layer	Middle layer	Dominant layer	The total number of recruited trees
	Year	The number of recruited tree			
Chamaecyparis obtusa	1998	8	34	6	48
	2003	3	19	5	27
	2008	4	18	3	25
Thujops dolabrata	1998	315	2	0	317
	2003	323	1	0	324
	2008	389	2	0	391

Prediction for suitable sites of tree growth of *Chamaecyparis obtusa*

The number of the recruited trees can be used to explain the change of forest dynamics and to suggest whether the region meets the growth conditions of the trees or not. But forecasting the suitable sites of tree growth needed much time and survey data. According to survey data, average DBH increment of *Chamaecyparis obtusa* was only 0.5-1.5 cm in every 5 years. In order to improve forecast accuracy and grasp the numbers of the recruited trees of *Chamaecyparis obtusa*, the DBH of every tree was grouped by 2 cm intervals and all of trees were classified into under layer, middle layer or dominant layer based on their DBH. In this study, the DBH range of understory layer was 5 cm to 24 cm, middle layer was 24 cm to 58 cm, and dominant layer was 58 cm to 80cm. Using Gray theory of mathematics, this research developed a program of calculating tree growth by using the data of the stand surveyed in year 1988, 1998, 2003, 2008 and the presumed data of 1993 by average growth method. By this program, the growth of every *Chamaecyparis obtusa* individual was predicted in 2018, 2028 and 2038 respectively (Nan Wang et al., 2012). On the other hand, by the prediction program, the distance from recruited tree to the reference line within one rectangular area can be forecasted by every 5-year respectively, and then the results were used to create the buffer based on prediction distance data in 2018, 2028 and 2038 respectively by ArcGIS 10 software. The overlapping portions of these buffers were considered suitable sites of tree growth (Figure 20). Results of prediction indicated that the numbers of the recruited trees of *Chamaecyparis obtusa* $\leq$ 24cm had no obvious change in the rectangular areas in the next 30 years (Table 9). This is because sufficient light is necessary for the growth of *Chamaecyparis obtusa*, but in understory of the stand, illuminance was no enough due to the closed canopy, which led to the slow growth of *Chamaecyparis obtusa* in understory. Additionally, a frost disturbance in 1998 may be a large part of a cause of mortality for stems in smaller size classes (Morisawa, 1999). The recruited trees will increase 7, and most of them will be distributed in the rectangular area of A2 in the next 30 years. This is because the small trees of *Thujopsis dolabrata* almost will not be distributied in this area, so there will be no tree species competition. On the other hand, the light intensity of rectangular areas A2 is 15%, which provides a good light environment for the growth of *Chamaecyparis obtusa* in understory.

In middle layer of the forest, the number of the recruited trees of *Chamaecyparis obtusa* may be decrease with time in the rectangular areas except area A7 (Figure 20) (Table 9). This is because the forest floor of A7 locates at the area where, there is no rock coverage and good conditions of soil and light intensity with 30% for growth of *Chamaecyparis obtusa* (Hoshino D and Yamamoto S 2004). In the dominant layer, the total number of the recruited trees of *Chamaecyparis obtusa* has no significant change in the rectangular areas, but the appearance area for the recruited trees have significant change. Even though some trees in middle layer will come into dominant layer, some old trees will die with natural succession and old-growth *Chamaecyparis obtusa* will grow very slowly. In summary, the recruited trees of *Chamaecyparis obtusa* appear most at the area where the light intensity is from 10% to 20%, while they appear least at the area with light intensity from 40% to 50%. High light intensity is not conducitve for tree growth.

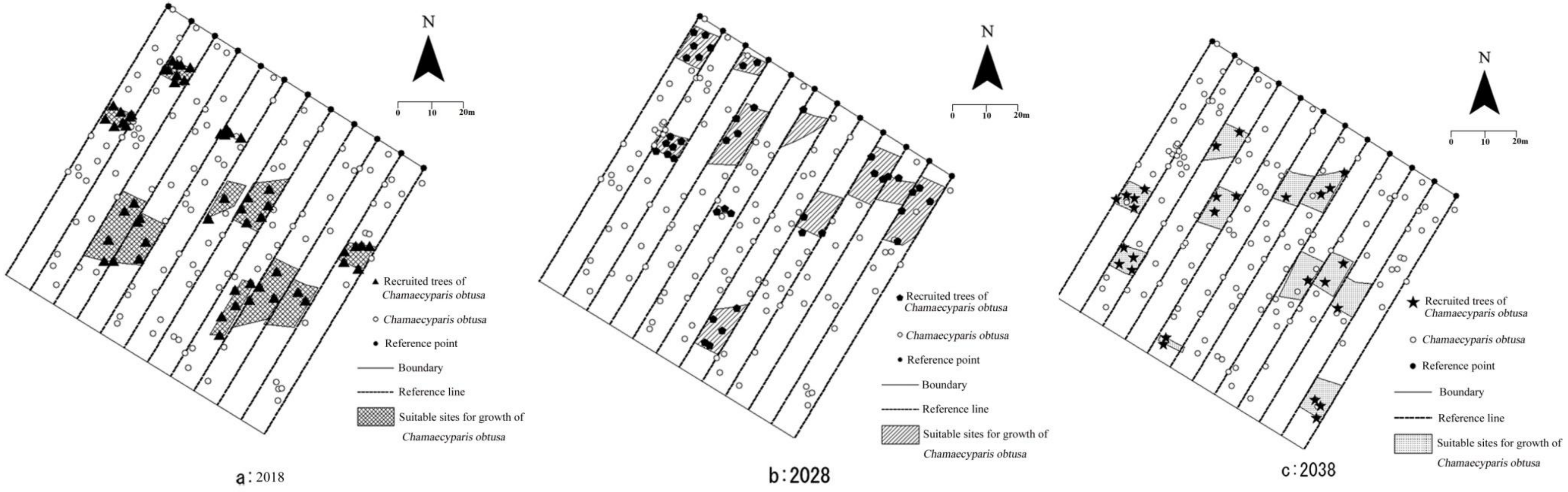

Figure 6-2 Forecast rescult of suitable sites for growth of *Chamaecyparis obtusa*

Table 6-2 Forecast rescult for recruited trees of *Chamaecyparis obtusa*

Layer	Year	Rectangular areas											Total
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	
	2018	0	2		1	1		1			0		5
Understory	2028	1	3		1	1		0			1		7
layer	2038	0	2		0	0		1			0		3
Total		1	7		2	2		2			1		15
	2018	2	3	2	3	4	2	3	3	4	1	4	31
Middle	2028	1	2	3	2	3	3	5	2	3	2	3	29
layer	2038	3	2	2	2	2	3	6	3	3	1	4	28
Total		6	7	7	9	9	8	11	8	10	4	11	90
	2018	1	1		0	1	0	0	1	0	0	1	5
Dominant	2028	2	0		0	1	1	0	1	1	1	0	7
layer	2038	1	0		1	1	0	1	2	0	0	1	7
Total		4	1		1	3	1	1	4	3	2	2	22

Blank area represents that there is no recruited trees

Prediction for suitable sites of tree growth of *Thujopsis dolabrata*

Thujopsis dolabrata was absent in the larger classes, and most of them occurred in the smaller classes. Saplings of *Thujopsis dolabrata* predominated understory of the stand together with broad-leaved trees. Forecast results showed that the number of recruited trees of *Thujopsis dolabrata* will be increased in the A1, A3, A4 and A11 in understory in the future 30 years (Table 10). Because lots of *Thujopsis dolabrata* saplings in the understory were distributed in these areas. Besides, the forest state of canopy closure makes the dark forest floor which led to the protection for air humidity and the prevention for drying of soil, the appropriate environment for growth of *Thujopsis dolabrata*. The recruited trees in middle layer will be increased significantly with time, which mainly results from fast growth of the trees distributed in the understory now. Closed canopy formed by big *Chamaecyparis obtusa* and *Thujopsis* *dolabrata* provided a suitable environment for the growth of regenerated *Thujopsis dolabrata* trees. On the other hand, the total number of recruited trees in the dominant layer will not be changed in the next 30 years, because the lack of trees distributed in middle layer now (Figure 21) (Table 10). In summary, the recruited trees of *Thujopsis dolabrata* will appear most at the area with the light intensity from 10% to 20% with time. However, they will appear least at the area where the light intensity is from 40% to 50% in future 30 years.

Table 6-3 Forecast rescult for recruited trees of *Thujops dolabrata*

Layer	Year	Rectangular areas											Total
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	
	2018	13	13	13	17	20	24	27	34	26	25	26	238
Understory	2028	15	15	16	20	22	27	29	33	24	22	30	253
layer	2038	18	14	20	24	21	26	32	38	29	26	33	281
Total		46	42	49	61	63	77	88	105	79	73	89	772
	2018	2	2	0	3	0	2	1	0	2	1	2	15
Middle	2028	1	3	1	2	0	3	2	1	1	0	3	17
layer	2038	3	4	0	2	0	3	1	0	1	1	2	17
Total		6	9	1	7	0	8	4	1	4	2	7	49
	2018	0	0	0	0	0	0	0	0	0	0	1	1
Dominant	2028	0	0	1	0	0	1	0	0	0	0	2	4
layer	2038	0	0	1	0	0	0	0	0	0	0	1	2
Total		0	0	2	0	0	1	0	0	0	0	4	7

Blank area represents that there is no recruited trees

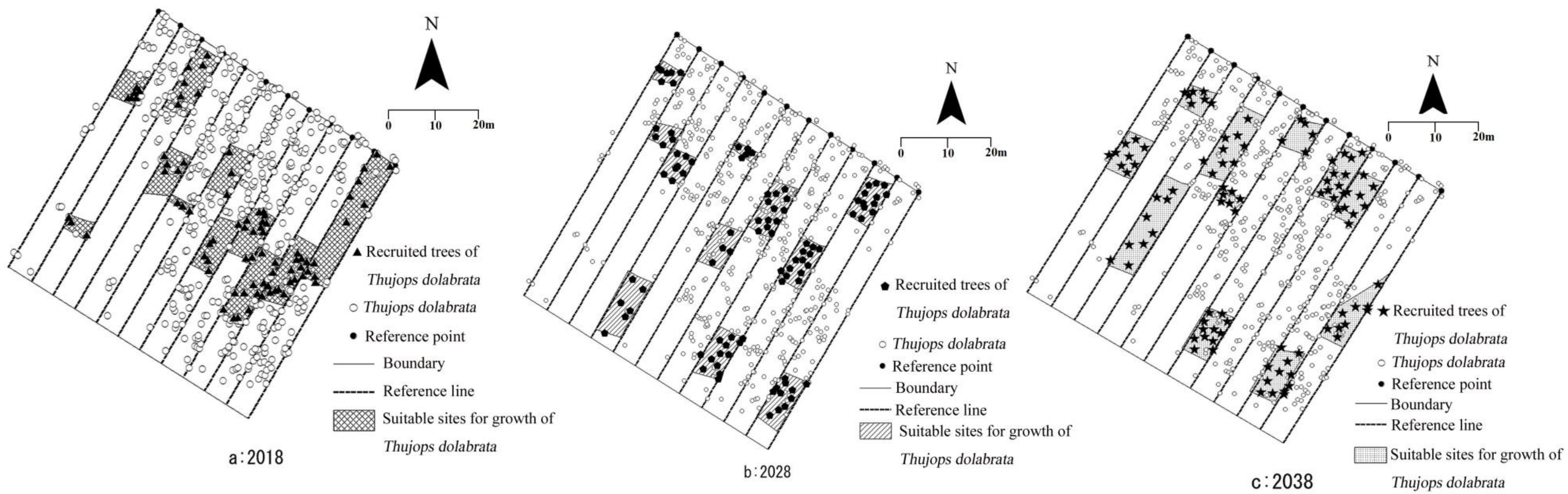

Figure 6-3 Forecast rescult of suitable sites for growth of *Thujops dolabrata*

Prediction accuracy of suitable sites

In the understory, according to the predicted number of recruited trees, the average forecast error of *Chamaecyparis obtusa* was 12.3% in 1998, 11.9% in 2003 and 10.5% in 2008. For *Thujopsis dolabrata*, it was 23.6%, 14.3% and 10.2% respectively in the three years. In middle layer, *Chamaecyparis obtusa*'s errors were 31.5%, 30.3% and 27.4% respectively, while they were 28.7%, 15.6% and 13.1% for *Thujopsis dolabrata*. In the dominant layer, they were 18.7%, 17.9% and 13.2% for *Chamaecyparis obtusa*, and 22.4%, 13.8% and 10.7% for *Thujopsis dolabrata* in the year of 1998, 2003, 2008 respectively (Table 11). On the other hand, based on the forecast results of suitable sites of the recruited trees, the errors of the suitable sites were calculated by each rectangular area in 1998, 2003 and 2008 respectively (Table 12). In the understory, the average error for *Chamaecyparis obtusa* ranged from -38.3% to 40.3% in 1998, 2008 and 2008 respectively. For *Thujopsis dolabrata*, it was 45.7%, 39.4% and 53.1% respectively in the three years. In middle layer, *Chamaecyparis obtusa*'s errors were 31.8%, 26.3% and 23.5% respectively, while they were 28.4%, 32.6% and 24% for *Thujopsis dolabrata*. In the dominant layer, they were 16.9%, 25.6% and 21.3% for *Chamaecyparis obtusa*, and 33.3%, 20% and 14.2% for *Thujopsis dolabrata* in the three years respectively. In view of the total stand, two kinds of errors were highest in 1998, because snow and ice occurred damage in that time. Additionally, results indicated that prediction accuracy increased with the increment of DBH, because anti-interference ability of dominant trees is higher than the trees in middle layer and saplings when natural disturbance occurred.

Table 6-4 Forecast accuracy validation based on recruited trees number

Species	Year	Average prediction error (%) understory layer	Middle layer	Dominant layer
	1998	12.3	31.5	18.7
Chamaecyparis	2003	11.9	30.3	17.9
obtusa	2008	10.5	27.4	13.2
	1998	23.6	28.7	22.4
Thujops	2003	14.3	15.6	13.8
dolabrata	2008	10.2	13.1	10.7

Table 6-5 Forecast accuracy validation of suitable sites based on distribution of recruited trees

Species	Year	Average prediction error (%) understory layer	Middle layer	Dominant layer
	1998	38.9	31.8	16.9
Chamaecyparis	2003	40.3	26.3	25.6
obtusa	2008	37.9	23.5	21.3
	1998	45.7	28.4	33.3
Thujops	2003	39.4	32.6	20.0
dolabrata	2008	53.1	24.0	14.2

In the 20 years, the growth rate of *Chamaecyparis obtusa* was small where the DBH is from 5 cm to 15 cm, and that of *Thujopsis dolabrata* was greater than *Chamaecyparis obtusa* in the same DBH range. This is because *Chamaecyparis obtusa* dominated canopy layer and *Thujopsis dolabrata* generally dominated the understory of this old-growth forest. *Chamaecyparis obtusa*, the dominant species in the canopy layer has resulted dark forest floor environment except for some places of canopy gap. The low light environment of forest floor may lead to the regeneration barriers of *Chamaecyparis obtusa*, and defeat the competition with *Thujopsis dolabrata* which has strong shade tolerance. Therefore, *Chamaecyparis obtusa* will decrease in importance in the understory layer and decline in the proportion of tree number in the future. Furthermore, a lot of *Thujopsis dolabrata* saplings will appear around *Chamaecyparis obtusa* saplings in the future, suggesting that *Thujopsis dolabrata* will interfere with the growth of young *Chamaecyparis obtusa* and its natural regeneration will become more and more difficult. In addition, forecast results showed that few of recruited trees of *Chamaecyparis obtusa* distributed in the place where most recruited trees of *Thujopsis dolabrata* distributed in. But some *Chamaecyparis obtusa* saplings were found in canopy gaps together with small broad-leaved trees. On the other hand, we found that abundant young stems of recruited *Thujopsis dolabrata* trees located in understory and middle layer of the plot, which had very few canopy stems, probably due to its high shade tolerance and vegetative reproduction. It also indicated that such environment is appropriate for *Thujopsis dolabrata*'s growth, which will increase in the canopy layer. However, the forest will be dominated by *Chamaecyparis obtusa* in the canopy layer at long term if no major disturbance. If no some measurement for promoting regeneration of *Chamaecyparis obtusa* saplings, *Chamaecyparis obtusa* will become less important, while the shade-tolerant species, *Thujopsis dolabrata,* will become more important (Hoshino et al., 2003), and the forest will be dominated by *Thujopsis dolabrata* finally after senescence and wilt of old-growth *Chamaecyparis obtusa*.

In this study, forecast error is highest in understory layer and lowest in canopy layer for either *Chamaecyparis obtusa* or *Thujopsis dolabrata.* Accidental factors cause a decline in forecast accuracy, such as disaster, plant diseases and insect pests, because Gray theory can not take into accidental factors. But the disturbance of accidental factors decrease in the long forecast period. Therefore, Gray theory is suitable for Long-term forecasts of forest growth.

Chapter 7 Conclusion

This paper, a prediction model for forest growth and growth suitable sites was developed including information collection system and prediction system, and verified the feasibility of the prediction model. The collection system can be used to detect and extract forest information at individual tree level based on high resolution remote sensing data and a new remote sensing method, and it can provide accurate data for prediction system to forecast forest growth and growth suitable sites at individual tree level. Satellite data can be used to collect the forest information in the wide rang of forest, but it can not provide sufficiently high accuracy data for prediction system using this information collection system. Although multispectral airborne data could be used to collect forest information using this collection system, it resulted in errors of tree crown and tree tops extraction. Thus, the collection portion of this system can be effectively used to extract the stems and estimate biomass of upper and intermediate canopy trees in pure conifer plantations when multiple layers or high densities are not involved.

The survey data of this study constitute a time series data for predicting using Gray Method. For prediction, Gray Method needs above four time series data collected with same time intervals. To constitute the time series data, we have to take a compromise. Because of lacking the survey data in 1993, the average growth of each tree from 1988 to 2008 was used to assess its DBH in 1993. This reason led to the errors f prediction. Time series prediction refers to the process by which the future values of a system is forecasted based on the information obtained from the past and current data points. This paper forecasts the tree growth and growth suitable sites for tree growth using Gray models in time series prediction. It showed that the performance of the Gray predictors can be further improved by taking into account the error residuals. The results o f accuracy examination show that GM(1,1) model is able to make accurate predictions. However, Gray method can not reverse the prediction in the intermediate data of time series data used in this paper. Furthermore, Gray method can not consider the accidental factors which include the time series; this is one reason of prediction error. In order to improve the modeling accuracy of Gray models, several remedies have been discussed in the literature (Tan and Chang, 1996; Tan and Lu, 1996; Guo, Song, and Ye, 2005). Among these Gray models, the modified GM (1,1) using Fourier series in time is the best model in fitting and forecasting.

Further application and testing are required to extend our results to larger areas, multiple scenes, varied topographies and different forest conditions. Field survey results will be required to better ascertain the ultimate accuracy of this system with the same time intervals in future. Improving the accuracy of the information collection system and prediction system and integrating the two parts of system are the subjects of ongoing research endeavors.

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