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Article

Urbanization and Forest Fragmentation in Georgia (USA): Challenges to Sound Forest Management

Michael L. Clutter[*1], Jacek P. Siry[*2] and Pete Bettinger[*3]

ABSTRACT

Urban sprawl has been identified as a major force affecting forests in the southern United States. Georgia has the largest metropolitan area in the South, Atlanta, which has experienced rapid growth since the early 1990s. Such growth continues to expand the urban-rural interface and affect forestland area and timber management practices, particularly in the vicinity of Metropolitan Statistical Areas (MSAs). We used data collected by the USDA Forest Service from the early 1980s to assess impacts of the ever expanding urban-rural interface on Georgia's forest resources. The variables that were significant in estimating the average size of forest stands in each county included the distance to Atlanta, the amount of forest industry land in the county, the amount of upland hardwood land in each county, and time. Per capita income, population, number of building permits issued, and the amount of planted pine area in each county (among others) were not found to be statistically significant in estimating the average stand size. Given the trends suggested by the data and highlighted by the analysis, we contend that urbanization and fragmentation will continue to increase, and land area suitable for growing trees as a timberland investment will continue to decline, and that landowners will need more assistance if forest management is one of their main goals.

Keywords: forest fragmentation, forest parcelization, urbanization

INTRODUCTION

The causes and effects of forest fragmentation are some of the most widely debated conservation issues among land managers because disturbances to the landscape are a noticeable consequence of land use change (McIntyre, 1995). Fragmentation has been described by Carsjens and van Lier (2002) as a landscape change process that spatially segregates areas of land that would normally belong together in order to function optimally, and the term has been used widely to describe the loss of habitat (e.g., Li *et al.*, 2001). While fragmentation has been frequently analyzed in the context of habitat changes, recently it has also been analyzed in the context of its implications for forest management (e.g., Sampson and DeCoster, 2000). In this paper we examine the causes of forest fragmentation in the State of Georgia and its implications for sound forest management.

Georgia is the largest U.S. state east of the Mississippi River, located at the center of the world's largest wood supply region, the U.S. South. Georgia timberland covers about 10 million hectares or 66 percent of the state's land base (Thompson, 1998). This resource supports one of the largest forest industries in the world while also providing a timberland for a wide range of environmental uses and values. The forest products sector generates in excess of 20 billion U.S. dollars to

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the state's economy, making this sector one of the largest contributors to state GDP.

Georgia also has the largest metropolitan area in the South, Atlanta, which experienced rapid growth during the economic expansion of the 1990s. That economic expansion has also provided the wealth necessary for many individuals interested in rural recreation activities to lease or own timberland for a variety of uses. Such conversion of forestland into other uses continues to expand urban-rural interface and impact timberland area and management, particularly in the vicinity of Metropolitan Statistical Areas (MSAs, as defined by the USDA Economic Research Service's Urban-Rural Continuum Codes [Butler, 1990]). Another significant impact on the use of timberland comes as areas immediately adjacent to major metropolitan areas are increasingly used for recreational actives and weekend retreats. These areas are generally characterized by increased fragmentation (lower stand and parcel size), lower timber management intensity, and less inclination to use timber sales as a revenue provider.

The objectives of this analysis are to evaluate how fragmentation and urbanization may impact forest resources and their management in Georgia. Using data collected by Forest Inventory Analysis (FIA) work units within the USDA Forest Service we developed a model that assesses the possible impacts of increased fragmentation by estimating how the average stand size has changed over the past twenty years. County level estimates of timberland area, land managed by various ownership groups, population growth, tax revenue growth, and growth in building permits provide information on expanding economies and new development, and are used to further refine the assessment of the urban-rural interface. This work differs from previous studies in its focus on the relationships between fragmentation and forest resource conditions and the analysis of management implications of fragmentation. While Mehmood and Zhang (2001) assessed forest fragmentation based on FIA data, this study uses a different model and explanatory variables, including forest resource condition and socio-economic variables.

METHODS

The fragmentation analysis was conducted for forests classified as timberland, which represents forestland capable of producing 1.4 cubic meters of industrial wood per hectare (20 cubic feet of industrial wood per acre) and not withdrawn from timber utilization. Timberland accounts for over 97 percent of forests in Georgia.

Timberland area was estimated by three major ownership classes. Public ownership includes national forests and forests managed by public agencies. As of 1997, only 7 percent of forests in Georgia were publicly owned (Thompson, 1998). Timber management in these forests is generally limited. Primary wood manufacturers are classified as forest industry (FI), which owned about 21 percent of forests. In general, these forests were managed with the highest silvicultural intensity. Nonindustrial private forest (NIPF) ownership includes individuals, trusts, and corporations without manufacturing facilities, and accounts for about 72 percent of forests in Georgia. These stands represent a wide range of forest management approaches, ranging from very intensive management to no management.

Timberland area was also classified into five broad forest types. Planted pine (1) represents forests artificially regenerated with southern yellow pines (e.g., *Pinus taeda*). A substantial area of pine plantations is intensively managed, including the use of genetically improved seedlings, herbicides and fertilizers, and thinning. Following harvest, natural pine (2) forests were frequently replaced by plantations. Oak-pine (3) represents primarily hardwood forests, usually upland oaks (e.g., *Quercus falcata*), in which pines account from 25 to 50 percent of the stocking. Upland hardwood (4) represents stands classified as oak-hickory (*Quercus-Carya*) or maple-beech-birch (*Acer-Fagus-Betula*) types, and bottom-land hardwood (5) represents mesic hardwood forest types, including oak-gum-cypress (*Quercus-Nyssa-Taxodium*) and elm-ash-cottonwood (*Ulmus-Fraxinus-Populus*) types. Hardwood forests are generally managed with low silvicultural intensity-after harvest they are regenerated naturally.

The estimates of fragmentation are based on the "size of condition" variable collected as part of FIA forest inventory surveys. This variable represents the size of the forest stand, which is the area covered by a contiguous stand of trees, as observed in the field. Since the stand can belong to more than one owner, this variable may not always accurately represent ownership or tract size. FIA personnel collected the "size of condition" information in 1982, 1989, and 1997 surveys of Georgia which were used to assess changes in forest fragmentation across the State.

To assess the status of forest fragmentation in Georgia, timberland was classified by the size of condition into 6 classes (0-4ha; 5-20ha; 21-40ha; 41-80ha; 81-202ha, and > 202ha, respectively). Since sample plot location information was not available, FIA data were aggregated to county levels and the distances from county centroids to each of Georgia's MSAs were calculated. Average stand size for Georgia's counties was calculated as a weighted average using assumed medians for the size classes (2, 14, 30, 61, 142, 405ha, respectively).

To assess one aspect of urbanization and forest fragmentation in Georgia we developed a regression model that attempts to explain how the average stand size is affected by both resource and socio-economic variables. County-level data were used in this analysis, since this scale was the least common denominator among the data considered. For Georgia's 159 counties, data on forest conditions were supplemented by county level estimates of population, per capita income, and building permits issued, each of which are thought to represent aspects of urban development. The average forest stand size for each county was estimated from the FIA inventory data, and was used as a dependent variable. In addition to these socio-economic variables, potential explanatory variables for inclusion in the model were estimates of total timberland area in each county, timberland area in each county by major owner group, timberland area in each county by major forest management type, distances from the center of each county to Georgia's MSAs, MSAs dummy, growth, removals and inventory from each county, a time trend, and interaction terms. A stepwise selection procedure was used to select a final set of variables included in the model. This procedure will select variables with some discriminatory power, however small, that can be reliably estimated. The selected explanatory variables included per capita income, population, building permits, distance to Atlanta MSA, and timberland in forest industry ownership, timberland classified as planted pine and upland hardwood forest types, and a time trend.

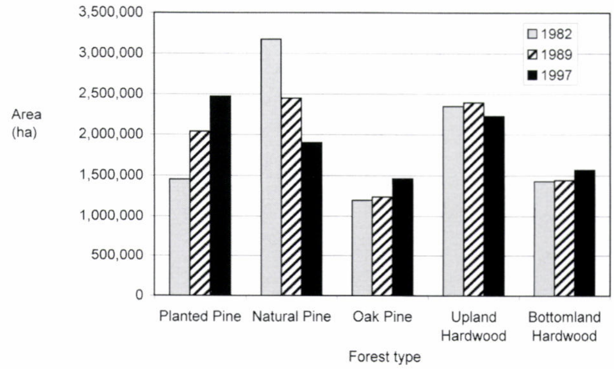

Fig. 1 Timberland area by forest type, all landowners.

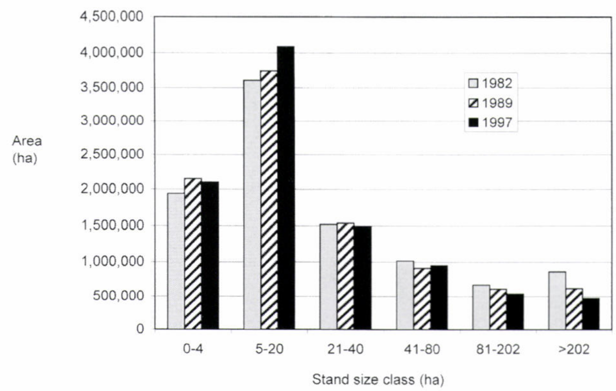

Fig. 2 Timberland area by stand size class, all landowners.

RESULTS

While the total timberland area in Georgia remained relatively unchanged between the FIA surveys, there were significant changes in the area of forest types. As shown on Fig. 1, the area of planted pine rapidly increased while natural pine forests became increasingly rare. Small increases were also noted in oak-pine forest types, while upland and bottomland hardwood forest types remained relatively stable.

The examination of FIA data for Georgia clearly indicates that forest fragmentation has progressed rapidly. Average stand size decreased from about 63 hectares in 1982 to less than 45 hectares in 1997, which represents nearly a 29 percent decline in stand size over past 15 years. Most of forest stands in Georgia fall into size class 2. The total area of forest stands in this class has increased from 1982 by more than 400 thousand hectares, reaching over 4 million hectares by 1997 (Fig. 2). The area of stands smaller than 5 hectares (size class 1) also increased, but to a lesser extent. In total, stands 20 hectares and smaller account for 66 percent of the timberland. Hence, there has been a decrease in the area of stands larger than 20 hectares. The largest declines in total area have been experienced in stands larger than 202 hectares. These trends indicate that large, contiguous forest stands are rapidly disappearing across Georgia's forested landscape.

As of 1997, the forest industry in Georgia had about 44 percent of its land in stands smaller than 20 hectares, compared to nearly 71 percent of stands in nonindustrial private ownership. This outcome reflects different holding structures as well as different investment and management approaches exercised by these two ownership groups. Over the period covered by FIA surveys, all forestland owners have lost timberland in the two largest stand size classes. Over this time period significant ownership changes have occurred with forest industry divesting its timberland and timberland investment management organizations (TIMOs) and private individuals acquiring timberlands. Between 1982 and 1997 the amount of land owned by the forest industry declined by nearly 18 percent. As long as this process continues, some of that land will likely be developed or subdivided into smaller parcels, which will contribute to the continued fragmentation of forest stands in Georgia. During the same period, nonindustrial private ownership expanded by nearly 400 thousand hectares, or about 6 percent, which also includes timberland transferred from industrial owners.

The parameter estimates of the selected county-level regression model are presented in Table 1. As expected, Atlanta has had a substantial impact on observed stand sizes in Georgia's counties, with larger stands being correlated with greater distances from Atlanta (Fig. 3). This result should be expected as Atlanta is the center of urban growth in the state. It also indicates that the distance from Atlanta may be a good predictor of forest fragmentation trends in Georgia's counties. The area of timberland held by the forest industry in each county is also positively associated with the average stand size. As one might expect, the size of land holdings necessary to support industrial timber production and processing operations is large. The area of upland hardwood in each county is

Table 1 Regression model parameter estimates

Variable	Estimate	Standard Error	*t*-value	Pr >|*t*|
Model intercept	64.733*	12.909	5.01	<0.0001
Distance to Atlanta MSA	0.553*	0.063	8.81	<0.0001
Forest industry area	0.309*	0.130	2.38	0.0175
Upland hardwood area	0.668*	0.125	5.34	<0.0001
Time trend	-13.367*	5.295	-2.52	0.0120
Planted pine area	-0.221	0.179	-1.23	0.2176
Average income for the county	-0.746	0.680	-1.10	0.2728
Population of the county	0.094	0.071	1.31	0.1900
Building permits issued	-0.012	0.007	-1.65	0.0995

Note: * indicates statistical significance at the .05 level.

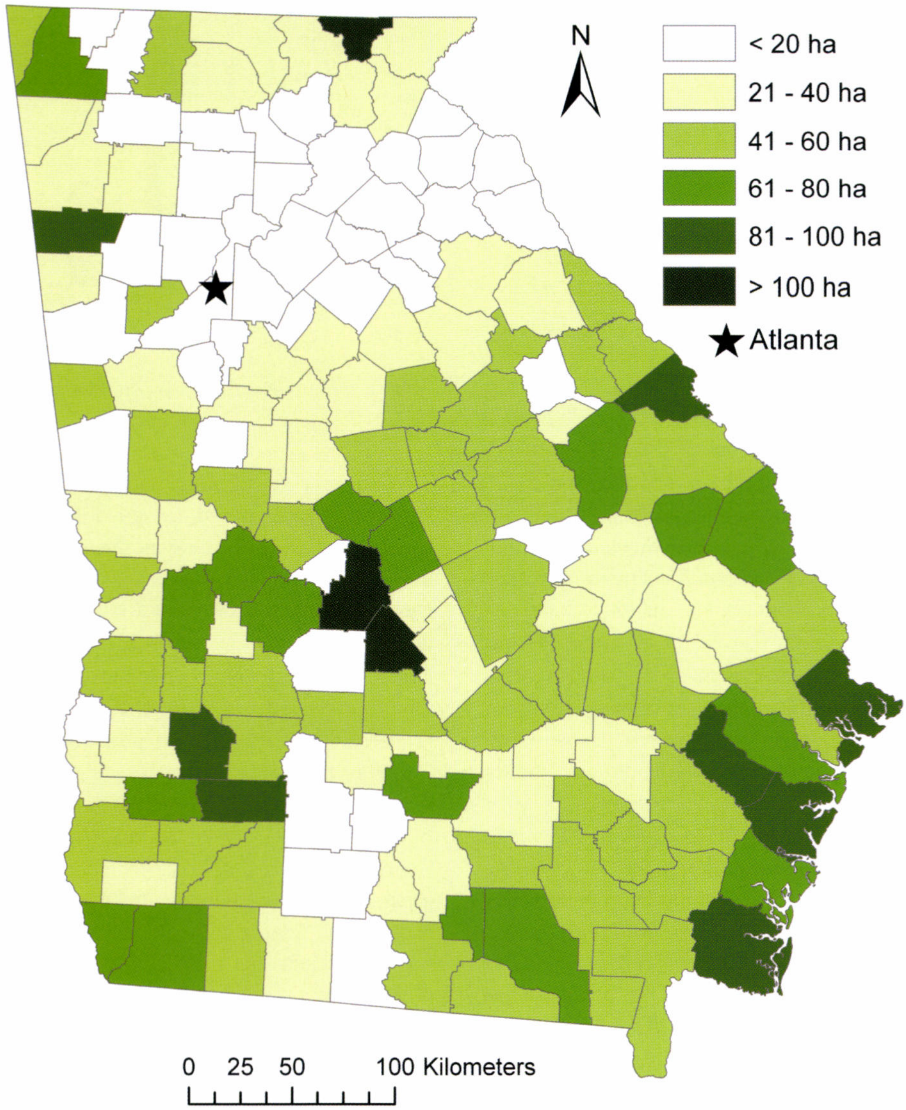

Fig. 3 Average forest stand areas in Georgia by county, 1997.

also positively correlated with the average size of forest stands, and significant in our final model. Upland hardwood forests are less intensively managed and harvested and, as a result, they are less fragmented than pine forests, as demonstrated by a positive and statistically significant parameter estimate. Finally, a statistically significant and negative time trend coefficient indicates that fragmentation of forest stands in Georgia's counties is progressing.

In contrast to what we might have expected, planted pine area in each county exhibits a negative relationship with average stand size. While not statistically significant, this outcome may result from the fact that pine plantations are intensively managed and harvested. Since the preferred harvest method is clearcutting, it is probable that the compliance with forest certification requirements and other regulations may have led to somewhat lower stand sizes in the planted pine category. Per capita income and the number of new building permits are, as expected, negatively associated with average stand size, yet again not statistically significant. Such results can be expected as more urban development, as measured by these two variables, leads to progressing fragmentation of forest stands. The population coefficient estimates, while close to zero, indicate a positive relationship between population and average stand size in each county, which is a somewhat counterintuitive and unexpected result.

DISCUSSION

Timberland located in metropolitan areas (as defined by MSAs) differs markedly from non-metropolitan timberland in terms of acreage changes, values, and management practices (HARRIS and DEFOREST, 1993; WEAR *et al.*, 1999). Part of this timberland has been or will be developed. While land clearing for development will produce some timber as trees are cut and processed, much of the remaining timberland is effectively removed from timber base because of high property values and the lack of interest in wood production. Some owners may continue to be interested in producing wood products; however, logging restrictions will likely make traditional forest management problematic. In all likelihood, metropolitan areas will provide less wood for forest products markets in the future. As shrinking timber supply prompts the processing industry to move to other areas, wood markets in urban and sub-urban areas become weaker, providing further disincentives to active forest management.

There are a number of concerns with the data and model we used to assess one aspect of urbanization and forest fragmentation in Georgia. The adjusted R-square for the model is 29 percent which indicates a rather poor fit. This is most likely the result of aggregating FIA data to the county level, which has removed much variability from the data. If individual FIA plot level data were available, then we would expect higher explanatory power of the model. However, the other resource and socio-economic data used in the regression analysis was only available at the county level, so the possibility of exploring the analysis at a finer spatial resolution was limited. But since distance from urban centers plays an important role in the county-level analysis, one might speculate that if the distances from each FIA inventory plot to the urban centers were used, the results may be even more pronounced. Another somewhat surprising result was that several of the socio-economic variables were not significant at the 5 percent level. This might suggest that other socio-economic variables could be important in assessing urbanization and forest fragmentation in Georgia. Research indicates, for example, that tax burden on forestland may be a good predictor of forest fragmentation (WEAR and NEWMAN, 2004; WEAR *et al.*, 1999); however, we were unable to explore this characteristic of timberland ownership in this analysis.

As urban areas have continued to expand, the area of timberland located in Georgia's MSAs increased from 1.7 million hectares in 1982 to nearly 1.9 million hectares in 1997, which represents a 17 percent increase. In total, a fifth of Georgia's timberland lies in metropolitan areas. The growing stock volume on this timberland increased by nearly 57 million cubic meters (29 percent), removals by 3.3 million cubic meters (60 percent), while growth decreased by about 450 thousand cubic meters (16 percent). These results appear to be consistent with observed trends in MSAs timberland use, where some land is converted to other uses (which could explain temporary increases in removals) and where some timberland is redirected from timber production to amenity or real estate uses (which could explain lower growth rates and higher inventory).

The tract (stand) size is one of the most important variables determining the economics of forest management. The small size of tracts makes traditional forest management difficult. They are, for example, more expensive to harvest and manage (COMOLLI, 1981; ROW, 1979). As a result, removals and planting rates are lower, as observed in South Carolina, Virginia, and Florida (THOMPSON, 1999). Further, GREENE *et al.* (1997) determined that timber sale size as measured by tract size had been steadily declining in Georgia over the past two decades. The smaller tracts received less interest from potential buyers or lower stumpage prices, and harvesting of tracts smaller than 8 hectares was often uneconomical. In the end, as management incentives continue to erode, these forests will provide less timber to forest products markets.

CONCLUSIONS

The results of this study demonstrate that urbanization and fragmentation of forest stands in Georgia continue at a rapid rate. They demonstrate that distance from MSAs and the extent of industrial forestland ownership are useful variables in predicting the progress of parcelization and fragmentation. Both urbanization and fragmentation result in loss of timberland allocated to wood production, smaller stand sizes, lower investment returns and ensuing lower management intensity. It is actually expected that forest fragmentation may have accelerated since 1997, the last data point used in the analysis, due to the forest industry having accelerated sales of its forestland in recent years.

The development of land is not necessarily bad. At the same time, it is clearly recognized that keeping some land in undeveloped uses is desirable for a variety of reasons and objectives. The question is of finding and achieving the right balance between developed and undeveloped uses. In metropolitan areas, the role of urban forest management will expand and eventually replace timber based management. Consequently, the role of urban foresters will grow in preserving that forestland. In suburban areas, more aggressive tools to protect traditional land uses could be developed. It is apparent that we currently do not have effective tools to manage this process. Forestland owners most likely will need more assistance than presently available in order to keep forest management a viable option.

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Article

Factors Affecting Deforestation in Paunglaung Watershed, Myanmar using Remote Sensing and GIS

Myat Su Mon[*1], Tsuyoshi Kajisa[*2], Nobuya Mizoue[*2] and Shigejiro Yoshida[*2]

ABSTRACT

The objective of this study is to predict the factors affecting deforestation based on the relationship between detected forest cover changes and biophysical factors of the study area by using spatial and statistical analysis. The study area is Paunglaung watershed, one of the important watersheds in Myanmar. This study used maximum likelihood classification (MLC) to compare Landsat TM images of 1989 and Landsat ETM+images of 2000 in order to assess deforestation. The study revealed that 32.61km² or 0.7% of the forest cover was annually lost in the watershed area. An empirical spatial model of deforestation was developed by relating a set of variables measuring landscape attributes to the spatial occurrence of deforestation. Variables derived from the GIS based analysis were used to verify spatially the close statistical relationship between dependent and independent variables by logistic regression model. This study provides both statistical and spatial confirmation of the importance of access in the location of deforestation.

Keywords: Landsat images, maximum likelihood classification (MLC), GIS, logistic regression, deforestation.

INTRODUCTION

Deforestation and forest degradation in developing countries have been major environmental concerns over the past few decades. As forest cover changes are particularly severe in the tropics and have significant global impacts (NAGENDRA *et al.*, 2003; SOUTHWORTH *et al.*, 2004), the destruction of tropical forests has received worldwide attention due to the significant effect on climate, carbon sequestration, water cycle and biodiversity (FEARNSIDE, 1997; TUCKER *et al.*, 2005). On the other hands, the forests of Southeast Asia comprise some of the world's most valuable and productive tropical forests, forming unique ecosystems of high biodiversity composition (STIBIG *et al.*, 2007). Deforestation and forest fragmentation are leading to the major threats to the flora and fauna that live therein (ZHAO *et al.*, 2006). Tropical deforestation and forest degradation has been occurring at an unprecedented rate and scale in Southeast Asia (GIRI *et al.*, 2003) and forest loss has remained at high levels during the period from the year 2000 to 2005 (FAO, 2005). The actual rate of deforestation varies over time and from region to region and is difficult to determine (BAWA and DAYANANDAN, 1997; GUPTA *et al.*, 2004).

Repeated observations of satellite images and/or aerial photographs are useful for both visual assessment of natural resources dynamics occurring at a particular time and space as well as quantitative evaluation of land cover changes (TEKLE and HEDLUND, 2000). Analysis and presentation of such data can be greatly facilitated through the use of GIS (ESCAP, 1997). Therefore, a combined use of remote sensing (RS) and GIS technologies can be invaluable to address a wide variety of resource management problems including the assessment of land cover changes and its causes (GAUTAM *et al.*, 2003). Time series analysis of land cover change and the identification of the driving forces responsible for these changes are needed

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for the sustainable management of natural resources and also for projecting future land cover trajectories (GIRI *et al*., 2003).

Myanmar is endowed with a highest percentage of forest cover in the Asia Pacific region; forests cover is 49% of the total land area of 676,000km² (STIBIG *et al*., 2007). The overall deforested area between 1955 and 1997 was about 3,160km² per year indicating that the actual forest area was annually decreasing at a rate of 0.5% of the total land area of the country (FOREST DEPARTMENT, 2003; THAN, 2000). However, FAO estimated that Myanmar is losing forest cover at a rate of 1.3% per year for 1990-2000 and 1.4% per year for 2000-2005 periods (FAO, 2005).

The study area, Paunglaung watershed, Myanmar is an important sub-catchment for Paunglaung multi-purpose dam which is intended to produce electricity and water irrigation. Therefore, conservation of forest cover in the upland watershed areas is crucial to get adequate water supply for the dam. Rural communities living in the watershed traditionally depend upon the natural resources, mainly forest resources for their livelihood. Due to increased population and continuous expansion of shifting cultivation, adverse effects and consequences in terms of deforestation, soil erosion, loss of biodiversity and watershed degradation are mounting in the study area (MYINT *et al*., 2002). Measures contributing to the emergence of a proper watershed management should urgently be taken based on the dynamic of forest cover changes. However, there was no systematic regional scale land cover change assessment and deforestation study for the Paunglaung watershed area. With this respect, detection on the land cover changes in Paunglaung watershed was conducted during the period of 1989 and 2000.

Factors affecting deforestation and land cover changes have been attributed by various reasons and those reasons are site specific (GIRI *et al*., 2003). Various spatial, statistical analysis of deforestation has already been applied in other countries, and these researches were attempted to identify predictors of the location of areas with the greatest propensity for deforestation (MERTENS *et al*., 1997). However, the information related with deforestation and land cover change model is very limited in Myanmar. The present study was conducted in order to fulfill the objectives; 1) to detect the changes of land covers of the study area between 1989 and 2000 through the application of RS and GIS; and 2) to predict the possibility of driving factors of deforestation through the establishment of a spatial logistic regression model.

We used logistic regression model to predict the driving factors of deforestation. The available biophysical data and location of the human settlement were applied to understand the potential driving factors of deforestation. The development of models of deforestation processes is motivated by several potential benefits to provide a better understanding of the causes and mechanisms governing deforestation, to generate predictions of future rates of deforestation and locate future forest clearing and, to support the design of policy responses to deforestation (LAMBIN, 1994; MAS *et al*. 2000).

METHODOLOGY

Study Sites

The study area, Paunglaung watershed is located in central Myanmar and lies between latitudes 19° 20' to 20° 35' north and longitudes 96° 15' to 97° 00' east (Fig. 1). It covers an area of about 4,600km² and most areas are mountainous with altitudes ranging from 180m to 1,800m above sea level. The study area is falling mainly in two administrative boundaries, Manadalay Division and Shan State. Generally, precipitation of the study area is higher in the eastern parts, i.e. Shan State and maximum and minimum annual total rainfalls are 2,167mm and 812mm, respectively (Local Meteorological and Hydrological Stations). Drainage is predominantly north to south and Paunglaung river is the main stream which running from north to south and turns to the west in the middle of the study area. Forests cover most parts of the watershed and they can be broadly classified as mixed deciduous forests and evergreen forests (FOREST DEPARTMENT, 1998a and 1998b). Mixed deciduous forests, which are by far one of the commercially important forests in the country, are found mostly in the parts of lower elevation area whereas areas at high elevations are covered with an evergreen type of forests. This area is an important source for both local and commercial timber supply. Besides, this watershed is also an important habitat for wild fauna including tiger, elephant and various wildlife species (WILDLIFE CONSERVATION SOCIETY, 1997). This area is also crucial to supply efficient water to Paunglaung dam that was located on the Paunglaung river (Fig. 1). It is first and largest underground facility project in Myanmar to supply electricity amounting to about 900 million kilowatt/hour annually and to irrigate water for 28,330ha of various crops (IRRIGATION DEPARTMENT, 2004). Accordingly Paunglaung watershed has diverse intrinsic values not only for the local and national economy but also for biological diversity conservation (ZIN, 2005).

Land Cover Change Assessment between 1989 and 2000

The main data used in land cover change assessment included landsat images, Landsat 5/TM for 1989 and Landsat 7/ETM+ for 2000 (Table 1). The study area was related to the area common to three landsat images, i.e. 133-46, 132-46 and 132-47 (Fig. 1.c).

Landsat TM satellite images of 1989 which were already georeferenced to the coordinate system of the study area (WGS84, projection: UTM, zone 46 N) were used as master images for georeferencing and image to image co-registration for the images of 2000. Classifications procedures were applied for TM images of two years using TNTmips 6.9 (Fig. 2). Band

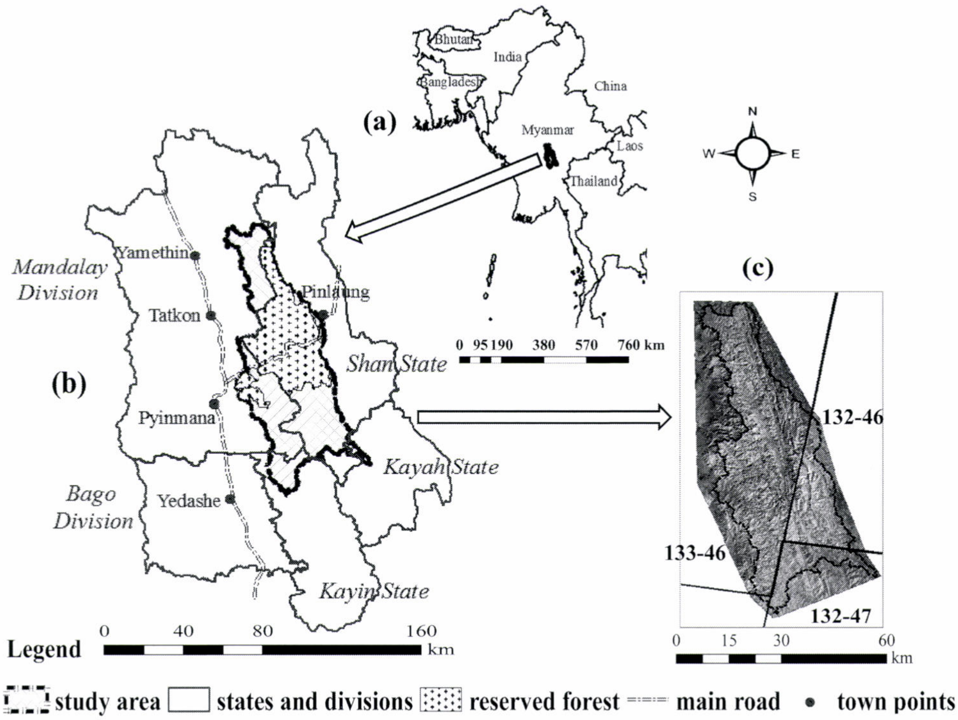

Fig. 1 Location of study area, Paunglaung watershed. (a) Study area located in central Myanmar. (b) Study area and its surrounding regions. (c) Paths and rows of three Landsat images used in the study

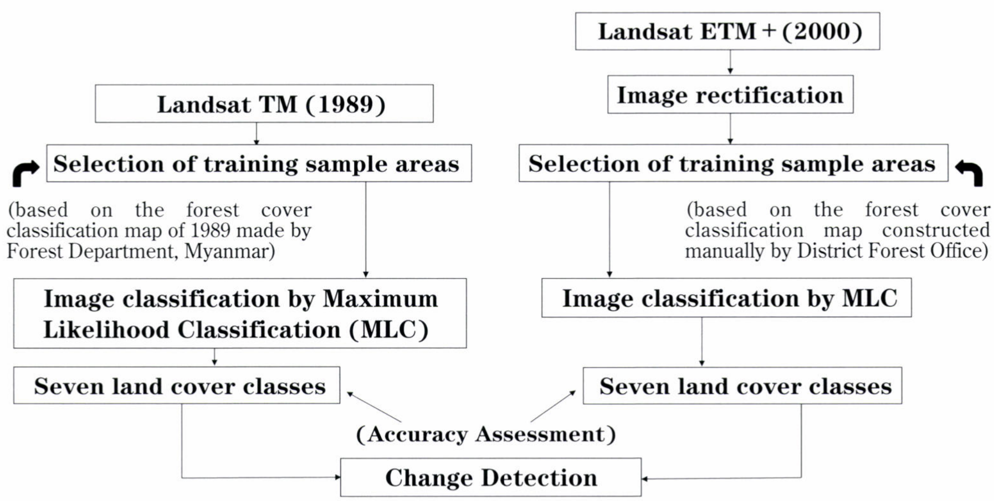

Fig. 2 Land cover change assessment between 1989 and 2000

Table 1 Images used for assessment of land cover changes of Paunglaung watershed

No.	Year	Scenes (Path & Row)	Satellites	Acquisition Date
		132_46	Landsat 5/ TM	10-2-1989
1.	1989	132_47		10-2-1989
		133_46		16-1-1989
		132_46	Landsat 7/ ETM +	24-1-2000
2.	2000	132_47		23-12-1999
		133_46		4-4-2000

combination of band 4 (Red), band 5 (Green), and band 3 (Blue) of Landsat5/TM and Landsat7/ETM+ satellite scenes was used in visual image classification. This is the best band combination used effectively for vegetation cover classification (SIDJAK and WHEATE, 1999).

Ancillary data such as ground verification records and vegetation maps were considered during the selection of training areas in order to obtain the greatest accuracy of the classification results (HUTCHINSON, 1982). Training areas representing the homogeneous spectral characteristics of the defined land cover categories, i.e., 10 to 13 of land cover categories related to the study area were selected to perform supervised classification. More than twenty training samples for each category were created visually by Area of Interest (AOIs) based on the homogeneity of the reflectance pixel values. For 1989, training samples were selected based upon the forest cover classification map conducted by Forest Department, Myanmar under the UNDP/FAO National Forest Management and Inventory Project in 1989. For 2000, training samples were selected based on the forest cover map prepared manually by the district forest office.

Maximum Likelihood Classification (MLC) was conducted by using the selected training samples in the analysis of multi-spectral image data. Classified land cover classes were finally combined into seven land cover classes; namely forest land, degraded forest land, waterbody, scrub and grass land, shifting cultivation, cultivated land and bare land including built-up areas (Table 2). For accuracy assessment, it was impossible to get the GPS positions of actual ground data for 1989 and 2000. Ground data, totally 140 GPS points (twenty GPS points for each land cover class) were obtained by the knowledge based data accepted from the interview survey with the local communities in the late 2004 and in the early 2005. After checking the accuracy of the classified images by classification error matrix, two land cover thematic maps were exported and overlaid in ArcGIS 9.1 to detect the forest cover changes of the study area. Actual change can be obtained by a direct comparison between classification results of one date with the other date. Temporal condition of land covers that have occurred between the two dates were measured by performing a change matrix (HOWARTH and WICKWARE, 1981).

Establishment of Logistic Regression Model

Logistic regression is a technique for analyzing problems in which there are one or more independent variables that determine an outcome and the outcome is measured with a dichotomous variable (in which there are only two possible outcomes) (MENARD, 1995; PAMPEL, 2000). Logistic regression model was constructed based upon the spatial information of forest cover changes as dependent variable and eight biophysical factors as independent variable explanatory to predict the possibility of deforestation.

Generation of Dependent Variables

The spatial prediction of deforestation or land cover changes requires an understanding of the proximate causes of changes (SERNEELS and LAMBIN, 2001). Deforestation taken place over eleven year period was detected as dependent variables based on the change detection. The addressed question to detect dependent variables was "where deforestation is taking place?" Land cover classification maps of 1989 and 2000 were simplified by seven land cover classes. Then forest and degraded forest were grouped into forest and other five classes into non-forest. The final images after completing this processing were binary coded using pixel size of 30×30m. Images were then overlaid in order to produce a digital map of deforestation that presents changes or decrease of forest cover. Some change combinations such as non-forest/non-forest or non-forest/forest (increase) were neglected in this analysis because this study focuses on the modelling of deforestation process only. As the interest is to determine the predictors for deforestation, the numerical coding for deforestation was 1 for yes (decreased of forest cover) and 0 for no (no change forest cover). Therefore, the deforestation thematic map present only two classes, deforestation taking place, coded as 1 and no-deforestation taking place, coded as 0 between 1989 and 2000.

Generation of Independent Variables

Independent variables used in logistic regression model were conducted and extracted from various GIS layers related with biophysical factors, accessibility and villages' locations of

Table 2 Recoding land cover classes in the study area

Land cover class	Characteristics
forest land	forest with more than40 % canopy cover
degraded forest land	forest with 10-40% canopy cover
shifting cultivation	area currently under shifting cultivation, fallow land
cultivated land	permanent agriculture land, home garden
scrub and grass land	forest with less than 10% canopy cover
bare land	villages, roads, non-vegetative areas
waterbody	river, streams

the study area. The road network, stream network, town points and village points were manually digitized from topographic maps of 1: 63,360 scale, published in 1945 by the Survey Department of Myanmar and updated with 2000 Landsat satellite images and local administrative records. A digital elevation model (DEM) was constructed in TNTmips based on the contour lines; at an interval of 50 ft (15.24m) that were also digitized from topographic maps. The thematic soil map of the study area was extracted from the Myanmar soil distribution map based on the FAO soil classification system and prepared by Land use division of Myanmar Agriculture service.

Generation of GIS Layers

i) Distance to roads: We used the road network which consists of two main roads (Fig. 1(b)) in this analysis as other roads can be used only during summer and especially used for timber extraction purpose. This variable was calculated as a series of buffers of 1km expanding from the road network.

ii) Distance to towns: Five towns where there are large markets, government services, and hospitals etc; located around the study area were taken into account to detect the variable in the model. Distances were calculated as a series of 1km buffer, expanding from the town points.

iii) Distance to villages: Totally 88 villages located in the study area were registered based on the topographic map and official records. Local communities are practicing shifting cultivation for subsistence living by clearing nearby forests around their villages. The areas around human settlements are mostly under the shifting cultivation cycle. They also established permanent agriculture like horticultural farms and low land rice cultivation for commercialization process (ZIN *et al.*, 2002). We hypothesized that there may be some effects on forest cover surrounding the village. A series of buffer circle of 1km radius from the village point was created for all the villages.

iv) Distance to water resources: Distance to water resources was calculated as a series of buffer of 1km, expanding from each stream network of the river and streams. Accessibility to permanent water sources is highly valued because most of the local community need regular access to water resources for daily use, livestock and agriculture.

v) Area under logging: According to the logging records of Myanmar Timber Enterprise, logging activities were conducted within the three reserved forests of the study area and not within the other regions (Fig. 1(b)) during the period of 1990s. Logging creates access roads that might encourage surrounding communities into forests for agricultural expansions especially shifting cultivation and illegal logging, thus a higher possibility of future deforestation was expected due to the logging concessions. Unfortunately, we could not define specific areas of logging within the reserved forest for concessions, and we used three reserved forests boundary and separated study areas into two, reserved forest as logging area and outside reserved forest as non logging area. Polygon features were coded as 1 for reserved forest and as 0 for others.

vi) Soil types: The exploratory soil map for the study area was extracted from the soil type distribution map of Myanmar made by Land use division of Myanmar Agriculture service under FAO project. The suitability for agriculture depends on the soil type. The possibility of clearing of forest for agricultural purpose is leading to deforestation. In the study area, there are four soil types, i.e. meadow and meadow alluvial soil (Gleysol Fluvic), red earths and yellow earths (Acrisols), light forest soil (Nitosol), and mountainous brown forest soil (Cambisol). Those soil types were coded according to the level of agricultural suitability indicating from smaller coded to higher coded categories. We coded meadow and meadow alluvial soil as 1, red earths and yellow earths as 2, light forest soils as 3 and mountainous brown forest soil as 4.

vii) Elevation and slopes: DEM created by surface modelling of TNTmips was exported into ArcGIS by 30×30m raster layer. Slope layer was created based on DEM by spatial analysis of ArcGIS.

The above eight GIS layers were created with coded attributes according to their categories, 0, 1, 2 and 3, etc. (Table 3) and all layers were converted and used as raster data

Table 3 GIS database used in logistic regression model

Variables	Type	Unit	How to generate
Deforestation	**Binary**	**0-1**	**Change detection (1989-2000)**
Distance to roads	Continuous	km	From road network
Distance to towns	Continuous	km	From town points
Distance to villages	Continuous	km	From village points
Distance to water resources	Continuous	km	From stream network
Soil types	Categorical	1-4	Extracted from soil type distribution map of Myanmar
Area under logging	Binary	0-1	Timber logging records
Elevation	Continuous	meter	From contour map/DEM
Slope	Continuous	degree	DEM

source by using pixel size of 30×30m. SPSS logistic regression models the relationship by computing the changes in the likelihood of falling in the categories of the dependent variable which has the highest numerical (CHAN, 2004; SCHWAB, 2004).

Sampling Procedure

Prior to performing the logistic regression, random points were created to select N observation points by the spatial extensions of Hawths tool of ArcGIS and the minimum distance between points is 1km. A random sample of 3,201 observations was selected and that distributed throughout the study area. Their attributes for dependent variables and independent variables were extracted by GIS and then logistic regression model was constructed by SPSS 11.5.

Logistic Regression Model

We modelled the logistic regression by SPSS to test the relationship between a dichotomous dependent variable (occurance of deforestation/ no occurance of deforestation) and eight independent variables of biophysical and location data. The overall ability of the independent variables to predict the dependent variable was compared.

Before establishing the logistic regression model, multicollineariy test was conducted by linear regression and checking variance inflation factor (VIF) and tolerance because this is necessary to avoid collinearity between the independent variables (GARSON, 1998). When VIF is high, there is high multicollinearity and for tolerance > 0.20 or VIF < 4 suggest no multicollinearity (BELSLEY *et al.*, 1980). The test showed no collinearity with the tolerance ranging from 0.27 to 0.99 which is higher than the critical value of 0.20 and all VIF were less than 4 (Table 4). Therefore, all the independent variables were used in the establishment of logistic regression by binary logistic regression analysis.

The fitting of the logistic regression model was assessed using model chi-square statistics ($p < 0.05$), which is an overall measure under the null hypothesis of perfect fit, and indicates the relationship between dependent variable and independent variables.

RESULTS

Assessment of Land Cover Changes

The overall accuracy of land cover classification for 1989 is 87.1% (Kappa Statistics of 0.86) whereas for 2000 the accuracy is 84.3% (Kappa Statistics of 0.82).

Total forest area decreased from 2,837km^2 to 2,478km^2

Table 4 Multicollinearity test for the independent variables

	Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	0.492	0.040		12.317	0.000		
slope	0.005	0.010	0.008	0.476	0.634	0.995	1.006
elevation	−0.051	0.010	−0.125	−5.294	0.000	0.540	1.851
soiltypes	−0.068	0.012	−0.125	−5.917	0.000	0.673	1.486
logging/non	0.183	0.018	0.245	10.257	0.000	0.523	1.910
dis-road	0.005	0.001	0.197	5.982	0.000	0.276	3.318
dis-town	−0.003	0.001	−0.114	−3.572	0.000	0.295	3.289
dis-water	−0.007	0.002	−0.110	−4.937	0.000	0.602	1.662
dis-village	0.005	0.000	0.002	0.137	0.891	0.997	1.003

notes: logging/non: area under logging or not, dis-road: distance to roads, dis-town: distance to towns, dis-water: distance to water resources, dis-villages: distance to villages.

Table 5 Change matrix for land cover classes (km^2) of 1989 and 2000

	For	Deg-For	SC	Culti-land	Sc-Gr	Bare Land	WB	1989
For	**1,857.1**	210.4	388.0	60.7	318.2	2.8	0.0	2837.2
Deg-for	598.7	**262.4**	41.0	40.7	52.2	1.8	0.1	997.0
SC	10.6	42.3	**163.5**	78.1	127.8	5.2	0.0	427.5
Culti-land	12.0	16.9	23.7	**38.7**	72.9	5.2	1.3	170.6
Sc-Gr	0.0	0.0	9.4	31.2	**65.7**	3.6	1.3	111.2
Bar	0.0	0.0	4.9	29.8	31.0	**11.4**	0.0	77.1
WB	0.0	0.0	0.0	9.1	0.0	0.7	**1.4**	11.3
2000	2478.4	532.0	630.5	288.3	667.9	30.7	4.1	**4,631.9**

notes: For = forest land, Deg-For = degraded forest land, SC = shifting cultivation, Culti-land = cultivated land, Sc-Gr = scrub and grass land, Bare = bare land and WB = waterbody

(Table 5) although degraded forest land and other land covers positively converted to forest area, i.e. 621km². Forests were converted into degraded forests mostly in the western part of Paunglaung watershed (Fig. 3). Forest area of 210km² negatively changed to degraded forest land. However, total degraded forest area was decreased from 997km² to 532km² because 735km² degraded forest land changed into other land cover, i.e. shifting cultivation, cultivated land, scrub-grass land and bare land.

Total area of shifting cultivation increased up to 631km² in 2000 from 428km² in 1989. Short fallow period for shifting cultivation was observed in the study area (Zin *et al.*, 2002; Myint *et al.*, 2002), This consequently lead to the increase of scrub and grass land from 111km² in 1989 to 668km² in 2000.

Some forest areas around villages and stream banks changed into cultivated lands. That was frequently observed along the bank sites of the Paunglaung river (Fig. 3). Total area of cultivated land increased up to 288km² in 2000 from 171km² in 1989 (Table 5), and conversion was mostly observed in the eastern parts of the watershed.

Total bare land areas also decreased between 1989 and 2000 from 77km² to 31km². This changes mostly related with conversion into shifting cultivation, cultivated land and scrub and grass land; i.e. 4.9km² of bare land areas converted to shifting cultivation, 29.8km² to cultivated land and 31km² to scrub and grass land respectively (Table 5).

The comparison of the areas of seven land cover classes of the study area between 1989 and 2000 is expressed in Fig. 4. The results of the classification of land covers show that forest area decreased by 7.7% from 1989 to 2000. The area under degraded forest also declined 10.0% between 1989 and 2000. On the other hands, scrub and grass land, shifting cultivation and cultivated land increased 12.0%, 4.4% and 2.5% of the total area respectively during the two periods.

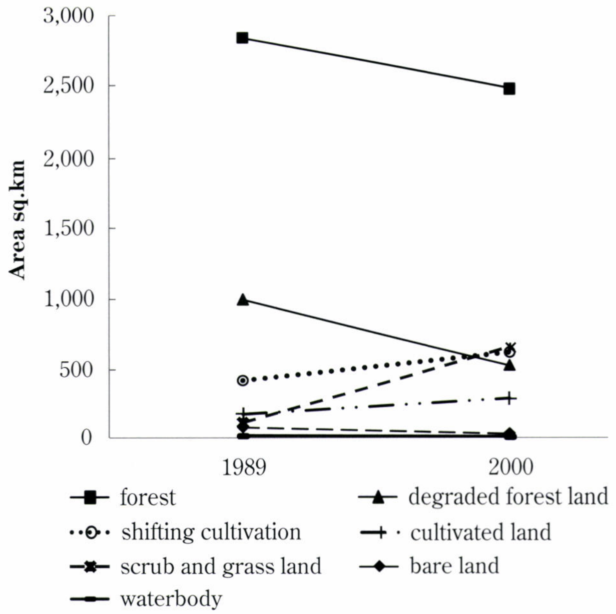

Fig. 4 Comparisons of areas of land cover classes for 1989 and 2000

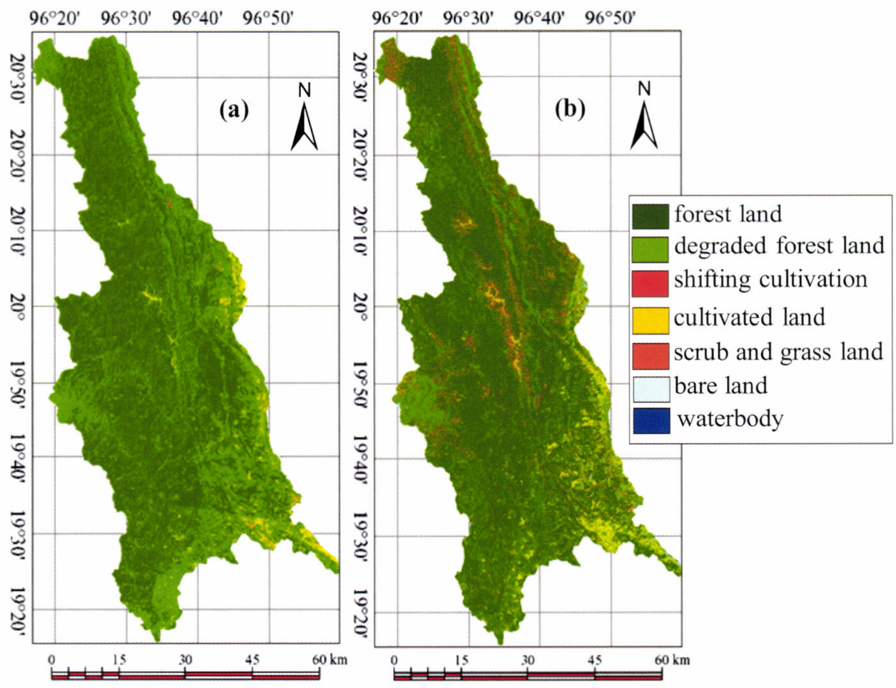

Fig. 3 Land cover classification of Paunglaung watershed, 1989 and 2000

Logistic Regression Model

Logistic regression model was constructed based on the spatial attributes of the randomly distributed points, i.e. 666 for deforestation and 2,535 observation points for no-deforestation. All eight predictor variables that were entered into the model passed the multicollinearty test and were fitted in the logistic regression model. Logistic regression model revealed that elevation, soil types, forest area under logging activities, distance to roads, distance to towns and distance to water resources were the significant factors in predicting the possibility of deforestation (Table 6).

Out of the six independent variables which are significant in the model, two variables; areas under logging activities and distance to roads are positively related with deforestation at the significant levels of 0.000 and 0.008 respectively. In the case of distance to roads, that factor is positively related with deforestation and it means that areas which are located far from main road have high possibility for deforestation. In this analysis, we could use only the effect of main roads. There might be significant effect of logging roads in the study area. Therefore, the effect of distance to roads to predict deforestation might be undetected. On the other hand, area under logging activities was also the significant factor in the logistic regression model.

The other predictor variables; i.e. elevation, soil types, distance to towns and distance to water resources were negatively related with deforestation at the significant levels of 0.011, 0.037, 0.000 and 0.000 respectively. According to the results of logistic regression, if the elevation becomes higher, the probability of deforestation becomes lower. The possibility of deforestation of the areas located far from the towns becomes lower than that of the areas close to the towns. Similarly, the areas closed to water resources have higher possibility of deforestation than the areas far form the water resources.

Factor of soil types is negatively related with deforestation, i.e. we gave high priority for the mountainous brown forest soil and SPSS modeled the relationship with highest numerical variables. Deforestation was mostly observed in the regions of meadow and meadow alluvial soil and red earths and yellow earths. These soil types are good for paddy land and very suitable for cultivation of seasonal and perennial crops (SETTLEMENT and LAND RECORD DEPARTMENT, 2002).

The importance of contribution of each variable in the model can be estimated by wald statistics. The higher the value of wald statistic in the model, the more important it is (CHAN, 2004). In logistic regression results (Table 6), distance to water resources has the highest contribution to prediction (Wald=44.594) of deforestation followed by the distance to towns (Wald=22.676) and then area under logging activities (Wald=20.231).

DISCUSSIONS

During a period of 11 years, 0.7% of the forest cover was annually lost in Paunglaung watershed. The estimated deforestation rate of study area; 0.7% was higher than the estimated annual deforestation rate by Forest Department, Myanmar (FOREST DEPARTMENT, 2003; THAN, 2000) and lower than that of FRA 2000 and 2005 by FAO at the national level. This might be because of using different remote sensing data, different technologies and also performed by different persons.

Forests are being converted into degraded forests due to increased population in the down-stream areas and consequently, encroachment upon the forest lands is gradually increasing (MYINT *et al.*, 2002). Due to gradually increasing population (Local Administrative Offices), total areas of cultivated land and shifting cultivation also increased up to 288km^2 (6.2%) and 630km^2 (14.0%) respectively in extent at 2000. Some forest areas of eastern parts were converted to agricultural land; i.e. farmlands growing green tea and orange which are the important economic products for household income at that region. The proximate causes of forest loss vary widely among Asian countries, though conversion for agricultural purposes is common. This study is also consistent with the results that one of the driving forces of deforestation

Table 6 Logistic regression result for deforestation

	B	S.E.	Wald	df	Sig.	Exp(B)	x^2	P value	R^2
slope	−0.066	0.078	0.726	1	0.394	0.936	210.13	0.000	0.103
elevation	−0.184	0.073	6.396	1	0.011	0.832			
soiltypes	−0.162	0.078	4.337	1	0.037	0.851			
logging/non	0.570	0.127	20.231	1	0.000	1.768			
dis-road	0.016	0.006	6.978	1	0.008	1.016			
dis-town	−0.033	0.007	22.676	1	0.000	0.967			
dis-water	−0.098	0.015	44.594	1	0.000	0.907			
dis-village	0.001	0.003	0.031	1	0.860	1.001			
Constant	0.727	0.300	5.864	1	0.015	2.068			

notes: logging/non: area under logging or not, dis-road: distance to roads, dis-town: distance to towns, dis-water: distance to water resources, dis-villages: distance to villages.

is expansion of agricultural land (LEIMGRUBER *et al.*, 2006; SONGER, 2006).

Shifting cultivation by indigenous ethnic groups is still considered a major cause of forest loss in the mountain zones of Myanmar, where there is an increasing pressure for land by the growing population (STIBIG *et al.*, 2007). Shifting cultivation is a common farming system traditionally practiced since time immemorial in the study area (ZIN *et al.*, 2002; MYINT *et al.*, 2002). The fallow period of shifting cultivation is reduced today because of increased population and limited land availability (ZIN *et al.*, 2002). On the other hands, the forests are also fragmented due to shifting cultivation and become open. Gap planting should be introduced in open areas to increase the forest cover. Community forestry and agroforestry could be viable options to reverse the current trend of deforestation (ZIN *et al.*, 2002).

According to the logistic regression results, forest areas located near the human settlement have high possibility to cause deforestation. The perspective of future research should be conducted to predict the drivers of deforestation based on increased population rate of the local communities, the detail information of their livelihood and how much that community depends on surrounding forests.

In Myanmar, shifting cultivation, logging and forest fire play a dominant role in forest degradation and forest type conversion (GIRI *et al.*, 2003). In this logistic regression model, areas under logging activities were significant and also one of the affecting factors of deforestation in the study area. The results of land cover change assessment and logistic regression show that deforestation took place especially in the low elevation area. Forest cover changes were observed mostly in the areas where soil types are good for agricultural purpose. That results were supported by the hypothesis of other research; biophysical and locational factors are strong determinants of regional deforestation, specifically, lower elevation and well-drained upland soils are more likely to cause deforestations (GEOGHEGAN *et al.*, 2004; MAS *et al.*, 2004; CHOWDHURY, 2006).

The possibility of deforestation is low in the high elevation area. As the saying goes "Prevention is better than cure", it would be prudent to constantly monitor the factors which contribute to deforestation. An effective watershed management programme should be launched according to an example of a multi-disciplinary way by local people participation and awareness conducted by Forest Department under the project of MYA/93/005 (THAN *et al.*, 1990; GAF, 1996).

CONCLUSIONS

Forest cover decreased during a period of 11 years and 0.7% of the forest cover was annually lost in Paunglaung watershed. Continued degradation of the forest resources will ultimately result in deforestation. Sustainability of Paunglaung watershed is necessary for social, eological and economic benefits. However, deforestation can be prevented through the application of effective management. With this respect, this study demonstrates and suggests a spatial logistic regression model to predict the possibility of driving factors for deforestation. Based on these results, effective remedial measures can be conducted to prevent deforestation in the study area. The quality of the current analysis for predicting deforestation could be improved by using together with socio-economic variables of local communities and other environment factors. Spatial information obtained by integrated application of RS and GIS is particularly an important basis for decision making process in natural resource management. The authors convince that the predicted driving factors of deforestation in this study will provide useful information for effective management of natural resources in Myanmar.

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Article

Applicability of Kriging to Predict Spatial Distribution of Carbon Stocks of *Acacia mangium* Plantations

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ABSTRACT

The prediction of carbon stocks is essential to evaluate the environmental benefits of forests. Although carbon stocks can be predicted by combining sample plots from several or all forest stands, this approach cannot directly provide spatial information on the distribution of the carbon stocks. We investigated the applicability of kriging as an alternative method to spatially predict the carbon stocks of an *Acacia mangium* plantation in Indonesia. The carbon stock data obtained from 247 sample plots and variogram analysis were used to characterize and model the spatial autocorrelation of the carbon stocks. The spatial prediction of carbon stocks was carried out using ordinary kriging (OK), universal kriging (UK), and co-kriging (CK) methods. UK used the geographical coordinates as a secondary variable, whereas CK used stand age. The prediction accuracy of the kriging methods was assessed using cross-validation. The carbon stocks were spatially autocorrelated up to a distance of 3,600m and tended to be more similar along the direction of 135°. The kriging methods produced similar prediction maps of the spatial distribution of the carbon stocks. There were no significant differences among the kriging predictions and their standard deviations. Cross-validation, however, confirmed that CK performed better than OK and UK. The predicted carbon stocks varied from 7.25 to 37.95tC/ha, with a standard deviation ranging from 9.44 to 12.21tC/ha. Thus, kriging can be used as an alternative method to predict the spatial distribution of carbon stocks or other forest attributes.

Keywords: carbon stocks, geostatistics, kriging, spatial autocorrelation, variogram

INTRODUCTION

The role of forest ecosystems in maintaining environmental balance has become an important issue because the world is facing the problem of global climate change. As pointed out by Murray *et al.* (2000), forest ecosystems can effectively absorb carbon dioxide (CO_2) from the atmosphere by transforming it into carbon stocks stored in various forest components, e.g., trees, woody debris, and soil. Compared to other terrestrial ecosystems, forests are the largest ecosystem for carbon storage (Davis *et al.*, 2003).

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Quantifying the carbon stocks of forest ecosystems has gained importance recently, particularly to provide the reliable estimates that are required to implement afforestation and reforestation (A/R) projects under the Clean Development Mechanism (CDM) of the Kyoto Protocol. In this context, Indonesia has a great opportunity to participate in the A/R CDM projects (Matsumura *et al.*, 2008; Murdiyarso *et al.*, 2008) by managing forest resources as carbon sinks. One promising forest resource for such purposes is *Acacia mangium* plantations (Velez and Valle, 2007). *A. mangium* is a fast-growing species that has been planted widely in Indonesia; it has a short rotation of 6-10 years and is especially managed for timber production. However, there is still relatively limited information related to the carbon sequestration benefits of this plantation species compared to its timber benefits.

The development of prediction models to quantify carbon stocks is essential to support the management of plantation forests as carbon sinks. Miyakuni *et al.* (2004) and Heriansyah *et al.* (2007) have developed biomass allometric models for *A. mangium* plantations in West Java and South Sumatra, respectively. These allometric models are essential to predict the carbon stocks of individual trees. More importantly, carbon stock predictions should also be available at a higher level such as the forest stand, compartment, or management unit. Such predictions can be obtained by combining the carbon stocks from several sample plots that are established in forest stands according to a specific sampling design (e.g., stratified, random, or systematic sampling). The average or total carbon stocks can then be calculated at the levels of compartment, stand type, stand age, or management unit. Nevertheless, combining sample plots from several or all stands tends to ignore the inherent variability of forest stands that vary continuously in space (Holmgren and Thuresson, 1997). Thus, such methods cannot directly provide spatial information regarding the distribution of carbon stocks that may vary within a forest stand; however, spatial information, which is usually present in a map, is required by forest managers (Rennolls *et al.*, 2007), especially for tactical forest planning.

One promising method to spatially predict carbon stocks is geostatistics. This method provides a means to predict carbon stocks at unsampled locations based on spatial autocorrelation among sample plots (Webster and Oliver, 2001). The spatial autocorrelation is modeled using a variogram, which is then used to perform spatial prediction using kriging methods. A number of studies have demonstrated the potential of kriging for predicting forest attributes. For example, Holmgren and Thuresson (1997) used kriging to generate continuous estimates of timber volume in a private forest estate; Nanos *et al.* (2004a) used this method to estimate stand-specific parameters of height/diameter models; and Sales *et al.* (2007) used this method to generate spatial predictions of forest biomass in the Amazon. To our knowledge, however, no study has assessed the applicability of this method for predicting carbon stocks of *A. mangium* plantations in Indonesia. Thus, our results could fill the gap in the spatial prediction method to support plantation forest management.

The purpose of this study was to investigate the applicability of kriging as an alternative method to spatially predict the carbon stock distribution of plantation forests. Specifically, we aimed to identify an appropriate kriging method and then use it for predicting spatial distribution of carbon stocks of an *A. mangium* plantation in Indonesia. We first modeled the spatial autocorrelation of the carbon stocks using exponential variogram models. We then used three kriging methods, i.e., ordinary kriging, universal kriging, and co-kriging, to predict the spatial distribution of the carbon stocks and compared and assessed the accuracy of the kriging predictions. Finally, we discuss the applicability of kriging for predicting carbon stocks or other forest attributes.

METHODS

Study Area

The study was conducted in a 1466.44-ha *A. mangium* plantation located in Tenjo district, West Java, Indonesia (6° 21' 0"-6° 24' 3" S, 106°26' 7"-106° 29' 58" E; Fig. 1). The annual rainfall is 3,000mm. The terrain is mostly flat and gently undulating (0-8%) with an elevation ranging from 60 to 100m above sea level, and the soil type is red-yellow podsols. The plantation is managed by Perum Perhutani (PP, a state-owned forestry enterprise) to produce timber, mainly for building construction and furniture. Thinning is conducted three times at 3, 5, and 7 years; harvesting occurs at 10 to 12 years (Perum Perhutani, 2006).

Data Set

The carbon stock data were obtained from measurements of 247 sample plots, which were established in 16 compartments of the plantation (Fig. 1) according to a stratified systematic sampling with random start design (see Shiver and Borders, 1996; Vries, 1986). In each compartment, the sample plots were located systematically at intervals of approximately 200m. The plots were circular, with three sizes: 0.02 ha for a stand age of 1-2 years, 0.04 ha for a stand age of 3-4 years, and 0.10ha for a stand age of ≥ 5 years.

In each sample plot, the diameter at breast height (dbh) of the trees was measured using a diameter tape, and the geographic coordinates (UTM system at zone 48S) of the plot center were recorded using a global positioning system (GPS). The tree diameters were then used to calculate the other stand parameters of each sample plot, i.e., basal area, volume (derived from a local volume table), and total biomass (leaves, branches, stems, and roots) based on the allometric biomass equation developed by Miyakuni *et al.* (2004). The carbon stocks of each sample plot (tC/ha) were determined by converting the biomass using a commonly used carbon fraction of 0.5 (Penman *et al.*, 2006).

In addition to these stand parameters, each sample plot had elevation data that were derived from a digital elevation model (DEM). The DEM was created using ILWIS 3.4 software (52°North GmbH, 2008) based on a digitized contour map at a scale of 1:25,000, which was obtained from the National Coordinating Agency for Surveys and Mapping, Indonesia. The spatial resolution of the DEM was 32 × 32m, corresponding to a sample plot size of 0.1ha.

Exploratory Data Analysis

We first used descriptive statistics to explore the data set (Table 1). The carbon stocks and other variables (except tree density) had skewness coefficients < 1.0, indicating that there

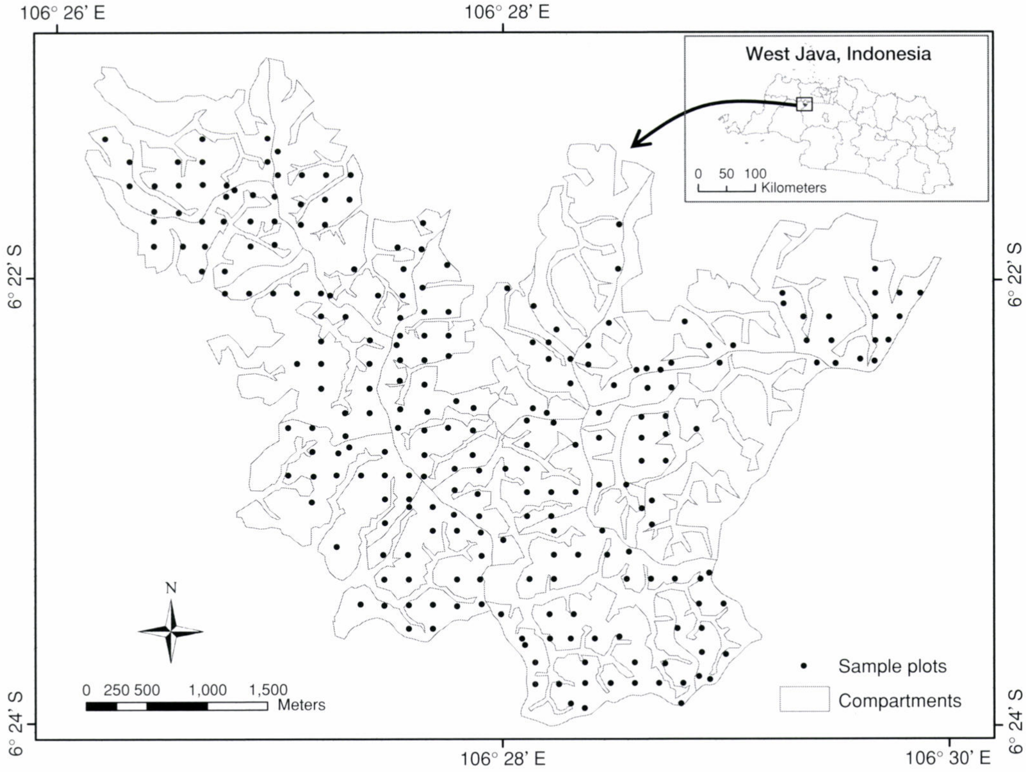

Fig. 1 Study area and layout of the sample plots

Table 1 Descriptive statistics of the sample plots (N = 247)

Statistic	Carbon stock (tC/ha)	Volume (m^3/ha)	Basal area (m^2/ha)	Tree density (trees/ha)	Age (yr)	Elevation (m)
Minimum	0.80	0.30	0.55	80	3.0	36.5
Maximum	62.97	117.90	18.01	2500	12.0	87.5
Mean	23.18	44.11	8.10	397	6.4	64.8
Median	21.76	41.11	8.05	320	7.0	63.5
Variance	158.67	559.50	11.82	82488	4.9	98.7
SD	12.60	23.65	3.44	287	2.2	9.9
CV (%)	54.34	53.62	42.43	72.35	34.46	15.33
Skewness	0.63	0.58	0.30	3.35	0.36	−0.20

SD, standard deviation; CV, coefficient of variation.

Table 2 Correlation coefficients among carbon stocks, volume, basal area, tree density, age, and elevation

	Carbon stock	Volume	Basal area	Tree density	Age
Volume	0.99**				
Basal area	0.93**	0.94**			
Tree density	−0.09	−0.09	0.22**		
Age	0.63**	0.62**	0.37**	−0.59**	
Elevation	0.23**	0.23**	0.20**	−0.21**	0.29**

**Correlation is significant at $P < 0.01$.

were only slight skews from a normal distribution. Accordingly, as suggested by WEBSTER and OLIVER (2001), we did not transform the data for the geostatistical analyses, allowing straightforward interpretation of the results.

In addition to carbon stocks (as the primary variable), we screened the other variables using correlation analysis to find any possible secondary variable for spatial prediction using the co-kriging method. The stand volume, basal area, and stand age had strong positive correlations with carbon stocks, whereas tree density and elevation had weak correlations (Table 2). The stand volume or basal area, however, could not be used as a secondary variable because they were calculated based on the trees' diameters, which were also used to calculate the carbon stocks. Thus, these latter variables were not independent of carbon stocks and could not be used for co-kriging. Accordingly, we used stand age as the secondary variable because it was independent and significantly correlated ($r = 0.63$) with carbon stocks.

Carbon stocks and stand age were then used in further geostatistical analyses involving three main steps: the modeling of spatial autocorrelation, spatial prediction using kriging methods, and validation of the predictions. We further explain these steps in the following sections.

Modeling Spatial Autocorrelation

Geostatistical prediction relies on the assumption that observations are spatially autocorrelated depending on their spatial distances. The spatial autocorrelation of carbon stocks (primary variable) or stand age (secondary variable) was quantified using the following empirical variogram (CHILES and DELFINER, 1999; ISAAKS and SRIVASTAVA, 1989; WEBSTER and OLIVER, 2001):

$$\hat{\gamma}(h)=\frac{1}{2m(h)}\sum_{i=1}^{m(h)}\{z(x_i)-z(x_i+h)\}^2 \quad (1)$$

in which $\hat{\gamma}(h)$ is the semivariogram of the carbon stocks or stand age at distance h; $m(h)$ is the number of data pairs within distance h; and $z(x_i)$ and $z(x_i+h)$ are values of the carbon stocks or stand age at locations of x_i and x_i+h. To determine the spatial structure of the carbon stocks and stand age, we first computed omnidirectional variograms by assuming that the spatial autocorrelation depends only on the distance (called isotropy phenomenon). We then computed directional variograms along four directions, i.e., 0°, 45°, 90°, and 135° from north, to look for anisotropy phenomena in which the spatial autocorrelation may differ not only depending on distance, but also on direction.

In addition to quantifying the spatial autocorrelation of the carbon stocks or stand age separately, we also quantified the spatial cross-correlation of both variables to be used in the co-kriging method. The empirical cross-variogram ($\hat{\gamma}_{uv}(h)$) between the carbon stocks (z_u) and stand age (z_v) was calculated as follows (WEBSTER and OLIVER, 2001):

$$\hat{\gamma}_{uv}(h)=\frac{1}{2m(h)}\sum_{i=1}^{m(h)}\{z_u(x_i)-z_u(x_i+h)\}\{z_v(x_i)-z_v(x_i+h)\} \quad (2)$$

All of the empirical variograms were computed by averaging all pairs of data within distance lags (h) of 400 m up to a maximum distance of 3,600m. After several trials using various distance lags, we found that the distance lags of 400m could produce a good spatial structure for the carbon stocks or stand age. In addition, the maximum distance of 3,600m was less than half of the extreme distance between various sample plots (i.e. 7,800m); hence it satisfies a requirement of the variogram modeling (OLEA, 2006).

To perform spatial prediction using kriging methods, we then modeled the empirical variograms using the following commonly used variogram models (OLEA, 2006; WEBSTER and OLIVER, 2001):

a) Spherical model:
$$\gamma(h)=\begin{cases} c_0+c_1\left[\frac{3h}{2a}-\frac{1}{2}\left(\frac{h}{a}\right)^3\right], & \text{for } h<a \\ c_0+c_1, & \text{for } h\geq a \end{cases} \quad (3)$$

b) Exponential model:
$$\gamma(h)=c_0+c_1\left[1-\exp\left(-\frac{h}{a}\right)\right] \quad (4)$$

c) Gaussian model:
$$\gamma(h)=c_0+c_1\left[1-\exp\left(-\frac{h}{a}\right)^2\right] \quad (5)$$

where: c_0 is the nugget effect, representing unexplained variability at a distance close to zero; c_1 is the partial sill (in which c_0+c_1 is called a sill), representing variability when the observations become independent; and a is range, indicating the maximal distance at which the observations are still spatially autocorrelated, in which an effective range (i.e., a range at 95% of a sill) of the exponential model is $3a$ and that of the Gaussian model is $a\sqrt{3}$ (see also Fig. 2). The percentage of the partial sill to the sill ($c_1/(c_0+c_1)$), which is called the Relative Structured Variability (RSV), indicates the degree of spatially structured variability of an observed variable (SCHABENBERGER and PIERCE, 2002). A large RSV indicates that the variogram is more structured, which is expected for an optimal kriging prediction.

For modeling the direct and cross-variograms of the co-kriging, we used a linear model of co-regionalization (LMC) in which the variance of any possible linear combination of the carbon stocks and stand age is always positive definite (see ISAAKS and SRIVASTAVA, 1989; WEBSTER and OLIVER, 2001). In the LMC, the direct and cross-variograms were modeled using the same basic variogram model. The LMC is commonly used in co-kriging (e.g. NANOS *et al.*, 2004a), mainly because it guarantees the existence of a solution of the co-kriging system.

If the sill or range tended to vary according to the direction (indicating the anisotropy phenomenon), then the variogram models were adjusted using an anisotropy correction factor derived from the ratio between the minimum and maximum axes of the spatial autocorrelation (WEBSTER and OLIVER, 2001). We selected the variogram models for the kriging methods that statistically (i.e., smallest sum of squared errors, SSE) best fitted the empirical variograms. The variogram modeling and other geostatistical analyses were performed using the Gstat library of R software (PEBESMA, 2004).

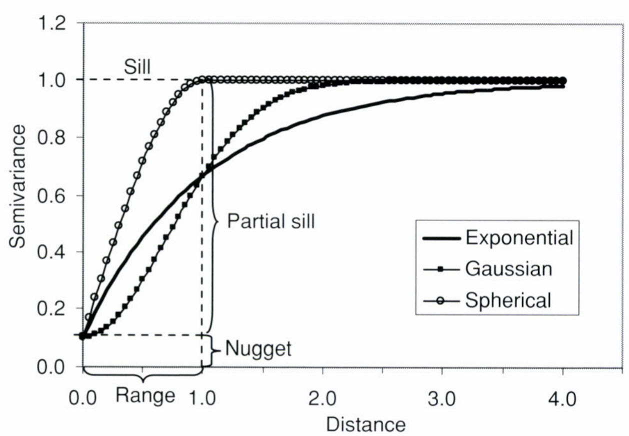

Fig. 2 Spherical, exponential, and Gaussian variogram models, in which nugget = 0.1, partial sill = 0.9, total sill = 1.0, and range = 1.0 (an effective range for the exponential model = 3.0 and that for the Gaussian model = 1.7)

Spatial Prediction using Kriging

The spatial prediction of carbon stocks was carried out using three kriging methods, i.e., ordinary kriging (OK), universal kriging (UK), and co-kriging (CK), to determine an appropriate prediction method. OK is a spatial prediction method under the assumption that there is no spatial trend (stationary) in the sample values, so that the regional mean (μ) is constant, but unknown. In OK, the carbon stocks at location x_0 (denoted as $\hat{Z}(x_0)$) were predicted based on their neighborhood values $z(x_i)$ weighted by λ_i according to the following equation:

$$\hat{Z}(x_0)=\sum_{i=1}^{N}\lambda_i z(x_i), \text{ where } \sum_{i=1}^{N}\lambda_i=1. \tag{6}$$

Universal kriging (UK) assumes that there is a non-stationary trend in the sample values, so that the regional mean $\mu(x_i)$ varies according to the following function:

$$\mu(x_i)=\sum_{j=1}^{p}\beta_j f_j(x_i) \tag{7}$$

in which β_j are unknown parameters and f_j are known functions of the geographical coordinates. The carbon stock at a certain location ($\hat{Z}(x_0)$) was predicted as in OK (Eq. 6).

Co-kriging (CK) is an extension of OK that takes into account additional correlated information between the primary and secondary variables. We used isotropic co-kriging in which the primary variable (carbon stocks) and the secondary variable (stand age) were measured at the same sample plot locations. The carbon stock predictions at an unknown location ($\hat{Z}(x_0)$) were computed as the sum of the weighted averages of both variables:

$$\hat{Z}(x_0)=\sum_{i=1}^{n_z}\lambda_i z(x_i)+\sum_{j=1}^{n_w}\mu_j w(y_j) \tag{8}$$

where $z(x_i)$ are sample values of the carbon stocks, $w(y_j)$ are sample values of the stand age; and λ_i and μ_j are weights for the carbon stocks and stand age values, respectively.

OK, UK, and CK used weights (λ_i or μ_j) derived from the variogram models defined previously. We used raster cells of 32 × 32m, which correspond to the sample plot size of 0.1ha (17.8m radius), to predict the carbon stocks at unsampled locations over the study area. More details on the kriging methods and their statistical theories can be found in CHILES and DELFINER (1999), ISAAKS and SRIVASTAVA (1989), and WEBSTER and OLIVER (2001).

VALIDATION

We assessed the accuracy of the OK, UK, and CK predictions using a leave-one-out cross-validation method, which is commonly used in geostatistical prediction. This method removed the n sample plots one by one, and the kriging was performed on the remaining sample plots; hence, the predicted carbon stocks ($\hat{z}(x_i)$) and kriging variances ($\hat{\sigma}(x_i)$) could be obtained accordingly. The actual carbon stocks ($z(x_i)$) were then compared several times with the predicted stocks to obtain the average accuracy, which can be expressed by the mean error (ME), root mean squared error (RMSE), and mean squared deviation ratio (MSDR) as follows (WEBSTER and OLIVER, 2001):

$$ME=\frac{1}{n}\sum_{i=1}^{n}\{z(x_i)-\hat{z}(x_i)\} \tag{9}$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\{z(x_i)-\hat{z}(x_i)\}^2} \tag{10}$$

$$MSDR=\frac{1}{n}\sum_{i=1}^{n}\frac{\{z(x_i)-\hat{z}(x_i)\}^2}{\hat{\sigma}^2(x_i)} \tag{11}$$

The kriging method with an ME close to 0 (zero), the smallest RMSE, and MSDR close to 1.0 (one) was then used to infer predictions of carbon stocks.

RESULTS

Spatial Autocorrelation

The carbon stocks and stand ages of *A. mangium* were spatially autocorrelated, as indicated by their omnidirectional variograms that were well modeled using exponential models (Fig. 3). Carbon stocks had a longer range of spatial autocorrelation with a higher nugget effect, whereas stand age had a shorter range with a negligible nugget effect. Further analysis of the spatial autocorrelation revealed a clear anisotropy pattern in the spatial distribution of carbon stocks (Fig. 4). The spatial autocorrelation of carbon stocks reached a maximum range ($3a_1$) of 3,600m in the 135° direction and a minimum range ($3a_2$) of 1,800m in the 45° direction (Fig. 4a). We found a similar anisotropy pattern, but with shorter ranges, in residual values of the carbon stocks (Fig. 4b) used in UK. The spatial autocorrelation of stand age did not exhibit anisotropy phenomena.

Despite the shorter range of spatial autocorrelation of stand age, the cross-empirical variogram between carbon stocks and stand age exhibited good spatial structure (Fig. 5). Using the LMC method, the exponential variogram model could be well fitted to both direct and cross-empirical variograms, especially at the short distances that were critical for the kriging. As a consequence of using the same basic model in the LMC, there were some adjustments to the parameters (nugget effects, sills, and ranges) of the direct variogram models of carbon stocks and stand age (Fig. 5), which were differ slightly from those of their omnidirectional variogram models (Fig. 3). Nevertheless, a good structure of the cross-variogram model (Fig. 5) indicated that such co-regionalization has satisfied the positive definite condition of the LMC, hence it is reliable to be used for the CK method.

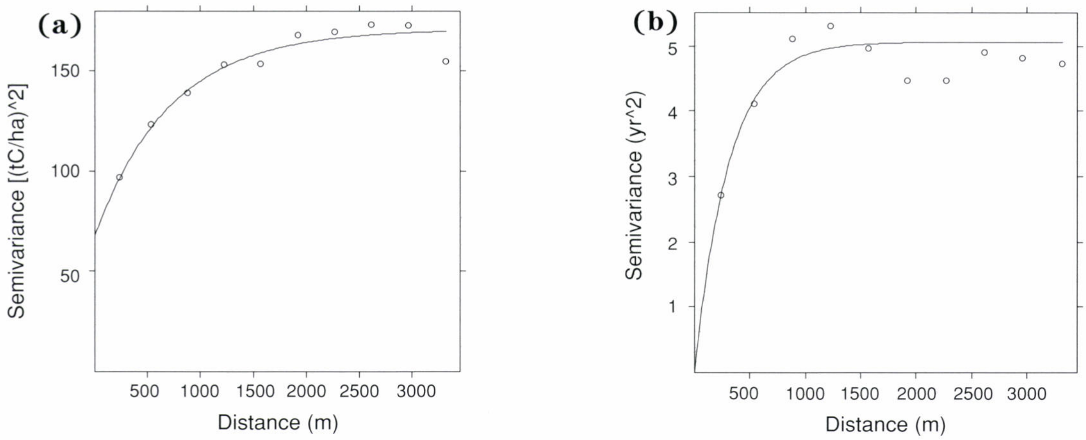

Fig. 3 Omnidirectional variogram models of (a) carbon stocks and (b) stand age; the dots are empirical variograms and the curves are exponential variogram models

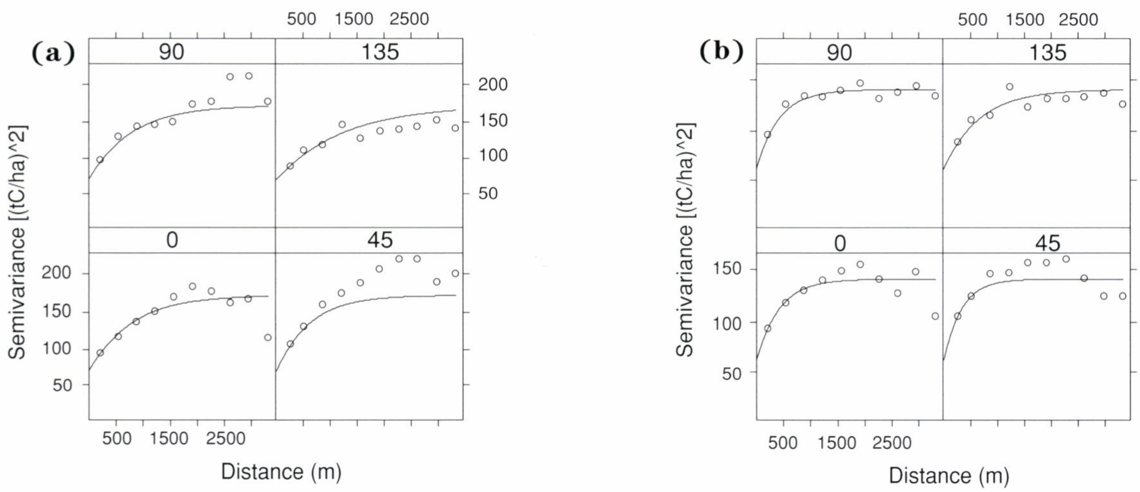

Fig. 4 Directional variograms of (a) raw values and (b) residual values of the carbon stocks

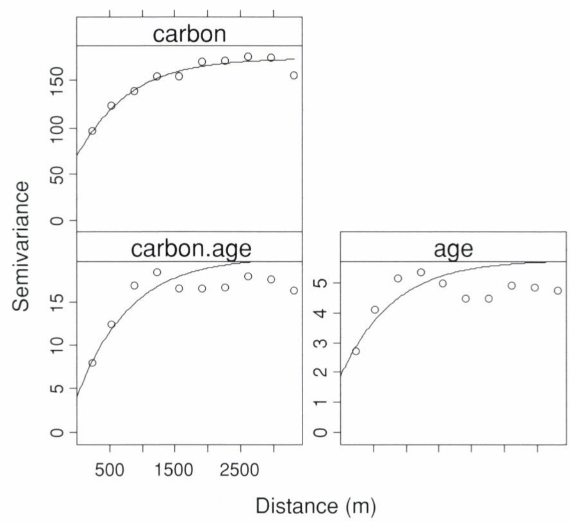

Fig. 5 Direct and cross-variograms of carbon stocks and stand age

Table 3 Parameters of the exponential variogram models used in the kriging methods

Variogram model	Nugget (c_0)	Partial sill (c_1)	Sill (c_0+c_1)	Anisotropy range (m)	Anisotropy direction (°)	RSV (%) ($c_1/(c_0+c_1)$)
Exp-1	70.43	101.59	172.02	3,636/1,818	135/45	59.1
Exp-2	62.44	78.10	140.54	1,973/ 986	135/45	55.6
Exp-3a	69.58	102.84	172.42	3,636/1,818	135/45	59.6
Exp-3b	1.86	3.86	5.72	3,636/1,818	135/45	67.5
Exp-3c	3.97	15.94	19.91	3,636/1,818	135/45	80.1

Exp-1 is the variogram model of carbon stocks used in ordinary kriging; *Exp-2* is the variogram model of carbon stocks residuals used in universal kriging; and *Exp-3a, Exp-3b*, and *Exp-3c* are direct variogram models of carbon stocks, stand age, and the cross-variogram model of both variables, respectively, used in co-kriging.
The ranges and directions of anisotropy refer to the maximum ($3a_1$) and minimum ($3a_2$) spatial autocorrelation, respectively.

Table 4 Cross-validation results of the kriging methods

Kriging method	ME	RMSE	MSDR
OK	−0.0443	10.1585	1.0119
UK	−0.0588	10.0910	1.0157
CK	−0.0121	8.8407	1.0062

Because there was obvious anisotropy, predicting the carbon stocks using the kriging methods was performed based on anisotropic exponential variogram models (Table 3). All of the variogram models indicated that the relative nugget effects of the carbon stocks were fairly large (approximately 20-44% of the sills). Nevertheless, these models also indicated that carbon stocks or stand age was spatially structured (with an RSV of approximately 60-80%). The variogram model used for UK was less structured than that used for OK, whereas the cross-variogram model used for CK was the most structured. Obviously, these models indicate the presence of fairly strong spatial autocorrelation of the carbon stocks, which allowed us to perform spatial prediction using kriging.

Kriging Predictions of Carbon Stocks

Spatial prediction using ordinary kriging (OK), universal kriging (UK), and co-kriging (CK) produced predictions of the carbon stocks and their standard deviations (Fig. 6). OK predicted carbon stocks ranging from 8.10 to 38.01tC/ha (1st and 99th percentiles), with standard deviations varying from 9.55 to 12.24tC/ha. The carbon stocks predicted by UK varied from 7.26 to 38.68tC/ha, with standard deviations varying from 9.28 to 12.02tC/ha. CK predicted carbon stocks ranging from 7.25 to 37.95tC/ha, with standard deviations varying from 9.44 to 12.21tC/ha. These prediction intervals indicate that, in the lower limits, the kriging methods produced higher standard deviations than their predictions. Such phenomena only occurred in small parts of the study area, i.e., 3.7% for CK, 4.1% for OK, and 6.5% for UK. These areas had relatively sparse sample plots that were located close to the study area boundaries in the directions of approximately 225° and 315°, as indicated by the darkest areas of the kriging prediction maps (Fig. 6, left). The higher carbon stocks were found near the middle parts of the study area, which were dominated by older stands.

Compared to OK, both UK and CK had slightly reduced carbon stock predictions, especially in areas with lower predicted values (Fig. 6, left). UK and CK also had slightly reduced standard deviations of the predicted carbon stocks, especially around sample plots in the center of the study area (Fig. 6, right). However, the differences in the predictions and standard deviations seemed not to be significant, as indicated by the similar spatial patterns of carbon stock distribution on the kriging maps.

To confirm these findings, we further assessed the accuracy of the predictions using a cross-validation procedure (Table 4). The three kriging methods produced unbiased predictions, as indicated by MEs ≈ 0. They also produced MSDRs of almost 1.0. In other words, the three kriging methods provided ideal values of ME and MSDR. The RMSEs, however, were not very small. Obviously, the RMSE of OK was almost the same as that of UK, meaning that their prediction accuracy was similar. CK slightly reduced the RMSE, resulting in an improvement in the prediction accuracy of 13% compared to OK. These findings confirm that CK produced the most reliable predictions of the carbon stock distribution of the *A. mangium* plantation.

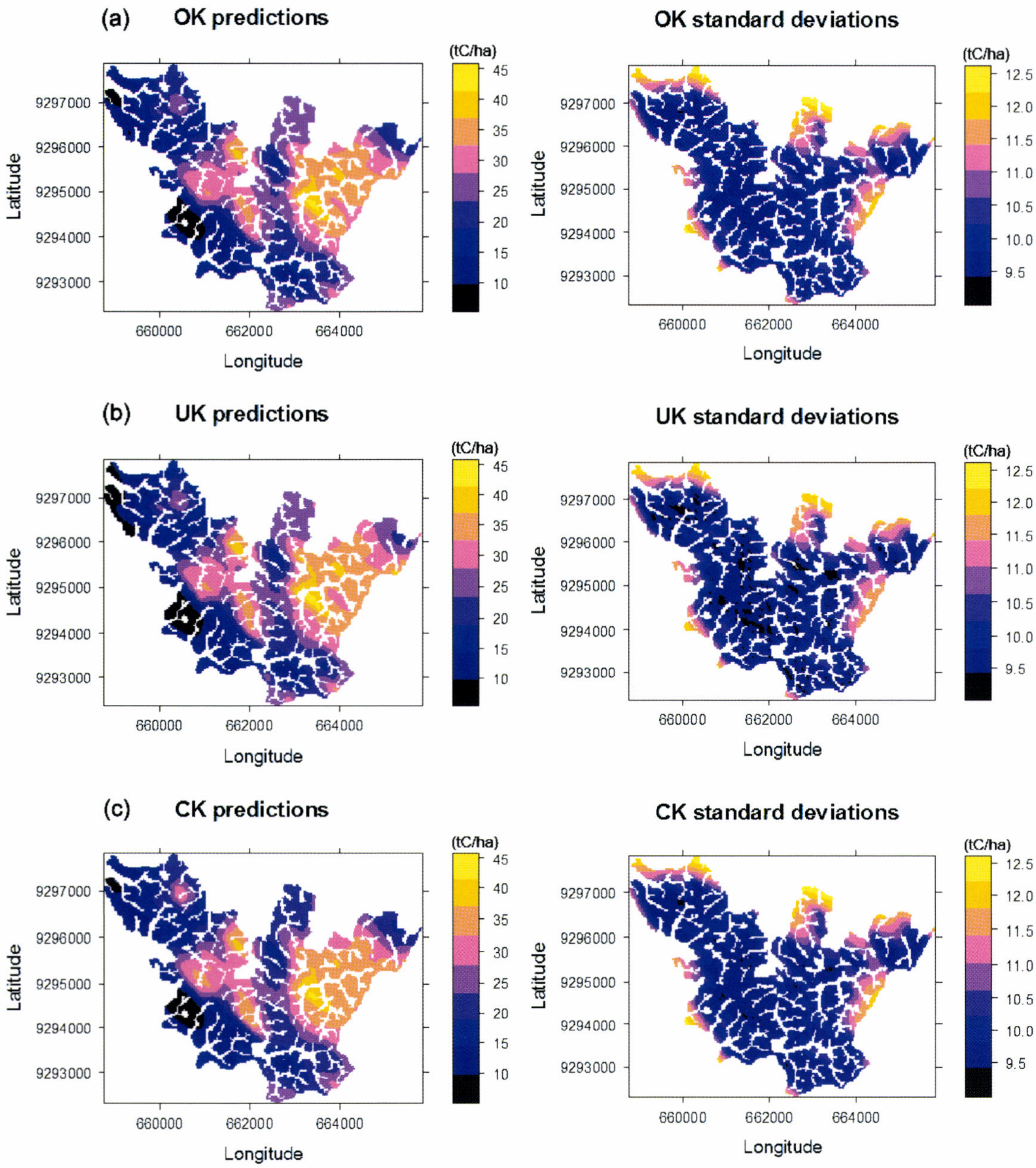

Fig. 6 Maps showing predicted carbon stocks and their standard deviations obtained from (a) ordinary kriging, (b) universal kriging, and (c) co-kriging

DISCUSSION

The variogram analysis indicated that the carbon stocks are spatially autocorrelated within a range up to 3,600m. This range of spatial autocorrelation is much longer than the sampling interval of approximately 200m, which implies that the current sampling design is appropriate to determine the spatial structure of the carbon stocks. This finding is in accordance with SALES *et al.* (2007), who found that forest biomass had strong spatial autocorrelation that also occurred with a range longer than the sampling interval. The spatial autocorrelation within the plantation was fairly strong (Fig. 4a), which indicates that the carbon stocks are fairly heterogeneous throughout the forest stands. The coefficient of variation (CV = 54.34%; Table 1) also confirms fairly high variability in the carbon stocks. Whereas the CV only provides a measure of non-spatial variability within the sample plots, the variogram gives more valuable information regarding the spatial structure of carbon stock distribution. By using a variogram, one can calculate the RSV to measure the degree of spatial variability of an observed variable (SCHABENBERGER and PIERCE, 2002). It is not surprising that the carbon stocks exhibit obvious spatial variability because the *A. mangium* plantation within the study area is composed of several stands that have different conditions (e.g., age, tree density, and thinning treatment) that may vary from site to site.

The anisotropy in the spatial distribution of the carbon stocks indicates that the stocks tended to be more similar (with lower semivariances) in the 135° direction, whereas they tended to have greater variability along the 45° direction. This phenomenon could be attributed to spatial variations in the stand volume, basal area, and stand age that are significantly correlated with the carbon stocks (Table 2). Another cause maybe microhabitat gradients (NANOS *et al.*, 2004b), which could not be determined from our data. The presence of anisotropy in stand attributes was also found in the spatial distribution of the height and age of trees, as reported by NANOS *et al.* (2004b) and SAMRA *et al.* (1989). Our results, however, contrast with those of SALES *et al.* (2007), who found no obvious anisotropy in the spatial distribution of forest biomass in the Amazon. Despite various factors that may cause anisotropy, which likely depend on the spatial processes of the observed variables, the main reason for dealing with anisotropy is to provide reliable variogram models for kriging.

The large nugget effect in the variograms of the carbon stocks can be caused by high variability of the stocks within distances shorter than the sampling interval (CHILES and DELFINER, 1999). Such variability could be attributed to inherent variability of the carbon stocks within each sample plot. In addition, some possible errors that arose from measurements of tree diameters and sample plot positions could also be sources of the large nugget effect. Indeed, a large nugget effect is often unavoidable in the geostatistical prediction of forest attributes (see FREEMAN and MOISEN, 2007; GUNNARSSON *et al.*, 1998; NANOS *et al.*, 2004a).

UK did not significantly improve the prediction accuracy compared to OK, mainly because of the lack of a strong trend in the geographic coordinates. This can be observed from the residual variogram used in UK (Fig. 4b) and its RSV (Table 3), which are similar to those of OK. MUSIO *et al.* (2004) also reported that a weak trend in geographic coordinates could be the main reason for the lower power of UK. The slight improvement in accuracy made by CK indicates that prediction errors can be minimized by incorporating stand age as a secondary variable. The value of CK strongly depends on the correlation between primary and secondary variables (WEBSTER and OLIVER, 2001). In our case, the correlation between carbon stocks and stand age is 0.63 (Table 2), and their cross-variogram is also fairly structured (RSV = 67.5%, Table 3), which could account for the slight improvement in accuracy. Moreover, we used the isotropic CK (fully sampled case) that is theoretically less powerful than the heterotropic CK (undersampled case), which uses a secondary variable collected in more dense sampling locations than the primary variable (WEBSTER and OLIVER, 2001). Nevertheless, compared to OK and UK, CK is a more flexible kriging method because it can incorporate stand age to improve prediction accuracy.

The kriging prediction maps provide useful information regarding the spatial distribution of carbon stocks. The predicted carbon stocks vary reasonably, depicting spatial patterns and variations in carbon stocks within the forest stands. Such spatial predictions can complement biomass predictions for the *A. mangium* plantation obtained by MIYAKUNI *et al.* (2004) and HERIANSYAH *et al.* (2007). Furthermore, the standard deviation maps could be used to evaluate the reliability of the predictions. The prediction errors show a strong dependency with distance to the closest sample plot in which higher standard deviations are found in areas with less dense sample plots (Fig. 6). This result contrasts to that of WALLERMAN *et al.* (2002), who used more dense sample plots. Therefore, these findings could be used to design an optimal sampling strategy to obtain better prediction results.

Geostatistics is a promising method to spatially predict carbon stocks and other forest attributes, even without using remote sensing data. However, the method is data demanding. WEBSTER and OLIVER (2001) recommend that, ideally, at least 150 sample plots should be used to obtain a reliable variogram model for kriging. We used 247 sample plots that were large enough to obtain reliable variograms and kriging predictions of the carbon stocks. By using such large data sets, one can analyze and model the anisotropy phenomenon that may occur in the carbon stock distribution. This amount of data should not be a serious problem for plantation forests in which a periodic forest inventory is conducted regularly such as in our study area. Alternatively, in the case of limited data availability, one can use the heterotropic CK to incorporate secondary variables that are easier to measure and available in denser locations than the primary variable. These secondary variables could be derived from remote sensing data. The integration of geostatistics and remotely sensed data would also provide another advantage in producing kriging maps with finer spatial resolution.

CONCLUSION

Geostatistical methods can be used to predict the spatial distribution of carbon stocks in an *A. mangium* plantation. The spatial autocorrelation of carbon stocks was fairly strong and occurred up to a distance of 3,600m. The carbon stocks were similar along the direction of 135°, but varied greatly along 45°. There were no significant differences in the predicted carbon stocks obtained from OK, UK, or CK. However, CK slightly improved the prediction accuracy by incorporating stand age as a secondary variable. The kriging maps provide useful information regarding the spatial distribution of carbon stocks and their uncertainties. Accordingly, we consider that kriging is a promising method to spatially predict carbon stocks or other forest attributes and can also be used to develop a spatial management plan for plantation forests.

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Short Communication

Relationship between Sunny Crown Volume Increment and Stem Cross-Sectional Area Increment at Sunny Crown Base for Hinoki Cypress, and its Application

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ABSTRACT

Vertical distribution of stem cross-sectional area increment (CSAI) for hinoki cypress can be described by combination of two linear equations derived from three tree attributes: sunny crown length (SCL), stem volume increment (SVI), and CSAI at the base of sunny crown ($CSAI_{SCB}$). In this study, to propose a method for estimating $CSAI_{SCB}$, a relationship between $CSAI_{SCB}$ and sunny crown volume increment (SCVI) was investigated. Data were obtained from 112 sample trees selected in six stands of even-aged hinoki cypress. The proportional relation can be assumed between SCVI and $CSAI_{SCB}$, and the relationship could be expressed by the regression equation: $CSAI_{SCB} = 2.88 \times 10^{-4}SCVI$. For each sampled tree, two vertical distributions of CSAI were obtained: one is the distribution obtained by using $CSAI_{SCB}$ estimated from the regression equation, and both of SCL and SVI observations, and the other is the distribution obtained by using observations of SCL, SVI, and $CSAI_{SCB}$. The two distributions were compared using root mean squared error (RMSE). Although the vertical distribution obtained by using $CSAI_{SCB}$ estimate produced a larger RMSE value than that by using $CSAI_{SCB}$ observation did, the difference in RMSE was small. In conclusion, the assumption of the proportional relationship between SCVI and $CSAI_{SCB}$ provides a useful approach for predicting vertical distribution of CSAI for hinoki cypress.

Keywords: sunny crown volume increment, stem cross-sectional area increment at sunny crown base, proportional relation, hinoki cypress

INTRODUCTION

The prediction of a tree stem form, described by the decrease in stem diameter from the butt to the apex, resulting from stand density management is important in forestry because of the economic value of timber quality. The stem diameter at a particular height depends on the previous-year stem diameter and the current-year stem cross-sectional area increment (CSAI). Therefore, the ability to predict the vertical distribution of CSAI along the stem allows the prediction of the stem form, which in turn is useful to determine the optimal thinning regime for a stand.

When the total height of a hinoki cypress (*Chamaecyparis obtusa* ENDL.) tree is known, the vertical distribution of CSAI can be described by combination of two linear equations derived from three tree attributes: sunny crown length (SCL), stem volume increment (SVI), and CSAI at the sunny crown base ($CSAI_{SCB}$) (WAGUCHI and UEDA, 2006a). Since SVI often exhibit strong correlations with sunny crown dimensions such as sunny crown volume and surface area (INOSE, 1982; KAJIHARA, 1982; SAIGUSA *et al.*, 1996), SVI would be a factor which can be estimated from sunny crown dimensions. Therefore, estimating $CSAI_{SCB}$ from sunny crown dimensions would make predicting the vertical distribution of CSAI from characteristics related to the sunny crown because SCL is undoubtedly a dimension of the sunny crown. However, relationships between sunny crown dimensions and $CSAI_{SCB}$ remain largely unexplored.

Since stem cross-sectional area at sunny crown base (CSA_{SCB}) for a tree supports mechanically the sunny crown, it is probable that the unit CSA_{SCB} supports a constant amount of

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sunny crown. This assumption still allows the interpretation that the $CSAI_{SCB}$ is the result of an amount of tissue necessary to support the increments of sunny crown dimensions. If it is true, proportional relationships might exist between CSA_{SCB} and sunny crown dimensions, and between $CSAI_{SCB}$ and increments of sunny crown dimensions. For Douglas-fir (*Pseudotsuga menziesii* FRANCO), MAGUIRE and HANN (1989) have regressed stem sapwood cross-sectional area at crown base ($SCSA_{CB}$) on the product of crown length (CL) and square of crown radius (CR), and on the square of stem diameter at crown base (SD_{CB}), resulting in

$$SCSA_{CB} = 1.71727 CL \cdot CR^2 \qquad (R^2 = 0.701) \tag{1}$$

and

$$SCSA_{CB} = 1.417224 SD_{CB}^2 \qquad (R^2 = 0.917) \tag{2}$$

where R^2 is the coefficient of determination of the regression equation. Combining eqs. (1) and (2) gives the directly proportional relation between $CL \cdot CR^2$ and $SD_{CB}{}^2$ (*i.e.*, crown volume and stem cross-sectional area at crown base). This leads to the proportional relation between increments of the crown volume and the stem cross-sectional area at the crown base, and is thus expected that the sunny crown volume (SCV) and the sunny crown volume increment (SCVI) are directly proportional to the CSA_{SCB} and the $CSAI_{SCB}$, respectively.

The objective of this study was to propose a method for estimating $CSAI_{SCB}$, which could be utilized for the CSAI distribution predicting model proposed by WAGUCHI and UEDA (2006a). First, it was ascertained whether proportional relations could be assumed between SCV and CSA_{SCB}, and between SCVI and $CSAI_{SCB}$ for hinoki cypress. Next, it was confirmed that the proportional relationship between SCVI and $CSAI_{SCB}$ could be utilized for predicting the vertical distribution of CSAI.

MATERIALS AND METHODS

Field Measurements

Samples were obtained from six stands of even-aged hinoki cypress in Nara Prefecture, Japan. Summaries for the stands are presented in Table 1. Stand age ranged from 10 to 72 years, with densities ranging from 5,250 to 1,000 trees/ha, mean diameter at breast height measuring 6.8 to 29.1cm, and mean total height varying from 5.5 to 16.8m.

Table 1 Stand descriptions

Stand	Age (year)	Density (trees/ha)	Mean diameter at breast height (cm)	Mean total height (m)	Number of sample trees
A	10	5,250	6.8	5.5	20
B	16	3,006	11.8	10.1	15
C	19	3,828	11.9	9.4	20
D	29	2,602	12.6	12.7	22
E	41	1,820	18.6	16.4	15
F	72	1,000	29.1	16.8	20

One hundred and twelve sample trees were selected at random in the stands. Before felling, diameter at breast height (DBH) for each tree was measured with calipers. The trees ranged from 3.6 to 32.5cm in DBH. The height of the sunny crown base for each tree was measured with a Spiegel relascope using the percentage scale. A 5-m pole was placed upright against the tree trunk for the measurements. The SCL was calculated by subtracting the height of the sunny crown base from the total height.

After each tree was felled, the total height (H) was measured with surveyor's tapes. The total heights ranged from 4.1 to 18.7m. To measure SVI and CSAI, disks were removed from the stem at stump height (0.2m), at intervals of 0.5, 1, or 2m below the lowest live branch, and at intervals of 0.5 or 1m within the crown beginning at stump height. To measure the shape and size of the sunny crown, each segmented crown was set vertically on the ground and the crown radii at the middle of the layer were measured in four directions at right angles using surveyor's tapes.

Laboratory Measurements

The removed disks were brought to the laboratory and the annual rings were counted. For each disk, the current- and previous-year radii in four directions at right angles were measured. The current- and previous-year stem cross-sectional areas (CSAs) were calculated using average radius measurements with the stem cross section assumed to be circle in shape. The CSAI was calculated by subtracting previous-year CSA from current-year CSA. The current- and previous-year log volumes for each segment were calculated using SMALIAN's formula. The each log volume increment was calculated as the difference between the current- and previous-year log volumes. The SVI for each tree was computed as the sum of the log volume increments. The CSA_{SCB} and $CSAI_{SCB}$ were estimated by interpolating from each of CSAs and CSAIs at the top and bottom of the log where the sunny crown base was located, respectively.

Computation of SCV and SCVI

To obtain SCV, the sunny crown profile for each tree was represented using the following equation:

$$r = a_1 z^{a_2} \tag{3}$$

where r is the crown radius (m) at the distance z (m) from the apex, and a_1 and a_2 are parameters. The parameters were estimated using non-linear least squares method minimizing the sum of squared residual (SSR):

$$SSR = \sum_{i=1}^{n} \sum_{j=1}^{4} \left(r_{ij} - a_1 z_i^{a_2} \right)^2 \tag{4}$$

where r_{ij} is the j-th crown radius ($j=1$, 2, 3, 4) at the i-th distance z_i ($i=1, 2, \cdots, n$) from the apex. The SCV was calculated by rotating eq. (3) on the trunk axis.

The SCVI was calculated by subtracting the previous-year SCV above the current-year sunny crown base from the current-year SCV as shown in Fig. 1. Since it is difficult to measure the previous-year SCV objectively, under the assumption that the shape and size of the previous-year sunny crown are the same as those of the current-year sunny crown, the SCVI was calculated as follows:

$$\mathrm{SCVI} = \pi \int_0^{\mathrm{SCL}} r^2 dz - \pi \int_0^{\mathrm{SCL-HI}} r^2 dz \quad (5)$$

where HI is the total height increment (m/year). The assumption would be acceptable because one year is sufficiently short for the growth of the crown. The HI was calculated by subtracting the previous-year H from the current-year H. The previous-year H was estimated using the ordinary stem analysis technique.

Evaluation

To ascertain whether proportional relations can be assumed between SCV (m^3) and $\mathrm{CSA_{SCB}}$ (m^2), and between SCVI (m^3/year) and $\mathrm{CSAI_{SCB}}$ (m^2/year), the following equations were fitted using the least squares method:

$$\mathrm{CSA_{SCB}} = b_1 \mathrm{SCV} \quad (6)$$

and

$$\mathrm{CSAI_{SCB}} = b_2 \mathrm{SCVI} \quad (7)$$

where b_1 and b_2 are regression constants, and the coefficient of determination (R^2) for each regression equation was calculated and tested statistically using the F-test.

WAGUCHI and UEDA (2006a) have proposed a model that predicts the vertical distribution of CSAI using the combination of two linear equations derived from SCL (m), SVI (m^3/year), and $\mathrm{CSAI_{SCB}}$. In the model, CSAI (m^2/year) at a distance z from the apex is expressed as

$$\mathrm{CSAI}_z = c_1 z I_1 + (c_2 + c_3 z) I_2 \quad (8)$$

where c_1, c_2, and c_3 are parameters defined as

$$c_1 = \frac{\mathrm{CSAI_{SCB}}}{\mathrm{SCL}},$$

$$c_2 = (c_1 - c_3)\,\mathrm{SCL},$$

$$c_3 = \frac{2\mathrm{SVI} - (2\mathrm{H} - \mathrm{SCL})\,\mathrm{CSAI_{SCB}}}{(\mathrm{H} - \mathrm{SCL})^2},$$

and I_1 and I_2 are dummy variables defined as

$$I_1 = \begin{cases} 1 & \text{If } 0 \le z \le \mathrm{SCL} \\ 0 & \text{Otherwise} \end{cases},$$

$$I_2 = \begin{cases} 1 & \text{If } 0\ \mathrm{SCL} < z \le \mathrm{H} \\ 0 & \text{Otherwise} \end{cases},$$

Therefore, to confirm that eq. (7) representing the proportional relationship between SCVI and $\mathrm{CSAI_{SCB}}$ could be utilized for the model, the root mean square error (RMSE) of eq. (8) with $\mathrm{CSAI_{SCB}}$ estimated using eq. (7) was compared with that of eq. (8) with $\mathrm{CSAI_{SCB}}$ observed. Both of SCL and SVI observations were substituted in eq. (8).

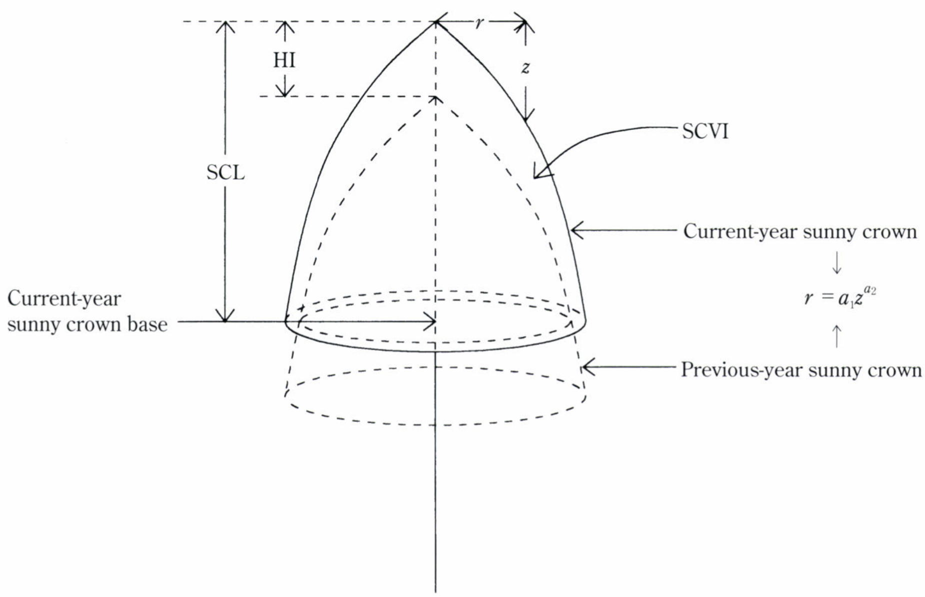

Fig. 1 Diagram of current- and previous-year sunny crowns
HI, SCL, and SCVI are the total height increment, the sunny crown length, and the sunny crown volume increment of the current year, respectively.

RESULTS AND DISCUSSION

Fig. 2 shows the relationship between SCV and CSA_{SCB}. The CSA_{SCB} significantly increased in proportion to SCV, and the relationship could be expressed by the following equation:

$$CSA_{SCB} = 3.24 \times 10^{-4} SCV \quad (R^2 = 0.916, P < 0.001). \quad (9)$$

Although no report has shown the proportional relation between SCV and CSA_{SCB} for any tree species, as mentioned above, the results for Douglas-fir by MAGUIRE and HANN (1989) describe the proportional relation between crown volume and stem cross-sectional area at crown base. The result in this study shows distinctly that the proportional relation can be assumed between SCV and CSA_{SCB} for hinoki cypress. Therefore, these results might allow the assumption that unit CSA_{SCB} supports a constant amount of SCV, and imply the proportional relationship between SCVI and $CSAI_{SCB}$.

Fig. 3 shows the relationship between SCVI and $CSAI_{SCB}$. As expected, the $CSAI_{SCB}$ significantly increased in proportion to SCVI, and the relationship could be expressed by the following equation:

$$CSAI_{SCB} = 2.88 \times 10^{-4} SCVI \quad (R^2 = 0.751, P < 0.001). \quad (10)$$

For Japanese cedar (*Cryptomeria japonica* D. DON) and hinoki cypress, KAJIHARA (1980; 1981) has showed that crown mantle volume was a good indicator of foliage mass. The SCVI in this study is the sunny crown mantle produced in a current year, and foliage which constitutes the SCVI was undoubtedly produced in the year. Thus, SCVI would be a good indicator of foliage mass produced in a current year. On the other hand, according to pipe-model theory (SHINOZAKI *et al.*, 1964), the foliage mass is in proportion to the cross-sectional area of the stem sustaining the foliage (YODA, 1971), implying that the increment of the foliage mass is in proportion to that of the cross-sectional area. The result in this study, which indicates the proportional relationship between SCVI and $CSAI_{SCB}$ as shown in Fig. 3, might be supported by these previous studies.

Fig. 4 demonstrates examples of the vertical distribution of CSAI for sampled trees. The vertical distributions obtained by eq. (8) with $CSAI_{SCB}$ estimated using eq. (7) with parameters shown in eq. (10) fit well to CSAI observations. Fig. 5 shows the comparison of RMSEs in eq. (8) with estimated and observed $CSAI_{SCB}$s. Although the RMSE in eq. (8) with estimated $CSAI_{SCB}$ was larger than that in eq. (8) with observed $CSAI_{SCB}$ for each sampled tree, the vertical distribution obtained by eq. (8) with estimated $CSAI_{SCB}$ closely matched that of eq. (8) with observed $CSAI_{SCB}$ (Fig. 4). Furthermore, for overall fit, although eq. (8) with estimated $CSAI_{SCB}$ returned a larger RMSE value than eq. (8) with observed $CSAI_{SCB}$ did (RMSE = 1.58cm^2 for eq. (8) with estimated $CSAI_{SCB}$ and 1.15cm^2 for eq. (8) with observed $CSAI_{SCB}$), the difference in RMSE was only 0.43cm^2. This overestimation of the area of a circle results in slight overestimations of diameter as well; 0.055cm for a 5-cm diameter circle, 0.028cm for a 10-cm circle, and 0.014cm for a 20-cm circle. For measuring stem diameter, a diameter tape is the most consistent instrument. However, even if the tape is level and pulled taut, the measurement error is at most 0.05cm because the tape is usually graduated in 0.1cm. In view of this fact, the difference in RMSE would be sufficiently small for predicting stem form.

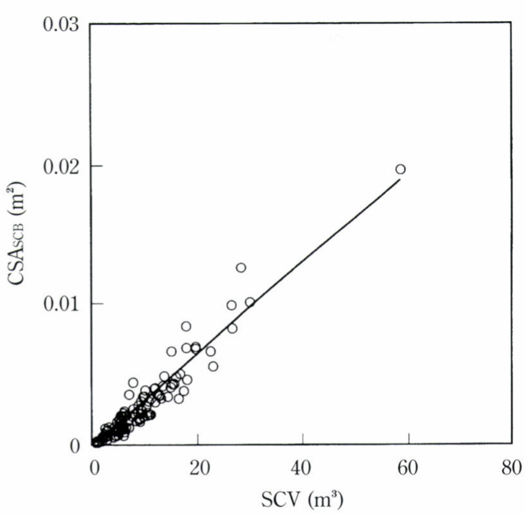

Fig. 2 Relationship between sunny crown volume (SCV) and stem cross-sectional area at sunny crown base (CSA_{SCB}) The solid line indicates the regression equation (9).

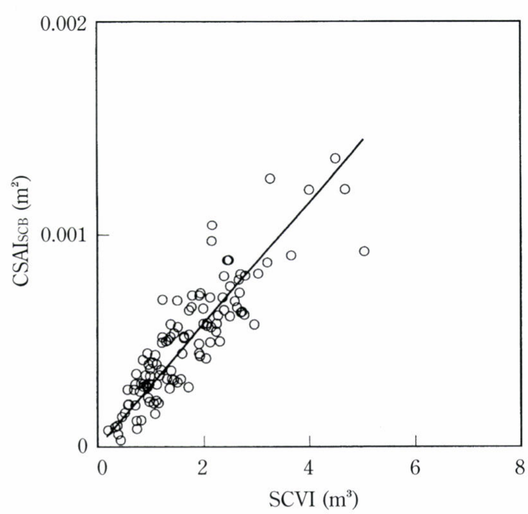

Fig. 3 Relationship between sunny crown volume increment (SCVI) and stem cross-sectional area increment at sunny crown base ($CSAI_{SCB}$)
The solid line indicates the regression equation (10).

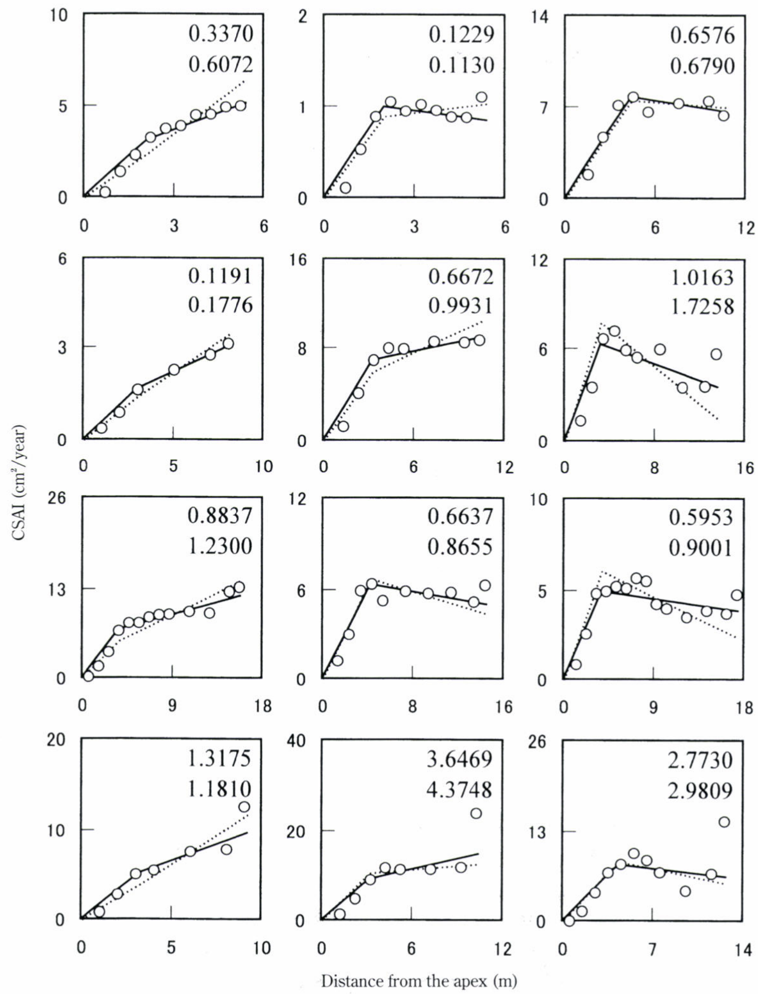

Fig. 4 Examples of the vertical distribution of stem cross-sectional area increments (CSAI) Open circles represent observations. Solid and dotted lines are fitted to eq. (8) with observed and estimated $CSAI_{SCB}$s. Upper and lower values in each graph represent root mean squared errors (cm^2) for eq. (8) with observed and estimated $CSAI_{SCB}$s, respectively.

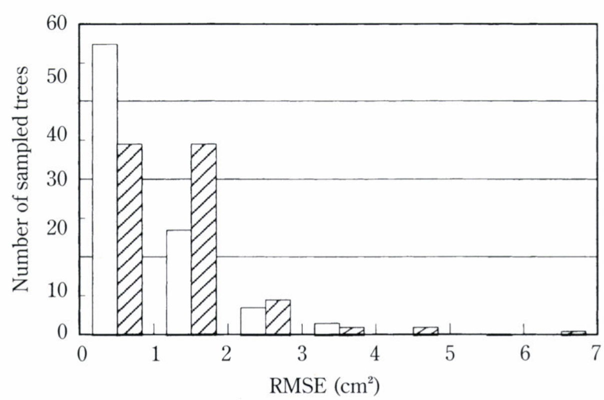

Fig. 5 Distribution of the root mean squared error (RMSE) for each sampled tree
Open and striped bars represent numbers of sampled trees for eq. (8) with observed and estimated $CSAI_{SCB}$s, respectively.

SCVI can be estimated by using a model provides time streams of both sunny crown profile and SCL. WAGUCHI and UEDA (2005) have found that sunny crown profile for hinoki cypress could be described by the following equation:

$$r = d_1 \mathrm{HI}^{d_2} z^{d_3} \qquad (11)$$

where d_1, d_2, and d_3 are constants. Furthermore, WAGUCHI and UEDA (2006b) have developed a model for estimating SCL from stand density and HI for even-aged hinoki cypress stands. These results indicate that SCVI for hinoki cypress can be estimated from time streams of both stand density and HI. Thus, when $\mathrm{CSAI}_{\mathrm{SCB}}$ can be estimated using SCVI, combining these results reported by WAGUCHI and UEDA (2005; 2006b) with a total height growth model allows us to estimate $\mathrm{CSAI}_{\mathrm{SCB}}$ because stand density is generally a known variable. In conclusion, the assumption of the proportional relationship between SCVI and $\mathrm{CSAI}_{\mathrm{SCB}}$ provides a useful approach for predicting vertical distribution of CSAI for hinoki cypress.

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Short Communication

Analyzing the Relationship between Periodic Height Increment and Height at the Beginning of the Increment Period in Even-Aged Pure Stands of Japanese Larch (*Larix kaempferi*) Based on Stem Analysis

Akio Inoue[*1], Keigo Yoshida[*2] and Takashi Kunisaki[*3]

ABSTRACT

The relationship between periodic height increment and height at the beginning of the increment period was analyzed in two even-aged (30 and 36 year-old) pure stands of Japanese larch (*Larix kaempferi*). To obtain the initial height data as accurately as possible, all living trees within the stands were felled, and then the heights for each tree for a series of ages were estimated by stem analysis. The result indicated that a significant weak correlation between periodic height increment and height at the beginning of the period in the larch stands could occur for some increment periods. In conclusion, it is not necessarily the case that relationships do not exist between periodic height increment and height at the beginning of the increment period in even-aged pure stands.

Keywords: even-aged pure stand, height growth, Japanese larch, periodic height increment, stem analysis

INTRODUCTION

Even-aged pure stands generally exhibit a positive linear relationship between periodic diameter increment and diameter at the beginning of the increment period (e.g., SHIRAISHI and TANAKA, 1985; TANAKA, 1986, 1991b). On the other hand, there is no relationship between periodic height increment, HI, and height at the beginning of the increment period, HBP (e.g., SHIRAISHI and TANAKA, 1985; TANAKA, 1988, 1991b; MITSUDA, *et al.* 1997), except in young stands (CANNELL *et al.*, 1984; SOUTH and MASON, 1991; TANAKA, 1991b). Such growth patterns determine the size structures of the stand, and hence analysis of these relationships enables us to predict the shifts in height-diameter relationship (TANAKA, 1991a) and to describe the dynamics of diameter and height distributions (TANAKA, 1986; 1988).

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Past analyses of relationships involving height and height increment have mostly been performed with tree height data measured using hypsometers. Generally, the measurement of the height of a standing tree is inaccurate, whereas the diameter can be measured accurately. As trees in a stand grow larger, the accuracy of height measurement diminishes. Because of the difficulty of making accurate height measurements, MITSUDA, *et al.* (1997) pointed out the necessity of further analyses based on more reliable data. Stem analysis provides more reliable height growth data, compared to the height measurements with hypsometers. KOBAYASHI (1978) and INOSE (1984) analyzed the relationship between HI and HBP using the stem analysis data of selected sample trees from studied stands. However, to our knowledge, there has been no study on the relationship between HI and HBP using the stem analysis data of all living trees in a given stand. The objective of this study was thus to verify the relationship between HI and HBP based on the stem analysis data of all living trees in two even-aged pure stands of Japanese larch (*Larix kaempferi*).

MATERIALS AND METHODS

This study was conducted in two Japanese larch even-aged pure stands in the Hiruzen Experimental Forest of Tottori University, Okayama Prefecture, western Japan (35° 18' N and 133° 35' E). The annual average temperature, annual average precipitation and maximum snowfall of the

Table 1 Attributes of each plot

Plot	A	B
Stand age (year)	36	30
Topographic position	Ridge	Middle slope
Slope direction	S	N
Average slope inclination (°)	10	5
Mean DBH (cm)*	15.5 ± 5.1	17.1 ± 5.0
Mean height (m)*	15.6 ± 3.7	15.3 ± 2.2
Stand density (trees/ha)	1244	1244

*: Average ± SD

Experimental Forest were 11.3℃, 2,140mm and 2.1m, respectively. The soils are mainly gray volcanic ash soils. The larch stands were located on gentle 5-10° slopes at about 600-700m asl. In these stands, larch seedlings were planted at a density of about 3,000 trees per hectare; no thinning had been conducted since planting. The attributes of each plot are summarized in Table 1.

A square plot of 15m × 15m was established in each larch stand. Next, all living trees in the plot were felled for stem analysis. The number of felled trees was 28 for both plots. Stem disks were sampled from 0.2m, 1.2m and the upper portions at 2.0m intervals, whereas only final disk at the highest position was taken at 1.0m interval. Each sample disk was measured along four different radii to determine ring width corresponding to growth intervals of three-years. The average stem diameter was computed, and then the tree height for a series of past year was estimated from the stem diameters for the given age on the final and semi-final stem disks (Nagumo and Minowa, 1990). The estimated periodic height increments at three- and six-yearly intervals, HI_3 and HI_6, and heights at the beginning of the increment period, HBP, were used for the analysis.

Tanaka (1988) found a significant correlation between HI and HBP when lower-story trees were included in the analysis. For this reason, the lower-story trees were similarly excluded from the analysis in this study. The lower-story trees were selected for each stand age based on the skewness of the height distribution of upper-story trees (Tanaka, 1983). That is to say, the skewness of the height distribution of upper-story trees was calculated by selecting the lower-story trees in the order of increasing height. The trees were then divided into upper- and lower-story trees with the boundary at which the skewness was nearest to zero. Previous studies have shown that there was a positive linear relationship between HI and HBP in young stands (Cannell *et al.*, 1984; South and Mason, 1991; Tanaka, 1991b). Therefore, the data of which stand age at the beginning of the period was less than 15-years was also excluded from the analysis. Pearson's correlation coefficient test was performed for each plot, each stand age and each increment period using Excel 2000 with the add-in software Statcel 2 (Yanai, 2004).

RESULTS

Fig. 1 depicts the relationships between periodic height increment at three-yearly intervals, HI_3, and height at the beginning of the increment period, HBP, in an even-aged pure stand of Japanese larch (Plot A). For stand ages of 15 and 21 years at the beginning of the increment period, the Pearson's correlation coefficient test indicated that there was no correlation between HI_3 and HBP ($p > 0.05$ for both; see Table 2). However, for ages of 18, 24, 27, 30 and 33 years, a

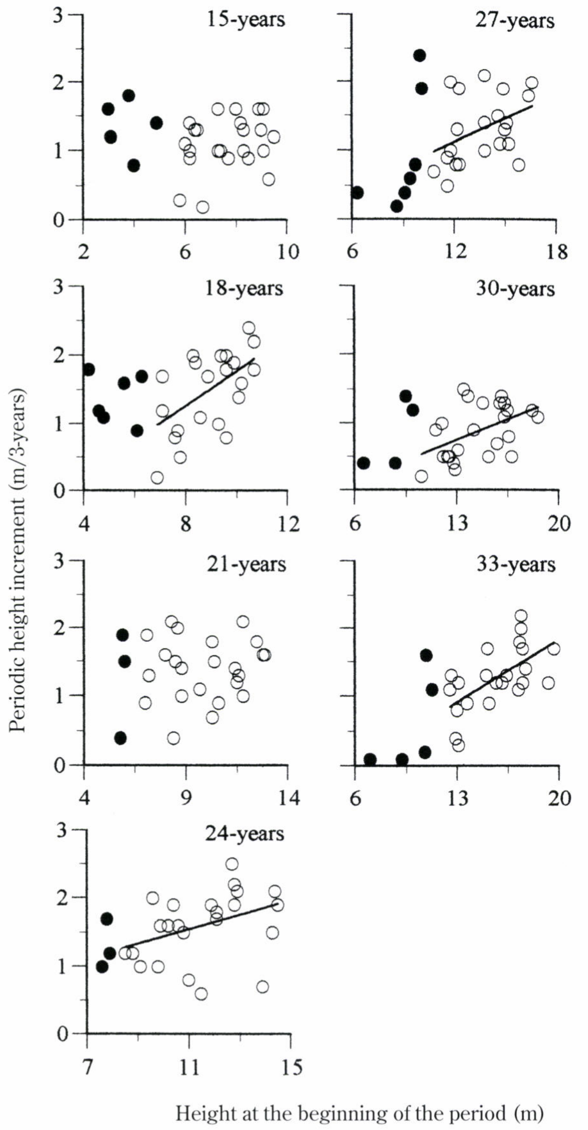

Fig. 1 Relationships between periodic height increment and height at the beginning of the increment period at three-yearly intervals for an even-aged pure stand of Japanese larch (Plot A). The open and closed circles mean the upper- and lower-story trees, respectively, and straight lines indicate the regression lines.

Table 2 Pearson's correlation coefficient between periodic height increment and height at the beginning of the increment period for even-aged pure stands of Japanese larch

Plot	Increment period (years)	Age at the beginning of the period (years)						
		15	18	21	24	27	30	33
A	3	0.248 n.s.	0.545 **	0.091 n.s.	0.371 *	0.425 *	0.482 **	0.632 ***
	6	0.491 **	0.356 n.s.	0.296 n.s.	0.365 *	0.441 *	0.708 ***	
n (upper-story trees/plot)		23	22	25	24	21	24	23
B	3	−0.453 *	0.139 n.s.	−0.351 n.s.	0.372 n.s.	0.161 n.s.		
	6	−0.068 n.s.	0.059 n.s.	−0.023 n.s.	0.450 *			
n (upper-story trees/plot)		20	23	18	18	23		

***: significant at 0.1% level; **: significant at 1% level; *: significant at 5% level; n.s.: not significant.

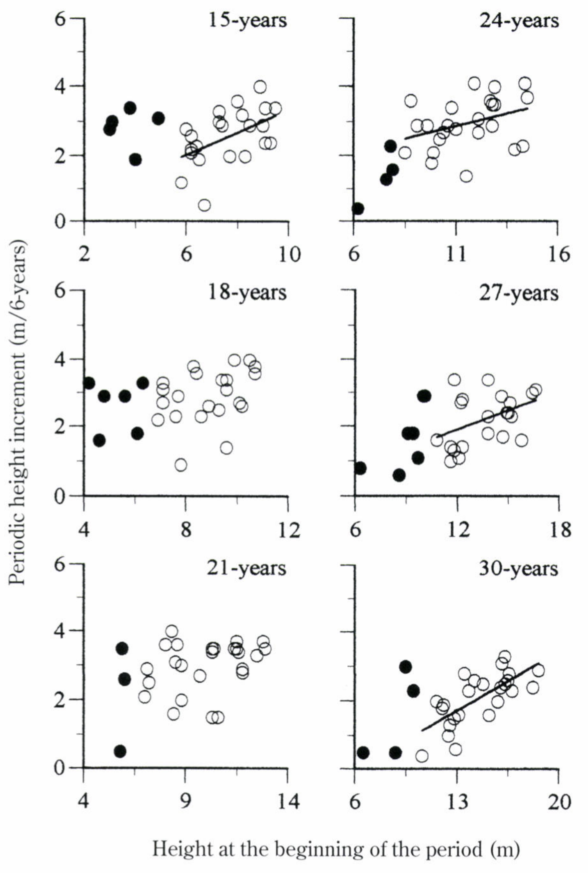

Fig. 2 Relationships between periodic height increment and height at the beginning of the increment period at six-yearly intervals for an even-aged pure stand of Japanese larch (Plot A). Legends are same as in Fig. 1.

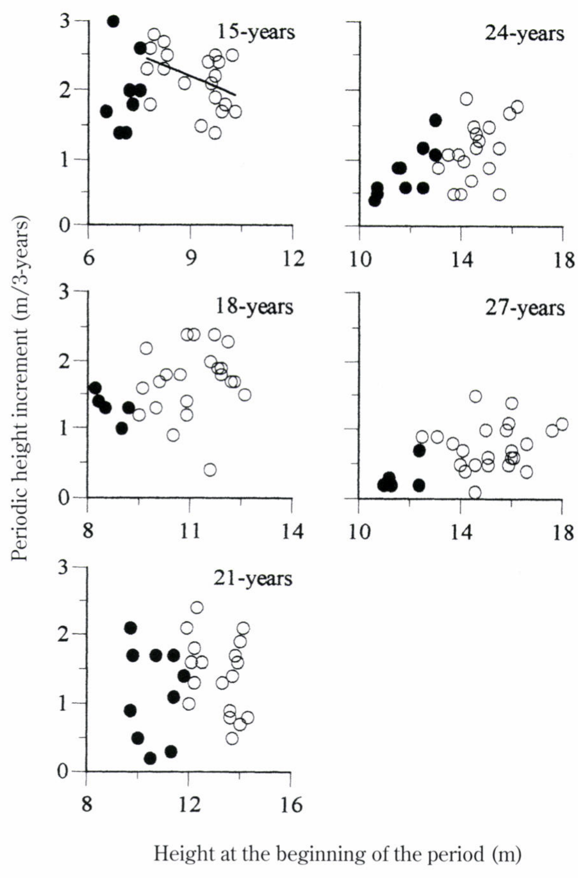

Fig. 3 Relationships between periodic height increment and height at the beginning of the increment period at three-yearly intervals for an even-aged pure stand of Japanese larch (Plot B). Legends are same as in Fig. 1.

significant correlation between HI_3 and HBP was found ($r = 0.545$, $p < 0.01$ for 18 year-old; $r = 0.371$, $p < 0.05$ for 24 year-old; $r = 0.425$, $p < 0.01$ for 27 year-old; $r = 0.482$, $p < 0.01$ for 30 year-old and $r = 0.632$, $p < 0.001$ for 33 year-old).

Fig. 2 shows the relationships between periodic height increment at six-yearly intervals, HI_6, and height at the beginning of the increment period, HBP, in Plot A. For stand ages of 18 and 21 years, no correlation between HI_6 and HBP was found ($p > 0.05$ for both). However, for ages of 15, 24, 27 and 30 years, there was a positive correlation between HI_6 and HBP ($r = 0.491$, $p < 0.01$ for 15 year-old, $r = 0.365$, $p < 0.05$ for 24 year-old, $r = 0.441$, $p < 0.05$ for 27 year-old, and $r = 0.708$, $p < 0.001$ for 30 year-old).

The relationships between HI_3 and HBP in plot B are

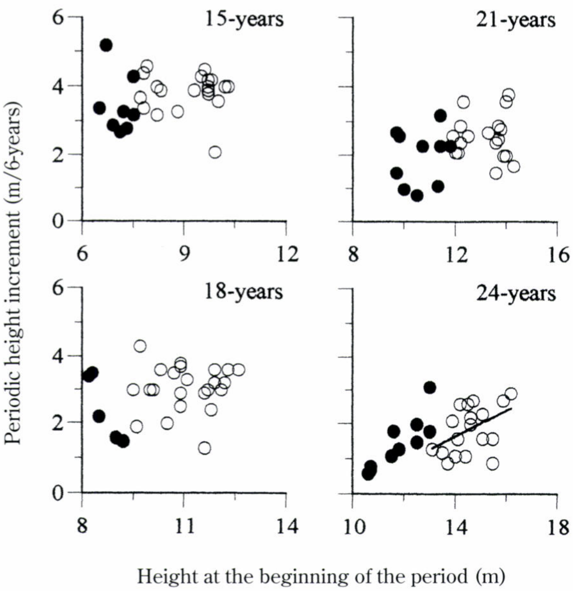

Fig. 4 Relationships between periodic height increment and height at the beginning of the increment period at six-yearly intervals for an even-aged pure stand of Japanese larch (Plot B). Legends are same as in Fig. 1.

shown in Fig. 3. For stand ages of 18, 21, 24 and 27 years at the beginning of the increment period, no correlation between HI_3 and HBP was found ($p > 0.05$ for all). By contrast, for age of 15 years, there was a negative correlation between HI_3 and HBP ($r = -0.453$, $p < 0.05$).

As shown in Fig. 4, for stand ages of 15, 18 and 21 years, HBP was not significantly correlated with HI_6 in Plot B ($p >$ 0.05 for all). By contrast, for age of 24 years, a positive correlation between HI_6 and HBP was observed ($r = 0.450$, $p <$ 0.05).

DISCUSSION

Several studies have analyzed the relationship between periodic height increment, HI, and height at the beginning of the increment period, HBP, based on the tree height data measured with hypsometers. CANNELL *et al.* (1984) reported that HI depends on HBP in young Sitka spruce (*Picea sitchensis*) and lodgepole pine (*Pinus contorta*) stands. SOUTH and MASON (1991) also found positive linear relationships between HI and HBP in young Sitka spruce and hybrid larch (*Larix* × *eurolepis*) stands. SHIRAISHI and TANAKA (1985) reported that HI was near uniformly independent of HBP class, except when suppressed trees were included, in 21 year-old Japanese cypress (*Chamaecyparis obtusa* ENDL.) stands. TANAKA (1988) found that there was no relationship between HI and HBP, except when the suppressed trees were included, in 21 year-old Japanese cedar (*Cryptomeria japonica* D. DON) and 22 year-old Japanese cypress stands. MITSUDA *et al.* (1997) reported that there was no relationship between HI and HBP in Japanese cedar and Japanese cypress stands of various ages.

Other scientists have studied the relationship between HI and HBP based on the stem analysis data. INOSE (1984) used stem analysis data from 30 sample trees per stands to analyze the difference in height growth between the upper-, middle- and lower-story trees in three Todo-fir (*Abies sachalinensis*) stands (stand age: 37-44 year-old). The results showed that HI of the lower-story trees was low compared to that of the upper-story trees (INOSE, 1984), suggesting that there would be a positive linear relationship between HI and HBP. Using stem analysis data from 12 upper-story trees, KOBAYASHI (1978) studied the change in the correlation coefficient between HI and HBP with stand age in a 60 year-old Japanese larch stand, and reported that the coefficient varies from 0.1 to 0.55 between stand ages. KOBAYASHI (1978) also analyzed the variation in tree height within the stand, and suggested that there would be a positive correlation between HI and HBP. The present study was performed with the stem analysis data of all living trees collected from 36 and 30 year-old Japanese larch stands. The results indicated that HI was significantly correlated with HBP for some increment periods, whereas a negative correlation between HI and HBP was found for stand age of 15 years in Plot B (see Fig. 1-4 and Table 2). Similarly, INOSE (1984) reported that HI of the lower-story trees was often equivalent to or greater than that of the upper-story trees.

These various results suggest that tree height data measured with hypsometers do not reveal a linear relationship between HI and HBP in even-aged pure stands, except when suppressed trees are included and in young stands. By contrast, data based on stem analysis indicate that the relationship between HI and HBP is intermittent. This inconsistency suggests that the relationship between HI and HBP may vary with stand ages as well as with the method of measuring tree height. Therefore, it is not necessarily the case that relationships do not exist between HI and HBP in even-aged pure stands. Even though several studies (e.g., SHIRAISHI and TANAKA, 1985; TANAKA, 1988, 1991b; MITSUDA *et al.*, 1997) have found no relationship between HI and HBP, this should not be regarded as a universal growth phenomenon. To clarify the variation in HI among trees in an even-aged pure stand, there is a need for further analyses of reliable data from various districts, species and stand ages.

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