Use of GIS-derived Environmental Factors in Predicting Site Indices in Japanese Larch Plantations in Hokkaido

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The objectives of this study were (1) to evaluate the effects of environmental factors derived from GIS on tree-height growth of Japanese larch (*Larix kaempferi*) and (2) to develop a best-fit regression model for its site index. Based on data from 40 sample plots situated in an even-aged (38 years), pure, and undamaged Japanese larch stand, multiple regression models for a site index of Japanese larch were constructed using environmental factors as independent variables. The average slope gradient, effective relief, distance from ridge, flow accumulation, degree of exposure, shading, solar radiation index, and gravitational water index were used as environmental factors and calculated on GIS using digital elevation model data. These factors were related to the Japanese larch site index through multiple-regression analysis. The result showed that the most effective factor for estimating site index was the degree of exposure. Through a backward stepwise procedure, the degree of exposure, shading, and average slope gradient were selected for a best-fit regression model. This model explained 72% of the variance in site index, with standard error estimates of 1.75 m. This strong relationship suggests that GIS-derived environmental factors can be used to predict site indices of Japanese larch.

Key words: DEM, GIS, *Larix kaempferi*, site index

Knowledge of the autecology of tree species is necessary for decision-making in forest management on a site- and species-specific basis (Kayahara *et al.*, 1998). Potential productivity of a specific species becomes especially important to assist forest managers in selecting the most suitable silvicultural regime when timber production is the primary management objective (Klinka and Feller, 1984).

Site productivity is defined as the maximum amount of timber that a site can produce over a given time (Davis and Johnson, 1987). A number of methods have been developed to measure site productivity indirectly rather than directly. The site index, defined as the average height of individual dominant free grown trees in the stand at a specific site (*i.e.*, site trees), has been the most widely used measure of forest site productivity in many regions (*e.g.*, Davis and Johnson, 1987; Martin and Ek, 1990; Monserud *et al.*, 1990). In Japan, the site index is the most commonly used species-specific approach for assessing forest site productivity as well (*e.g.*, Nishizawa *et al.*, 1965; Fukushima *et al.*, 1974; Teraoka *et al.*, 1991; Chen and Abe, 1999).

The measured height and age of site trees are used as coordinates for determining the site index from a set of height-age curves (*i.e.*, site index curves). However, this direct determination of site index is often not possible because suitable site trees may only be found in older, even-aged, well-stocked, free-growing, undisturbed, pure species stands. As a result, we can't find site trees where the site is unstocked, stocked with trees unsuitable for productivity measurement, or stocked with different species from the one of interest (Wang, 1995; Wang and Klinka, 1996; Kayahara *et al.*, 1998). These situations call for indirect methods of assessing the site index, methods that rely on the relationships between environmental factors and the site index. Environmental factors (*i.e.*, geographical location, topography, and soil) have been widely used to estimate forest productivity because these environmental factors are easier to measure than causative factors (*i.e.*, light, heat, moisture, and nutrients) that control tree growth directly (Wang and Klinka, 1996). Most studies on these attempts have employed multiple-regression techniques that used a number of topographic, soil physical, and soil chemical properties as independent variables to predict site indices. Recently, many studies have attempted to integrate these environmental factors into a few synoptic ones (*e.g.*, Green *et al.*, 1989; McNab, 1989, 1993; Klinka and Carter, 1990; Wang and Klinka, 1996).

Although the site index is an effective tool for managing a forest ecosystem, the site index is an expensive and inconvenient variable to measure for large land areas because it requires field crews and sample surveys (Fox *et al.*, 1985). Recently, however, mapping techniques using the geographic information system (GIS) were developed and spread widely. GIS subsequently reduced the time and effort required to estimate site indices for large areas. With progress in GIS technology, many kinds of maps such as geological, topographic maps, and precipitation maps, have been converted to digital maps. We have thus been able to apply these digital maps to several analyses on GIS. In particular, a digital elevation model (DEM) can be used to derive a wealth of information about the morphology of a land surface, such as the slope, aspect, shaded relief, and hydrologic features (Jenson and Domingue, 1988). For example, Iverson *et al.* (1997) showed how to use the integrated moisture index to predict forest composition and productivity. This index was developed to integrate topographic features derived from the DEM and soil features derived from digitized soil-series map provided by the USDA Natural Resource Conservation Service into a single index on GIS.

Several indices that indicated environmental characteristics derived from GIS analysis were proposed in the past (*e.g.*, Blaszczynski, 1997; Iverson *et al.*, 1997; Murakami *et al.*,

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2000). However these indices have not been examined as to which indices or their combinations were better for estimating site productivity. At the same time a large number of past studies performed site classification using environmental factors by GIS (*e.g.*, Fox *et al.*, 1985; Chen and Abe, 1999). However more detailed information (*i.e.*, site index) is required for sustainable forest management. There are great needs not for site classifications but for predictions of site index to assess whether the potential productivity of a particular site warrants the cost of a particular treatment.

Japanese larch (*Larix kaempferi*) is one of the most important species in Hokkaido. In 1997, Japanese larch plantations made up 30.5% of all plantation forest areas, and new larch plantations made up 32.6% of all new plantation forest areas in Hokkaido. Managing this species for sustainable production requires a good understanding of its productivity attributes and accurate prediction of productivity. In the past, several articles devoted to the study addressed the site index of Japanese larch in Hokkaido (*e.g.*, Usui *et al.*, 1986; Yamane *et al.*, 1990). However a method to estimate site index for large land area without field survey has not yet been invented.

The objectives of this study were (1) to evaluate the effects of environmental factors derived from GIS on tree height growth of Japanese larch and (2) to develop a best-fit regression model for its site index.

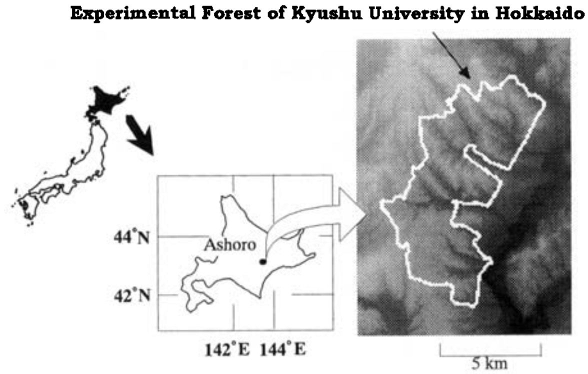

Fig. 1 Location of the Kyushu University Forest in Hokkaido.

Table 1 Summary of SI and environmental factors of the 40 plots.

Layer	Minimum	Mean	Maximum	SD	Units
SI	15.97	26.14	30.40	3.34	m
DBH	19.18	25.49	33.06	3.87	cm
ASG	− 1.84	0.29	2.63	0.88	degree
DE	0.00	55.00	220.00	42.17	degree
ER	34.00	63.20	100.00	17.23	m
DR	37.59	209.68	488.04	119.87	m
FA	0.00	13.25	183.00	35.01	cells
S	84.00	175.13	248.00	52.13	
SRI	0.46	0.82	1.00	0.15	cal cm^{-2} min^{-1}
GWI	12.00	13.93	20.00	1.91	day

SI, site index; other variable names are given in text. SD, standard deviation.

Materials and Methods

1 Study area and field survey

The study area is the experimental forest of Kyushu University in Hokkaido located in Ashoro district, Hokkaido Prefecture (Fig. 1). This forest is located from 43°17′ to 43°19′ north latitude and from 143°29′ to 143°33′ east longitude; it is 11.5 km long north to south and 8.0 km wide from east to west. The whole area is 3,735 ha and consists of broad-leaved and coniferous stand. Japanese larch has been planted in this forest since 1950 and currently occupies 1,067 ha. The elevation of the forest varies from 100 to 500 m above mean sea level. Most of this area is classified as Tertiary stratum. The surface is generally described as volcanic soil that covers the total area more than 10 cm deep. The average of annual temperature is about 6°C. In winter, the temperature may sometimes drop to − 30°C, while in summer, it may rise to a high of + 30°C. The average of total precipitation per annum is about 800 mm.

Forty 20 × 20 m sample plots, relatively uniform in topography, soil, and stand characteristics, situated in pure, even-aged, and undamaged stands of Japanese larch were established for an inventory to estimate the yield of thinning and record their locations on topographic maps (1:5,000 scale). On each plot, diameters at breast height (DBH) and heights were measured and recorded for all standing trees (Table 1). These stands where the plots were established were pure, even-aged, undamaged, and well stocked stands, so we could select the dominant trees in each plot as site trees. Because these plots were the same age (38 years), we could analyze relationships between height growth and environmental factors without the effect of age. For these reasons, in this study we defined the site index as heights of site trees at age 38, so three dominant trees were selected and the average of their heights were calculated as a site index for each of the 40 plots.

2 Environmental factors

To relate the site index and environmental factors for each of these 40 plots, we needed to acquire numerical values for environmental factors as predictor variables for each plot. Raster layers of environmental factors were thus created, and their values were extracted for each plot using GIS. To generate layers of environmental factors on GIS, elevation data must be in a digital elevation model (DEM). Therefore, the point data with X–Y–Z coordinates had to be converted to DEM data. The point data used in this study was obtained from two data sources. One set of data was derived from digitized topographic maps (1:5,000 scale) within the study area (approximately 1,400 points/km^2). The other set was imported from DEM data (approximately 50m resolution) published by the Geographical Survey Institute as 3D point vector data to supply the outside of the study area. These data were imported into TNTmips's world and used to create triangulated irregular network (TIN) data using TNTmips's "Triangulation" operation. The TIN data were interpolated and rasterized at 25 m resolution using TNTmips's "Surface Fitting" operation by the kriging method (Iverson *et al.*, 1997). Kriging is an optimal prediction method designed for geophysical variables with a continuous distribution (Cressie, 1990). In this study the linear model was used as

Table 2 Summary of layers of environmental factors.

Layer	Minimum	Mean	Maximum	SD
ASG	− 6.34	0.00	6.14	0.87
DE	0.00	103.21	360.00	81.22
ER	3.00	51.28	130.00	21.78
DR	8.18	137.60	644.88	108.51
FA	0.00	15.55	1930.00	75.13
S	0.00	192.01	254.00	41.82
SRI	0.22	0.77	1.00	0.14
GWI	12.00	14.46	27.00	1.99

All variable names and units are given in Table 1.

variogram model, the ordinary kriging was used as drift model, and the number of points per sector were 15. After the DEM was built, raster layers of environmental factors were created.

The following environmental factors were used in this study: average slope gradient (ASG), effective relief (ER), distance from ridge (DR), flow accumulation (FA), degree of exposure (DE), shading (S), solar radiation index (SRI), and gravitational water index (GWI). These factors were selected for this study based on two criteria: (1) that factors were probably highly correlated with site productivity based on previous studies; and (2) factors could be obtained from DEM data (Fox *et al.*, 1985). Usui *et al.* (1986) found a strong relationship between site productivity and soil, topographic, and climatic factors in the Tokachi region where this study was conducted. They found this association related mostly to the soil-water reservoir. Assuming similar climate and soil features in this site, the variation in site productivity will be driven primarily by moisture holding ability. Moisture levels are higher where land surfaces are depressed (AGS in this model), in lower positions on slopes (ER, DR, and FA), where evaporation caused by wind is minimized (DE), and where direct solar radiation is minimized (S and SRI). These four factors were modeled, via GIS, in this study. Additionally, the GWI layer, which integrates effects of slope inclination, undulation, position, and solar radiation on soil moisture level into an index, was also created.

The average slope gradient (ASG) index describes a landform. The algorithm for ASG is given in Blaszczynski (1997). Positive values mean that the objective cells have a predominantly convex shape within a 3-by-3-cell neighborhood, while negative values indicate a predominantly concave surface. Zero values indicate either a uniform slope area or a saddle point.

The effective relief (ER) index describes local drainage (Teraoka *et al.*, 1991). ER is calculated as the difference between maximum and minimum elevation within circles with a radius of 100 m centered on objective cells with increasing scores equivalent to increasing adequacy of drainage.

The distance from the ridge (DR) is a synoptic index related to water and wind dynamics. DR is calculated as the distance from ridges obtained as line vector data through the "Watershed" function mentioned later. The TNTmips function "Distance raster," which calculates the distance from the nearest vector object to the cell being evaluated, was used to create the DR layer. Ridge tops thus have minimum values, and valley bottoms, maximum values.

The flow accumulation (FA) index describes water concentration. FA is calculated as the accumulated flow of water down a slope as water moves via gravity (Iverson *et al.*, 1997). The algorithm for FA is given in Jenson and Domingue (1988). The TNTmips function "Watershed," which basically determines watershed boundaries and counts the number of cells sending water down slope to the cell being evaluated, was used to create the FA layer. Ridge tops thus have a flow accumulation of only one, but valley bottoms have maximum accumulation.

The degree of exposure (DE) index describes the local openness related to strength of wind causing evaporation (Fukushima *et al.*, 1974). DE is calculated as the cumulative horizontal angle that is not closed by surrounding mountain when looking all around with an elevation angle of 3 degrees from objective cells. The algorithm for DE on GIS is given in Murakami *et al.* (2000). An increasing DE score means that the objective cells have greater openness and therefore a larger amount of evaporation caused by wind.

The shading (S) and solar radiation indices (SRI) describe intensities of solar radiation varying with variation in the slope angle, aspect, and position, and account for shading from adjacent hills for shading only. According to Usui and Miyaki (1991), the site productivity of Japanese larch in the study area was restricted mainly by a shortage of water during the summer season, so we computed S and SRI at 14:00, 25 July. S is calculated as the brightness of the surface when it is illuminated from a particular sun direction and elevation angle. In this case the sun direction is 244.5 degree and solar elevation angle is 51.5 degrees. The "Raster/Elevation" process in TNTmips was used to create shading raster with decreasing scores equivalent to decreasing brightness, or direct solar radiation. The algorithm for SRI is given in Okaue (1957). Increasing SRI scores represent increasing direct solar radiation, or evaporation causing soil water shortage.

The gravitational water index simulates the runoff process including water flux, infiltration, and evaporation processes on a slope. The basic model of this index was proposed by Kubota *et al.* (1987), and the method to calculate it with DEM data was proposed by Usui and Miyaki (1991). According to Usui and Miyaki, in the absence of soil and the soil depth layer, we assigned a single value to saturated hydraulic conductivity and depth of soil, fixed the position of the sun, and used a single SRI layer created before. In calculating GWI, we simulated soil water reduction on this condition day-by-day, and counted the days it took for soil water moisture to rise from pF 1.0 to 1.8 for each cell. Thus, an increasing score indicates a higher water-holding capacity.

Layers that could not be created by the TNTmips function directly (*i.e.*, AGS, ER, DE, SRI, and GWI layers) were made by programs that encoded their algorithms into TNTmips's programming language.

Table 3 Peason's correlation coefficient between site index and environmental factors.

	SI	ASG	ER	DR	FA	DE	S	SRI
ASG	0.223							
ER	**− 0.455**	0.225						
DR	**0.518**	− 0.090	**− 0.490**					
FA	0.160	0.076	− 0.254	0.289				
DE	**− 0.720**	**− 0.628**	0.118	− 0.248	− 0.111			
S	**0.558**	− 0.066	**− 0.658**	**0.516**	0.174	− 0.185		
SRI	**− 0.518**	0.045	**0.430**	**− 0.398**	− 0.065	0.191	**− 0.931**	
GWI	**0.483**	− 0.016	**− 0.312**	0.304	− 0.019	− 0.170	**0.849**	**− 0.974**

Boldface indicates significant correlation ($p < 0.05$).

After producing layers on GIS, we extracted the index values of environmental factors for each plot by TNTmips's "Raster property" operation (Table 2).

3 Data analysis

Pearson's correlation analysis was used to examine relationships between site index and environmental factors (Chen *et al.*, 1998). Site index prediction models were developed through regression analysis using environmental factors and their combinations as predictors. To limit the number of predictors, we used the backward stepwise procedure in selecting independent variables (Green *et al.*, 1989; Chen *et al.*, 1998). To facilitate comparisons among models with different numbers of predictors, the standard error of estimation (SEE) and the R^2 statistics that were adjusted for degrees of freedom (R_a^2) were reported for all regression models (Neter *et al.*, 1996). To compare effects of each environmental factor in each equation, we calculated standardized regression coefficients (SRC) and coefficients of partial determination (CPD) that measured the marginal contribution of independent variables when all others were already included in models for each independent variable in each model. If there is multicollinearity in the multiple-regression model, we can not evaluate coefficients of regression exactly. Multicollinearity was therefore detected using variance inflation factors (VIFs) that measured how much the variances of the estimated regression coefficients were inflated as compared to when the independent variables were not linearly related. A maximum VIF value exceeding 10 indicates the existence of serious multicollinearity problems in this model (Neter *et al.*, 1996).

Models employing factors related with groundwater evaporation were constructed using DE and SRI or S (Evaporation model). Models employing factors expressing topography were made using ASG and ER or DR or FA (Topography model). To improve prediction models to take account of groundwater evaporation, runoff, and concentration, factors used in the Topography model were added to Evaporation models (Evaporation plus Topography model). GWI simulated groundwater dynamics including effects of solar radiation and macro-scale topography, so we constructed models based on GWI. GWI-based models used GWI, DE indicating the intensity of wind that was not included in GWI, and ASG presenting meso-scale topography that was not sufficiently considered in GWI. We conducted multiple-regression analysis for all the above-mentioned combinations, then accepted models which were significant and for which all independent variables were significant.

All statistical analyses were conducted using SPSS for Windows (version 10.0J). Unless otherwise specified, the level of statistical significance level was set at $p = 0.05$; the sample size for all statistical analyses was 40.

Results

Relationships between the site index and environmental factors are shown in Table 3. The site index was significantly and positively correlated with DR, S, and GWI, and negatively correlated with ER, DE, and SRI. ASG and FA did not significantly correlate with site index ($p = 0.167$ and 0.323, respectively). In relation to geographical location, the site index was higher when farther from the ridge and with gentler undulation (DR: $r = 0.518$; ER: $r = -0.455$). The index decreased significantly ($r = -0.723$) for increases in DE. As direct solar radiation increased, the site index decreased (S: $r = 0.558$; SRI: $r = -0.518$). Site index was higher where gravitational water lingered longer after a rainfall ($r = 0.483$).

All accepted prediction models are shown in Table 4, and their statistics of independent variables are shown in Table 5. VIFs for all independent variables in all models ranging from 1.006 to 1.803 were sufficiently smaller than 10 (Table 5).

The descriptive measures (*i.e.*, R_a^2 and SEE) of model performance indicated that model 3-d was the best, followed by models 3-a, 3-b, 3-c, 1-b, 4-c, 1-a, 4-b, 2-b, 2-a, and 4-a (Table 4). Comparing Evaporation models, R_a^2 of model 1-b using DE and S was larger than that of the model (1-a) using DE and SRI. The performance of Topography models was very poor. R_a^2 and SEE were 0.282 and 2.822 for model 2-a, and 0.305 and 2.775 for model 2-b. Adding topographic variables to Evaporation models improved model accountability for site index. R_a^2 of models 3-a, 3-b, and 3-c were 0.700, 0.695, and 0.692 respectively, and were better that of model 1-a. Similarly, model 3-d was better than model 1-b (Table 4). In Evaporation and Topographic models, DE contributed to the model accountability more than other factors (Table 5).

Through the backward stepwise procedure, we selected ASG, DE, and S as independent variables of the best-fit model, which was equivalent to model 3-d ($R_a^2 = 0.723$, SEE = 1.752 m). In this model, DE had the greatest impact on site index (SRC = − 0.812). When DE was added to the model containing ASG and S, the model sum of squares

Table 4 Models of predicting site index from environmental factors.

No.	Constituent	Model	R_a^2	SEE (m)	p
1–a	Evaporational model	SI = 36.308 − 0.051 (DE) − 9.023 (SRI)	0.651	1.967	< 0.001
1–b		SI = 23.992 − 0.050 (DE) + 0.028(S)	0.690	1.855	< 0.001
2–a	Topographical model	SI = 32.265 + 1.298 (ASG) − 0.103 (ER)	0.282	2.822	0.001
2–b		SI = 22.683 + 1.028 (ASG) + 0.015 (DR)	0.305	2.775	< 0.001
3–a	Evaporational and Topographical model	SI = 37.377 − 0.050 (DE) − 6.540 (SRI) − 0.050 (ER)	0.700	1.825	< 0.001
3–b		SI = 32.997 − 0.047 (DE) − 6.970 (SRI) + 0.007 (DR)	0.695	1.838	< 0.001
3–c		SI = 36.526 − 1.075 (ASG) − 0.066 (DE) − 7.912 (SRI)	0.692	1.848	< 0.001
3–d		SI = 25.580 − 0.989 (ASG) − 0.064 (DE) + 0.025 (S)	0.723	1.752	< 0.001
4–a	GWI-base model	SI = 14.423 + 0.841 (GWI)	0.213	2.953	0.002
4–b		SI = 19.983 + 0.647 (GWI) − 0.052 (DE)	0.634	2.014	< 0.001
4–c		SI = 22.151 + 0.579 (GWI) − 0.068 (DE) − 1.179 (ASG)	0.686	1.866	< 0.001

All variable names and units are given in Table 1. R_a^2, adjusted R^2; SEE, standard error of estimate.

Table 5 Statistics of independent variables in prediction models.

Model	Variable	SRC	p	CPD	VIF
1–a	DE	− 0.645	< 0.001	0.548	1.038
	SRI	− 0.395	< 0.001	0.312	1.038
1–b	DE	− 0.639	< 0.001	0.572	1.035
	S	0.440	< 0.001	0.388	1.035
2–a	ASG	0.343	0.019	0.141	1.054
	ER	− 0.533	< 0.001	0.283	1.054
2–b	ASG	0.271	0.050	0.100	1.008
	DR	0.542	< 0.001	0.307	1.008
3–a	DE	− 0.635	< 0.001	0.583	1.039
	SRI	− 0.286	0.006	0.190	1.258
	ER	− 0.257	0.012	0.162	1.229
3–b	DE	− 0.601	< 0.001	0.577	1.077
	SRI	− 0.305	0.003	0.216	1.201
	DR	0.247	0.016	0.150	1.233
3–c	ASG	− 0.284	0.020	0.279	1.731
	DE	− 0.832	< 0.001	0.576	1.792
	SRI	− 0.346	< 0.001	0.141	1.089
3–d	ASG	− 0.261	0.025	0.132	1.749
	DE	− 0.812	< 0.001	0.589	1.803
	S	0.391	< 0.001	0.352	1.097
4–a	GWI	0.483	0.002		1.000
4–b	GWI	0.372	< 0.001	0.279	1.030
	DE	− 0.657	< 0.001	0.547	1.030
4–c	GWI	0.333	< 0.001	0.016	1.057
	DE	− 0.859	< 0.001	0.594	1.743
	ASG	− 0.311	0.011	0.165	1.693

SRC, standardized regression coefficient; CPD, coefficient partial determination; VIE, variance inflation factor. All variable names and units are given in Table 1.

error was reduced by 58.9%. The site index predicted for the sample plots using model 3-d were generally in a strong 1:1 relationship with the measured site index (Fig. 2). The residuals of this model were not biased, but extraordinary large errors existed in a few plots.

Using GWI alone as a predictor variable, R_a^2 and SEE were 0.213 and 2.953, respectively. Adding measures of evaporation (*i.e.*, DE) and meso-scale topography (*i.e.*, ASG) as independent variables improved model accountability. R_a^2 and SEE were 0.634 and 2.014 for model 4-b, and 0.686 and 1.866 for model 4-c (Table 4). In both models, GWI had smaller impacts on the variation in site index than DE (Table 5).

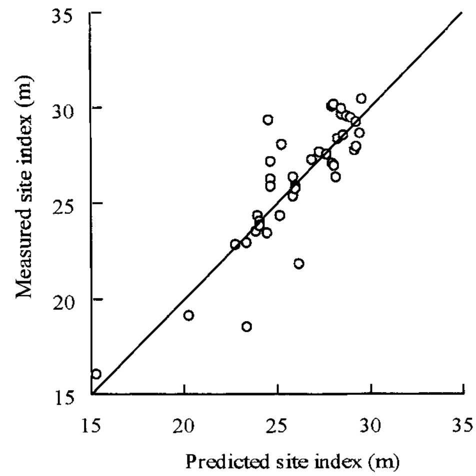

Fig. 2 Comparison of measured and predicted site index.

Discussion

We observed significant relationships between Japanese larch site indices and GIS-derived environmental factors, with the exception of ASG and FA. McNab (1993) reported that yellow poplar site indices were significantly correlated with the landform index that described landform based on field measurement. However, ASG indicating landform was not significant as a single predictor in this study. Although FA had an important role in the integrated moisture index proposed by Iverson *et al.* (1997), FA was not a significant predictor variable in any single or multiple-regression model. FA was not accepted in any regression model because the distribution of FA of sample plots was extraordinarily biased.

Regression models were developed to establish a quantitative link between Japanese larch site indices and environmental variables. These models were based on the assumption that site indices of Japanese larch were restricted mainly by soil water conditions when climate and soil features were similar. The Evaporation models demonstrated that significant proportions of the variation in site index could be explained by environmental factors that related to soil water evaporation. Comparing these models, R_a^2 of the model including S as an independent variable was higher than the model including SRI because S accounted for shading from adjacent hills that was not considered in SRI. In recent studies on relationships between the site index and topographic factors, the slope aspect has had a great impact on the site index as a predictor indicating intensity of solar radiation (Fox *et al.*, 1985; Corona *et al.*, 1998; Chen and Abe, 1999). In these studies, however, the slope aspect was treated as a categorical variable. We can thus say that S and SRI are better predictors than the slope aspect for expressing the intensity of solar radiation.

The accountabilities of the Topographic models, which used indices describing land surface shape and geographical location, were poor. Adding these indices to the Evaporation models, however, improved their accountabilities for the variation of site indices. In other studies, position on the slope greatly impacted site indices (Chen *et al.*, 1998; Chen and Abe, 1999). However, only ASG, DE and S were selected for the best-fit regression model through backward stepwise process. Factors describing position on the slope were not selected because the hills gently undulate equally within the study area. As a result, drainage derived from topography does not drastically vary within the area. For example, Teraoka *et al.* (1991) showed that ER had greater impact than DE on regression models of the site index of sugi with greater standard deviation of ER (21.44 m) than that of sample plots in this study (17.23 m, Table 1).

Usui and Miyaki (1991) showed a strong relationship between height growth of Todo-fir (*Abies sachalinensis*) and GWI ($r = 0.78$). In this study, the coefficient of correlation between the site index and GWI was 0.48, and the CPD of GWI was lower than that of DE in models 4-b and 4-c. The resolution of our DEM data (25 m) was coarser than theirs (12 m), and the study area was approximately 3,800 ha greater than theirs (about 6 ha). For this reason, the GWI simulation became less accurate, so GWI was not a good predictor in this study.

It has been reported that resolution, raw data quality and interpolation method of DEM had a direct effect on topographical analysis. For example, the effect of grid size on simulation of soil water content and runoff was studied by Kuo *et al.* (1999), and that of grid size and raw data quality on estimation of forest composition and productivity were tested by Iverson *et al.* (1997). In this study DEM was created only by the kriging method with 25 m cell size from digitized 3D point data. So we must examine the effects of different cell sizes, data sources and surface fitting methods on environmental factors and site index prediction models presented in this study.

Through all regression analyses, the site index of Japanese larch within the study area was found to be mostly influenced by the variation in DE, so we suggested that the site productivity of Japanese larch was restricted by groundwater shortage caused by high wind. The relative low/high DE caused the great over/under estimation of site index shown in Fig. 2. In other research, the importance of DE on site index was reported for Japanese larch by Usui *et al.* (1986) and Yamane *et al.* (1990), for sugi (*Cryptomeria japonica*) by Teraoka *et al.* (1991), and for hinoki (*Chamaecyparis obtusa*) by Fukushima *et al.* (1974) and Teraoka *et al.* (1991).

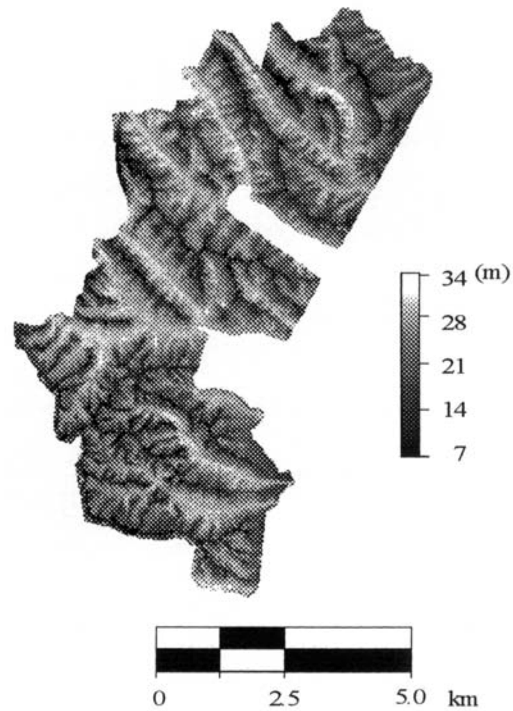

Fig. 3 Distribution map of predicted site index.

Several studies have demonstrated the importance of soil properties on site productivity. In British Columbia, soil moisture regimes, soil aeration regimes, and soil nutrient regimes are used as synoptic variables in predicting white spruce site indices (*e.g.*, Klinka and Carter, 1990; Wang and Klinka, 1996). Yamane *et al.* (1990) showed that soil type had a greater effect on the site index of Japanese larch than other climatic and topographical factors. We assumed uniform soil properties, so the influence of soil properties on the site index was not included in our model. Even without soil information, however, we could create a good prediction model. Adding variables describing soil features such as soil type and soil depth will improve the accountability of our model for the variation in site indices.

The final step of constructing a regression model is to validate the model (Neter *et al.*, 1996). Specifically, we must validate our model with a data set that is independent from model development (Chen *et al.*, 1998; Kayahara *et al.*, 1998). Through the tests of model precision and bias, we must examine whether our model may be used for predicting a site index in a practical situation.

Site productivity is usually not evaluated in Ashoro district because there are no convenient tools to measure it. The GIS procedure proposed in this study can provide a realistic distribution map of site indexs and can assist forest managers to make their management decisions (Fig. 3). Unlike traditional methods used to measure site indices, the method presented here using GIS techniques is not affected by disturbances and does not need stands evaluated to be old, pure, and evenly aged. This method can therefore estimate site productivity potential across landscapes. Predictions using this method may be used for growth and yield projections and forest management planning.

Conclusion

Within the study area, site index of Japanese larch strongly correlated with environmental factors. The correlation and multiple-regression analyses showed that the critical factor to determine the site productivity of Japanese larch was DE that indicated soil water evaporation caused by wind.

We proposed a convenient tool for estimating the site index based on extracting environmental factors from DEM by GIS analysis. Developing a site index prediction model and creating site index distribution map as the end product of this procedure will facilitate Japanese larch plantation management in Hokkaido.

Finally, we recommend that this GIS-based procedure to estimate site indexes of Japanese larch be applied in the study area.

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