SPRUCE STAND MONITORING BASED ON THE SUCCESSIONAL SPECTRAL TRAJECTORY USING LANDSAT TM DATA

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ABSTRACT:

A forest monitoring method, which was based on the exponential function and the minimum distance classifier, was proposed. Averages and standard deviations of age classes were estimated and used for the classification of four Landsat Thematic Mapper images, which were obtained in winter and summer. The method was applied for spruce stands, and it was found that the method reduced effects of seasonal spectral variation on classification. The results suggested that successional stages can be monitored quite well using summer images, and comparison of winter and summer imagery showed forest structure differences, which were mainly due to difference of spruce density in stands.

1. INTRODUCTION

Vegetation changes its spectra seasonally and it disturbs consistent vegetation monitoring using remote sensing. On the other hand, it has been recognized for a few species that forests change their spectra in accordance with their growth stages. The relationship between reflectance and stand age of species can be expressed by an exponential function in a spectral measurement from a helicopter, and it is called the successional spectral trajectory (Peterson and Nilson, 1993: Nilson and Peterson, 1994). The successional trajectory can be expressed very well through four seasons for reflectance or radiance data of channel 3, 4 and 5 of Landsat Thematic Mapper (TM3, TM4 and TM5)(Awaya and Tanaka, 1996: Awaya et al., 1996). The trajectory may be appeared by increase of leaf biomass, forest coverage (namely background effects), composition of planted and non-planted species, and so on (Nilson and Peterson, 1994: Awaya et al., 1996). Those suggest that forests in the same successional stage can be identified based on the trajectories using remote sensing images in any seasons. The objective of this paper is to demonstrate a monitoring method based on the minimum distance classifier and the successional spectral trajectories, and to make confirm usefulness of the trajectories using summer and winter TM imagery.

2. TEST SITE AND DATA

A test site was selected in the national forest near Tomakomai city in Hokkaido island in Japan. The test site is located in the border of boreal forest and cool temperate forest. The forest has very rich undergrowth comparing with the boreal forest in southern Finland. Most part of forests in the study site is artificial, and their major species are spruce (Ezo spruce, *Picea jezoensys Carr.* and Akaezo spruce, *Picea glehnii Mast.*), fir (*Abies sachalinensis Mast.*) and Japanese larch (*Larix leptolepis Gord.*). As the forests stand on a very flat area, there is little topographic effect on satellite imagery. The soil is made of volcanic ash and it is thin, then tree growth is poor and wind throw happens often. Though Ezo spruce was the main planting species, a very strong typhoon caused a severe damage on the forests in early 1950's. Some tree species were planted experimentally after that. Japanese larch was planted in late 1950's, however a disease and mice caused severe damages. Though Scotch pine (*Pinus sylvestris Linn.*) was also planted in late 1950's, it was suppressed by broad-leaved trees due to its declining. Fir seems to be quite successful, but its commercial value is not good. Then Ezo spruce and Akaezo spruce become to be the major planting species since early 1960's. However, they are planted in smaller areas making stripes interleaved by natural broad-leaved trees as shelters from winds.

Four TM images, which were 2 images in snowy season (March 12, 1985, D0312; March 9, 1993, D0309) and 2 images in mid summer (August 10, 1985, D0810; July 8, 1993, D0708), were used. Those images were resampled and overlaid on D0708 using first order polynomials derived from control points in areas lower than 400 meters in elevation to make registration of images in different paths best. The images were also geometrically corrected in the same manner of image overlaying using the Universal Transverse Mercator Map Projection. Forest planning maps were digitized and overlaid on the imagery and used as ground truth data. Black and white aerial photos, which was taken in 1990 and were 1 to 20,000 in scale, were also used as ground truth.

3. METHOD

3.1 Successional Spectral Changes

Twenty one spruce stands, which were the darkest in the same age class in D0708 and D0309, were selected as training areas. Average DNs of training areas from each imagery were plotted against the stand age in TM3, TM4 and TM5. Then an exponential curve was fit, and successional spectral changes were evaluated in each image (Figure 1, Table 1).

<u>Exponential Curve Fitting:</u>

$$DN(CHj,k) = a(CHj,k) + b(CHj,k) \cdot \exp(-c(CHj,k) \cdot Age) \quad (1)$$

where
DN(CHj,k) is estimated DN in channel j of image k. This is referred as 'average' hereafter. 'a(CHj,k)', 'b(CHj,k)' and 'c(CHj,k)' are regression coefficients for channel j of image k. 'Age' is the stand age of training area.

Relationships between the standard deviation of the training areas and the age were also checked using equation (1) for TM3, TM4 and TM5 (Table 1).

3.2 Classification

Averages and standard deviations of DNs in TM3, TM4 and TM5 at every stand ages between 1 and 100 years were estimated as training data using the exponential curves (Table 1). The average standard deviation of all training areas was used for all ages, when a correlation coefficient between the standard deviation and the stand age was very poor. The minimum distance classifier, which is defined as following equations (Takagi and Shimoda, 1994), was used to classify pixels into age classes.

<u>Distance Calculation:</u>

$$DST(i,CHj,k) = (DN(i,CHj)-AVR(CHj,k))^2 / SD(CHj,k) \quad (2)$$

$$DSTA(i,k) = \sqrt{\sum_{j=1}^{n} DST(i,CHj,k)} \quad (3)$$

where
DST(i,CHj,k) is the distance of pixel i about stand age k in channel j. DN(i,CHj) is DN of pixel i in channel j. AVR(CHj,k) is the estimated DN for stand age k in channel j using the exponential curves (Table 1). SD(CHj,k) is the standard deviation at stand age k in channel j defined by the exponential curves (Table 1). DSTA(i,k) is distance of pixel i from the training data of age k. 'n' is number of channels, where it was three, namely TM3, TM4 and TM5.

Each pixel of the four images was classified into an age class, which showed the minimum DSTA for the pixel. The age class is called spectral age hereafter.

3.3 Evaluation

Then relationships of spectral ages between images were evaluated using 62 evaluation areas, which were different from training areas for exponential curve fitting, using the regression analysis (Figure 2). The relationship between spectral age and stand age was also checked (Figure 3). The evaluation areas included various age classes and dense or sparse spruce stands. Images of spectral ages were created, then they were visually compared between each other referring the black and white aerial photos.

4. RESULTS AND DISCUSSION

Spruce is one of common climax tree species in the boreal forest and is evergreen species. On the other hand, most of pioneer species in the cool temperate forests are deciduous, the seasonal spectral characteristics of these species are different. Above all, since snow covers small undergrowth in the boreal forest (spruce) in winter, satellite data were almost composed of radiation from spruce and snow. In the meanwhile, satellite data were composed of radiation from spruce and undergrowth vegetation in summer, a comparison of summer and winter images might show any differences caused by undergrowth or any other forest components. Thus winter and summer images were compared to know possibility of monitoring forest using images taken in different seasons and of detecting forest structure.

The estimated spectral ages agreed well between images except D0309 (Figure 2). Among 6 cases, the slope and offset appeared 1 and 0 in the regression line between D853 and D858. This would mean that the spectral age derived from different images are quite similar.

On the other hand, the combination of D933 and D937 showed a smaller correlation coefficient than that of D853 and D858, the spectral age didn't agree well. Such difference was probably caused as follows. There would be no snow attached with spruce crown in D853 and D933. However, the smaller DN of D933 suggested wetter snow surface than D853. The intensity may become closer between spruce and snow than dry snow condition.

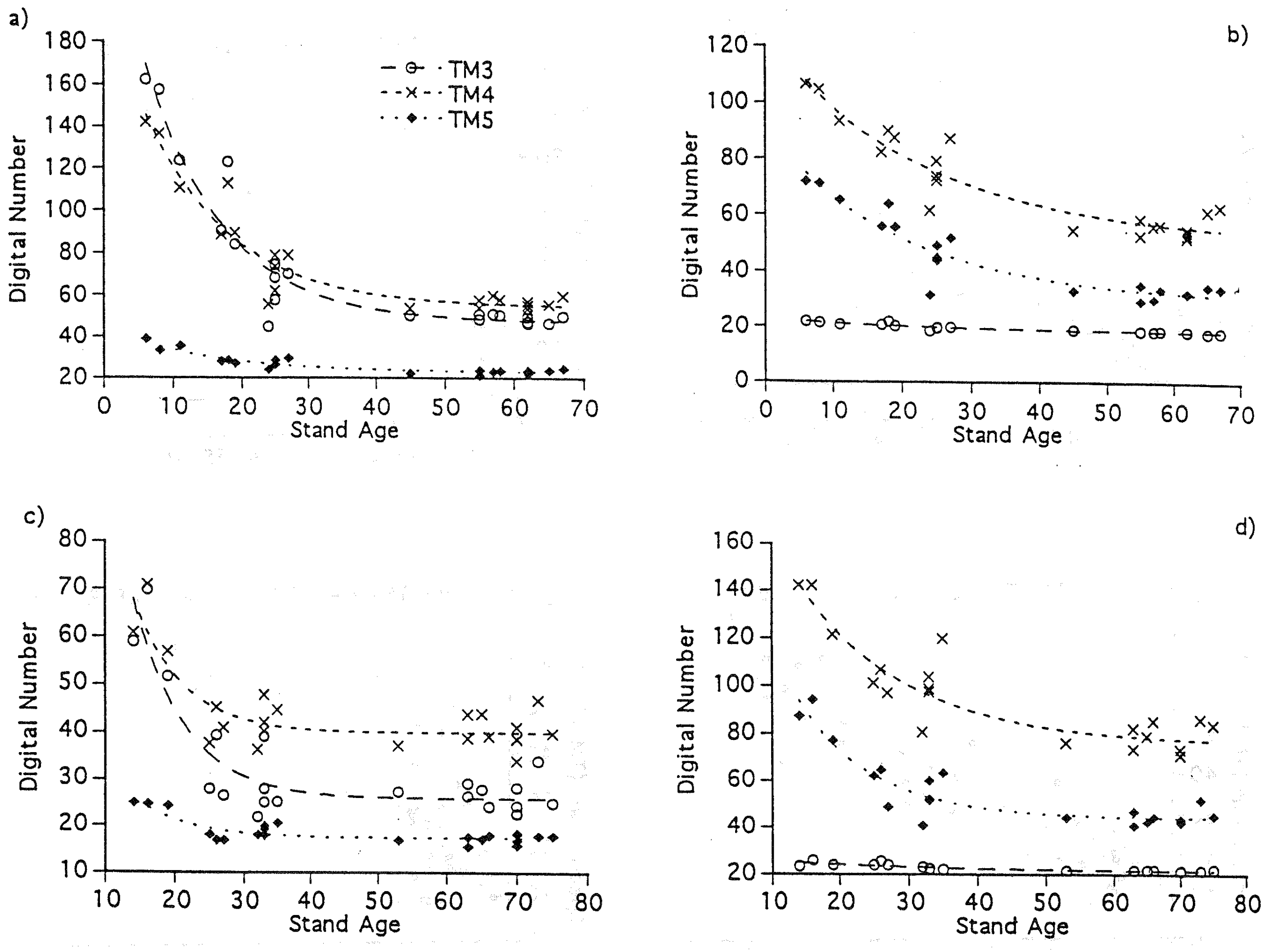


Figure 1. Successional Spectral Changes.
a) March 12, 1985, b) August 10, 1985, c) March 9, 1993, and d) July 8, 1993.

Table 1. Relationship between stand age and average or standard deviation of DN

DN = a + b · exp(-c · age)

Date	channel	for average a	b	c	r	for standard deviation a	b	c	r
March 12, 1985	TM3	46.694	207.72	0.08722	0.960	1.7407	17.192	0.0379	0.904
	TM4	54.202	147.4	0.07947	0.956	2.0597	10.757	0.03312	0.846
	TM5	22.839	22.633	0.07344	0.931	1.085	1.165	0.01644	0.535
August 19, 1985	TM3	18.144	4.8489	0.04316	0.913	1*	-	-	0.31**
	TM4	51.94	74.012	0.04621	0.943	4.2*	-	-	0.337**
	TM5	29.085	61.665	0.05160	0.942	3.9*	-	-	0.043**
March 9, 1993	TM3	25.776	276.79	0.03292	0.895	4.0353	35.442	0.12111	0.604
	TM4	39.913	206.87	0.1429	0.849	3.2205	31.882	0.15433	0.490
	TM5	17.387	50.376	0.1271	0.859	0.7277	1.6312	0.00771	0.389
July 8, 1993	TM3	21.014	6.6287	0.0381	0.486	0.8*	-	-	0.051**
	TM4	75.866	161.43	0.06271	0.914	2.5789	6.3372	0.02367	0.634
	TM5	43.874	177.0	0.09026	0.925	-3.767	9.0549	0.0036	0.613

No of samples: 21, r: correlation coefficient, *: A constant was used in the classification for each age class. **: Correlation coefficients between standard deviation and stand age.

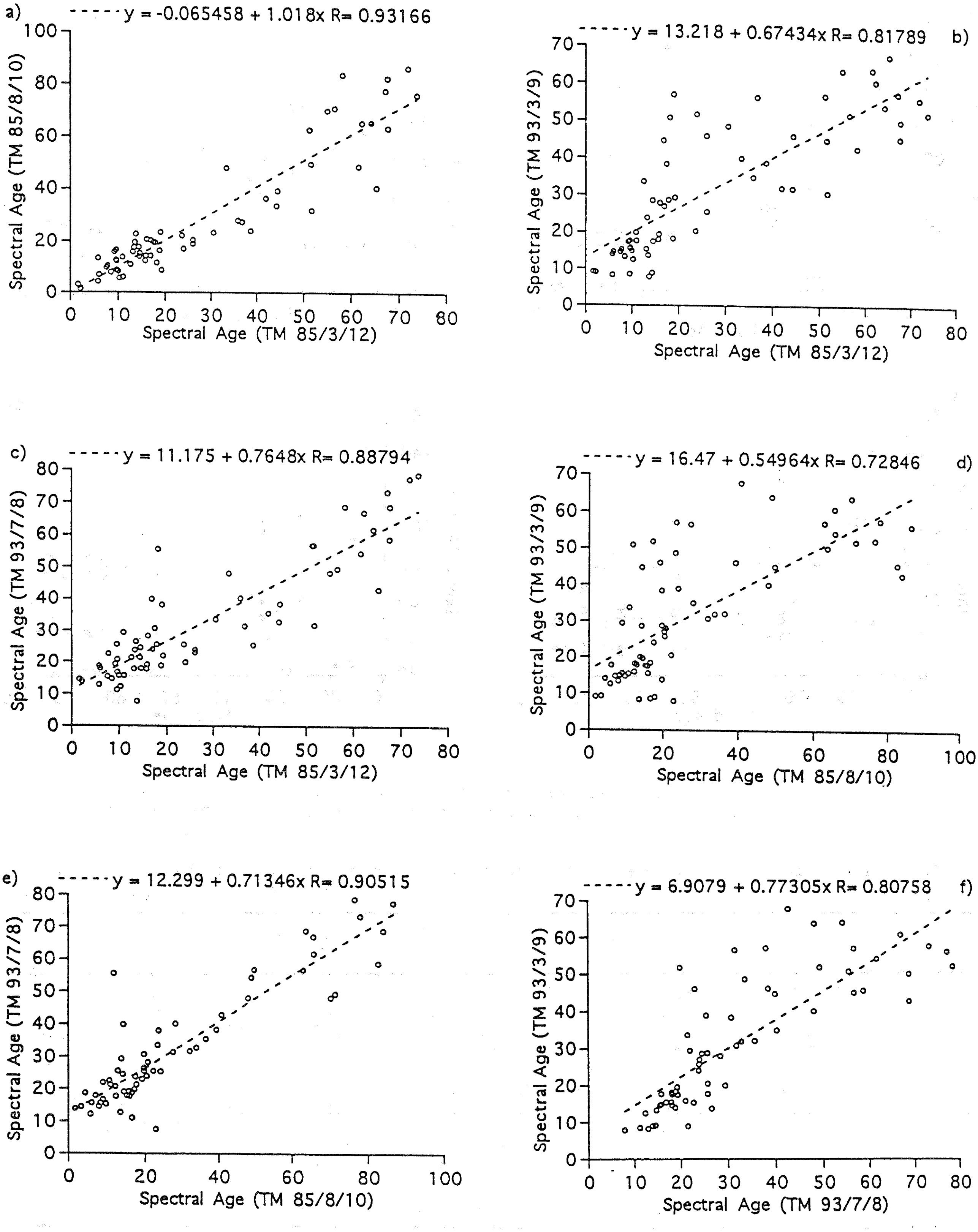


Figure 2. Relationships between Spectral Ages of 4 TM Images.
High correlation coefficients were observed among D0312, D0810 and D0708. For the case of a), which is a comparison between winter and summer images within the same year, the regression slope is almost 1 and crosses the origin. Thus the results are probably comparable between each other. Dots far from the regression lines probably suggests forests with big changes between two images (or dates).

It would make the data range smaller, and the estimated spectral age might be not accurate. Thus the correlation coefficients between winter images became smaller than that between summer images.

However, the good correlation coefficients among 3 images without D933 would suggest that the exponential curves were probably appropriate to define training data, and the three TM channels (TM3, TM4, and TM5) were also appropriate to classify spruce stands into age classes spectrally. However, the spectral age doesn't show exact stand age, but the forest condition, which is typical or ideal in each age for forest management.

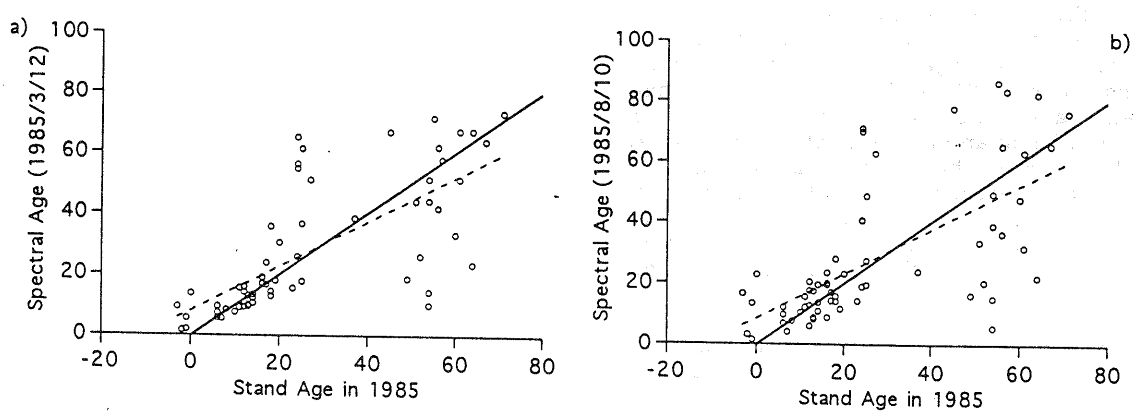
It was possible to identify relatively dense or sparse (poor) stands with spruce, when the spectral age was compared with the stand age. If spruce is densely populated, the spectral age will appear older than its stand age. Meanwhile, if spruce is sparsely populated with many deciduous broad-leaved trees, the spectral age will appear younger than its stand age. If two spectral ages are compared, changes in forests are evaluated as changes of spectral age. For example, dots, which appear far above the regression lines, show stands with increasing of spruce dominance during 8 years (Figure 2 c,e). It meant that spruce trees surpassed broad-leaved trees, or broad-leaved trees were selectively cut. On the other hand, dots, which appear far below the lines, show stands with decreasing of spruce dominance. It meant that spruce trees were suppressed by broad-leaved trees, or spruce trees were clearly or selectively cut during 8 years.

Since the trajectory reaches asymptotic values in every cases at around 30 years old, accurate successional monitoring would be difficult in old growth forests based on spectral signatures. The smaller slope of the regression lines in Figure 3 may be caused by the asymptotic nature of the successional spectral trajectory.

However, if the spectral age is compared with the stand age (Figure 3), differences between two age classes suggest forest condition, ex. dense or sparse spruce, clearly. If the spectral age is much bigger than stand age (ex. stands with stand age: 25, and spectral age: 40 to 70 in a and b), spruce canopies closed completely and the stands may need selective logging. It would hold true even for older stands.

On the over hand, if the spectral age is much smaller than stand age (ex. stands with stand age: 50 to 70, and spectral age: less than 20), the stand may be suppressed by broad-leaved trees and need any nursing operation.

When spectral ages of winter and summer images are compared, changes in deciduous



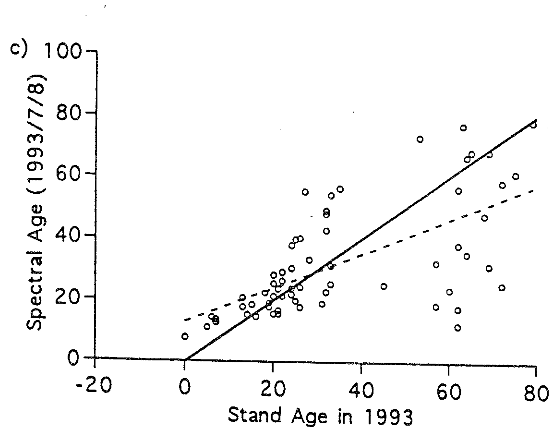


Figure 3. Comparison of stand age and spectral age

The solid line has 1 and 0 of the slope and offset respectively. Dashed lines are regression lines with the equations bellow.

a) $y = 7.961 + 0.7344 \cdot x$ $r=0.725$
b) $y = 8.452 + 0.7325 \cdot x$ $r=0.662$
c) $y = 13.079 + 0.5559 \cdot x$ $r=0.643$
r: correlation coefficient

trees appear as differences of spectral age. The comparison would give information about forest structures. Following features were interpreted visually from the four age class images.

a) Dense mature spruce stands showed older spectral ages in summer images than those in winter images.
b) Sparse spruce stands showed opposite tendency of dense stands. Namely, spectral ages appeared younger in summer images than those in winter images.

Those results suggested that it would be possible to monitor successional changes in spruce stands quite well. Thus the successional spectral trajectory is useful as the training data of forest age classification with less seasonal differences. This method would be utilized for growth monitoring practically in the forest managemant.

5. CONCLUSION

The exponential relationships made it possible to estimate averages and standard deviations of each stand age for the minimum distance classifier. They reduced effects of seasonal spectral variation in training areas. Thus, quite stable age class classification for spruce became possible using winter and summer imagery.

However, the exponential curve suggest that there is no clear relationship between the stand age and DN after about 30 years old. This caused that the estimated age class appeared rather younger in old stands older than that age. Though this may be the limitation of forest age class classification spectrally, the usefulness of successional spectral trajectory was confirmed from the four classification results.

Comparison of summer and winter imagery would make clear structural difference between stands, namely dense or sparse with spruce. These results should be analyzed further to make confirm what they mean.

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