The Use of Digitized Aerial Photographs and Local Operation for Classification of Stand Development Classes

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The increasing capacity of modern computers has created the opportunity to routinely process the very large data sets derived by digitizing aerial photographs. The very fine resolution of such data sets makes them better suited than satellite imagery for some applications; however, there may be problems in implementation resulting from variation in radial distortion and illumination across an aerial photograph.

We investigated the feasibility of using local operators (e.g., non-overlapping moving window means and standard deviations) as auxiliary data for generating stand development classes via three steps: (i) derive 6 local operators intended to represent texture for a 16 by 16 m window corresponding to a forest inventory sampling unit, (ii) apply a calibration process (e.g., accounting for location relative to a photo's principal point and solar position) to these local operators, and (iii) apply the calibrated local operators to classify the forest for stand development. Results indicate that calibrated local operators significantly improve the classification compared to what is possible using uncalibrated local operators and satellite images.

Keywords digitized aerial photographs, plot window location, calibration, classification, local operation
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1 Introduction

In order to improve the classification of forest stands and estimation of stand characteristics in forest inventory, digitized aerial photographs may be more useful than satellite images because of their higher spatial resolution. However, the relatively low flying height and wide camera angle of aerial photographs lead to difficulties for use. Similar forest plots falling in light and shadow parts of a photograph tend to have different pixel values. Thus, it is important to eliminate the effect of plot location on pixel values and to develop a calibration methodology for using digitized aerial photographs for forest inventory.

In addition to intensity and spectral composition of the light reflected from objects on the ground, the pixel values of a digitized aerial photo are affected by film type, film processing, flight elevation, solar direction, viewing angle, elevation, slope, aspect, and atmosphere conditions. Especially because of differential shading, the exposed sides of trees receive more radiation than shady ones, and therefore reflect more strongly (Holmgren 1995, Pellikka 1996). The differential shading leads to bi-directional reflectance effect, that is, the objects in the direction of incoming solar radiation expose their shady sides to the sensor, and those in the opposite direction expose their well-illuminated sides. This results in the change of the reflectance values of the same vegetation type depending on different position (Holopainen and Wang 1998).

The bi-directional reflectance is different between vegetation types (Holopainen 1992, Holopainen and Lukkarinen 1994, Leckie 1987). Holopainen and Wang (1998) studied the optimal operational scale and the calibration methods of digitized aerial photographs for forest stratification. They found that the optimal operational scale of digitized aerial photographs varied depending on the spatial resolution obtained by scanning. The pixel values within the optimal operational scale area were aggregated into coarser resolution by averaging and the averages were calibrated using ratios and regression models within each stand class obtained according to field measurements. Their results show that based on the statistical significance test of the means between stand classes, the calibration increased the possibility of separation of stand classes compared to the original, non-calibrated means, and the regression calibration was better than ratio calibration.

This study can be considered to be a continuation of the previous work (Holopainen and Wang 1998). The aim is to develop the regression calibration method in practice for using digital aerial photographs efficiently for forest inventory and monitoring based on plot sampling. A specific objective is to study the usability of local operators including means and standard deviations of pixel values in a fixed size window assumed to be an optimal operational scale. The effect of location on the means and standard deviations is explored for classification of stand development classes.

2 Material and Methodology

2.1 Material

The study area is located in the Helsinki University forest station, Hyytiälä, about 200 km northwest of Helsinki in Finland. The terrain slopes gently with low hills and the average elevation is 155 meters above sea level with a range from 140 to 185 meters. A color infrared aerial photograph of scale 1:5000 was taken at 12:30 on July 8th 1992. The azimuth of sunlight from the north and solar elevation were 149.827 and 43.431 degrees. In the Finnish National Coordinate System, the geographic x- and y-coordinates of the principal point of the photo were 358708 and 6861052.

The color infrared aerial photograph was digitized for red, green and blue channels by scanning with a desktop Hewlett Packard ScanJet IIC at 254 dpi. The pixel size was thus 0.5×0.5 m^2. The digitized aerial photograph was orthorectified into the Finnish National Coordinate System with eight control points. The control points were geo-referenced with GPS. A digital elevation model with spatial resolution of 25 m was used to derive the elevation, slope, and aspect values of the sample plots. In addition, Landsat TM images taken in 1992 were available and also used for comparison.

The digital aerial photograph covered about 130 ha. 75 permanent and 488 temporary relascope sample plots were measured in the area in 1992 and 1989 respectively. The plots with 12.5 m radius were systematically sampled and stand characteristics such as tree species and age for each plot were measured. For a more detailed description of field measurements, the readers are referred to Wang (1996). This study area was very dominated by Norway spruce and Scots pine. The sample plots were divided into four development classes according to the definitions widely used in the Finnish National Forest Inventory (Kuusela and Salminen 1969). The development classes included seedlings, young, middle-aged, and mature stands. The distribution of 75 permanent field plots into seedlings, young, middle-aged and mature stands was 18, 9, 27 and 21, respectively. The ages of 488 temporary field plots were updated to the level in 1992 and the corresponding distribution of the plots into four age classes was 55, 100, 138 and 195.

2.2 Methodology

The methodology used in this study is described as follows:

- i A fixed window size was determined and local operators; i.e., window means and standard deviations of pixel values in the fixed size window were calculated.
- ii Location variables in a photo coordinate system were derived and the correlation between them and the local operators was analyzed.
- iii The sample plots were pre-classified using visual photo interpretation, and within each of the classes by the pre-classification the local operators were calibrated by developing regression models as functions of the location variables. In addition, the sample plots were also pre-stratified using satellite images, and within each of the strata by the pre-stratification the calibration was carried out.
- iv The corrected local operators were estimated with the models and the sample plots were finally classified using the corrected local operators. The results were compared with those using the original, non-calibrated local operators.

A fixed window size had to be determined for calculating the window means and standard deviations of pixel values. According to Holopainen and Wang (1998), most of optimal window sizes of the digitized aerial photograph at scale 1:5000 for the stand types varied from 10×10 m^2 to 16×16 m^2. In the same study area, the window size 16×16 m^2 would cover most of a plot area and could be assumed to be an optimal operational scale.

The fixed size window in its original format consisted of 32×32 pixels (1024) of size 0.5×0.5 m^2. In the window, different size blocks were obtained by merging the original pixels and blocks of 0.5×0.5, 1×1, 2×2, and 4×4 m^2 were applied. The number of blocks within the window of 16×16 m^2 and the number of pixels per block would thus vary depending on block size. For the block size 4×4 m^2, for example, there were a total of 16 blocks and 64 pixels per block.

The window mean value was the mean of all 1024 pixel values. A block value was calculated as the mean of the values of the pixels belonging to the block. The standard deviation of the block values for each of the block sizes around the block means was calculated within the window. Thus, the window of four block sizes resulted in four standard deviations, and the standard deviation of these four standard deviations. The abbreviations used for the local operators and their definition were as follows:

Abbreviation	Definition
WM	Window mean of pixel values in the fixed size window.
Std05	Standard deviation of block values for block size 0.5×0.5 m^2
Std1	Standard deviation of block values for block size 1×1 m^2.
Std2	Standard deviation of block value for block size 2×2 m^2.
Std4	Standard deviation of block values for block size 4×4 m^2.
Stdstds	Standard deviation of four standard deviations above.

The local operators may be affected not only by the forest type, but also by the location of the window on the photo. The effect of location was studied with a transformed photo coordinate system having the photo center as its origin and the sunlight direction as its y-axis. The x-axis was perpendicular to the y-axis and divided the photo into two parts. The windows whose center y-coordinates in the photo coordinate system were larger than zero were said to be in the illuminated part of the photo, and the other windows whose y-coordinates were smaller than zero in the shadowed part of the photo.

The geographic coordinates of a window center, that is, a plot center, were transformed into new values in the photo coordinate system, x and y. The elevation, slope and aspect values for a sample plot center were calculated from the digital elevation model. To derive the slope and aspect values, the elevation values of eight points located in a circle around the sample plot at a distance of 20 m from the plot center were applied. In addition, the viewing angle – Camera Normal Angle (CNA) of each plot was computed and was used to describe the plot location, its slope and aspect. The camera normal angle was defined as the angle between the vector from camera to plot center and the normal vector of slope line through the plot center. For the geometric relationship between the sensor and plot, the readers should refer to Holopainen and Wang (1998).

The six location variables above (the transformed photo x- and y-coordinates, elevation, slope, aspect, and camera normal angle) were used to study the effect of location on the local operators. The coefficients of determination between the location variables and local operators were calculated as sensitivity indicators of the effect. The important location variables were selected and used to calibrate the local operators.

Suppose that the conditions for the local operators of the photo center on the photo were regarded as ideal and as such they should be used to calibrate the conditions of other parts of the photo. On the other hand, it was assumed that the effect of location would differ among various forest types, and regression models of the local operators should thus be derived as the function of the location variables within each of four stand development classes.

Because the stand development class of a sample plot that was not a field plot, was unknown in practice, pre-classification of the sample plots was carried out by visual photo interpretation. According to image features presented on the aerial photo, the study area was first delineated visually into homogeneous sub-areas, called compartments, and the compartment boundaries were digitized. The stand development class, or tree mean age within each compartment was visually interpreted. The mean age of the compartment was used as the mean ages of the sample plots belonging to the compartment.

In addition, the pre-stratification of the sample plots was also made using Landsat TM images and the unsupervised classification method described below. In the unsupervised classification, the sample plots were first divided into homogeneous strata and within each stratum the field plots were used to derive the estimate of stand development class. In the pre-classification, however, the estimates of strata were not needed and the homogeneous strata were directly applied. The regression models were developed within each of the homogeneous strata. The number of initial strata changed from 10 to 60 with an interval of 5 and the final number of initial strata was determined according to the percentage of the correctly classified permanent field plots.

The general regression model for the calibration was as follows:

$$\hat{y}_i = a_{0i} + \sum_{k=1}^{m} a_{ki} x_{ki} \tag{1}$$

Where,

$\hat{y}_i$ = A corrected local operator for plot window i,
a_{ki} = Regression coefficient (k = 0, ..., m),
x_{ki} = Value of the kth location variable in the photo coordinate system for plot window i,
m = Number of location variables used.

If the photo central point was p, its local operator was:

$$\hat{y}_p = a_{0p} + \sum_{k=1}^{m} a_{kp} x_{kp} \tag{2}$$

Equation (1) and (2) had the same a_{kp}. A local operator of a window at the photo central point represented the desirable level in calibration and its corresponding value was noted as y_p. Thus, the calibration model was:

$$\hat{y}_i = y_p + \sum_{k=1}^{m} a_{ki}\left(x_{ki} - x_{kp}\right) \quad (3)$$

The local operators and location variables of the window at the photo central point were first calculated and used for developing the models. The regression coefficients between the local operators and location variables for the sample plots were then derived within each of the development classes obtained by pre-classification using visual photo interpretation, or within each of the strata by the pre-stratification using satellite images. Using the models the corrected local operators were estimated.

Unsupervised classification was used for classifying the sample plots into four development classes. In this method, all the plots (75 permanent and 488 temporary sample plots) were first stratified into homogeneous strata with K-mean clustering and an Euclidean distance classifier (Peng 1987). The field information of 75 permanent plots for four development classes was studied within each of the strata. The development class having maximum frequency of the field plots was applied as the estimate of the stratum. The stratum estimates were assigned to 488 temporary plots as test plots based on the strata they belonged to.

The unsupervised classification depended on several factors including the number of initial strata, classifiers, and auxiliary data sets used (Peng 1987, Wang 1996). In this study, the number of initial strata varied from 10 to 60 with an interval of 5. According to Peng (1987), the classification accuracy increased with the number of initial strata. However, too large a number of initial strata might lead to small strata where no field plots existed. The best classification would have the highest accuracy with the smallest number of the small strata. Various classifiers such as minimum Euclidean distance classifier and Bayes classifier could be selected. The minimum Euclidean distance classifier was used in this study because it has been proved flexible in various conditions. Additionally, Bayes classifier often leads to the difficulty in calculation of correlation or covariance matrix when many variables are applied.

The auxiliary data sets used for this classification included the original, non-calibrated local operators and the corrected local operators of the digitized aerial photo, Landsat TM images, and a combination of the satellite images and digitized aerial photo. The local operators of the digitized aerial photo were further divided into the following six data sets for non-calibrated and calibrated respectively:

1. Red channel with one window mean (WM) and five standard deviations (Std05, Std1, Std2, Std4, and Stdstds),
2. Green channel as above,
3. Blue channel as above,
4. Three window means (WM_{red}, WM_{green}, and WM_{blue}) from three channels,
5. Three window means (WM_{red}, WM_{green}, and WM_{blue}) and three standard deviations ($Std05_{red}$, $Std05_{green}$, and $Std05_{blue}$)
6. The first six principal components obtained using three window means (WM_{red}, WM_{green}, and WM_{blue}) and six standard deviations ($Std05_{red}$, $Std05_{green}$, $Std05_{blue}$, $Stdstds_{red}$, $Stdstds_{green}$, and $Stdstds_{blue}$.

The Landsat TM image data set consisted of six channels (TM1, TM2, TM3, TM4, TM5, and TM7). TM6 was not used because it had different spatial resolution compared to these. The spectral values of the sample plots were derived using the nearest neighbor. In addition, the combination of the satellite images and digitized aerial photo meant that the satellite images were first used for pre-stratification, and based on the pre-stratification the local operators of the digitized aerial photo were then calibrated and the corrected local operators were applied for final classification.

The classification quality of stand development classes obtained using the data sets above were assessed using 488 test plots. Error matrices, correct percentages and Kappa values (Campbell 1987) were calculated. The error matrices were used to explain the performance of the classification including the number of correctly classified plots, omission and commission errors. The correct percentage was obtained by dividing the total number of correctly classified plots with the total number of test plots, and would suggest the relative effectiveness of a classification. However, the correct percentage can not be applied to assess precision for each class because the commission error is ignored and the full error matrix is not examined.

Kappa test is a quantitative assessment method of error matrices and explains the agreement between a classification and corresponding ground truth data. In this study, Kappa values were calculated as follows:

$$\hat{K} = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}}$$

“Observed” was the overall value for correct percentage. “Expected” was an estimate of the chance agreement with the observed correct percentage and calculated in the way that the products of row and column totals were assigned to each cell of the matrix, then the diagonal values were summed and divided by the grand total of the products. A Kappa value approaching 1.0 indicates perfect effectiveness of a classification, on the other hand, a Kappa value near zero suggests that the classification is no better than a random assignment of plots to classes.

3 Results

The window mean and five standard deviations within the fixed size window defined above were calculated for red, green and blue channels. The results using all 563 field plots are described in Table 1. The green channel had the largest window mean value (WM), followed by the blue and red channels. The order of standard deviations (Std05, Std1, Std2 Std4, and Stdstds) was blue, red and green channel. The standard deviations decreased with increasing block sizes.

The coefficients of correlation between six local operators and six location variables are listed in Table 2. According to the coefficients of correlation, the location variables could be divided into two groups. The first group, including x- and y-coordinates, and elevation, were significantly more correlated with the local operators than the second, consisting of slope, aspect, and camera normal angle. The elevation had the highest correlation in red and green channels, then y- and x-coordinates. In the blue channel, the y-coordinate was most correlated with the local operators, then elevation and x-coordinate. The correlation of the slope, aspect and camera normal angle with the local operators in all channels was very low and all the coefficients of correlation were less than 0.23.

The color infrared aerial photo was visually delineated into 52 homogeneous compartments and within each of them, stand mean age was considered to be similar. The stand development classes including seedlings, young stands, middle-aged stands, and mature stands were visually interpreted for all the compartments. The 488 test plots took the interpreted stand development classes of the compartments they belonged to and the 75 permanent plots took the field measurements of stand development classes. All the sample plots were then pre-classified into four development classes.

Regression models for calibrating the local operators to the level of the photo central point were developed for each of the development classes by the pre-classification, for each channel and each local operator according to equation (3) described above. The x- and y-coordinate and elevation were first used as the location variables for calibration because they were most correlated with the local operators. Then, the slope or camera normal angle was added. More than 140 regression calibration models were constructed using all 563 sample plots. As examples, 12 calibration models of mature stands for six local operators in green and blue channels are listed in Table 3. When the x- and y-coordinates and elevation were used in the calibration models, the coefficients of determination varied from 0.3814 to 0.6947, and most of them were larger than 0.55. When the slope or camera normal angle was added in the calibration models, the coefficients of determination were not improved (not listed).

The regression models were applied for deriving the corrected local operators (window means and standard deviations). The classification of the sample plots into four development classes was then made with different data sets. The data sets were divided into three groups: digital aerial photo only, satellite images only, and combination of satellite images and digitized aerial photo.

The digitized aerial photo data sets were fur-

Table 1. Statistical description of local operators from different block sizes in a fixed size window.

Channel	WM	Std05	Std1	Std2	Std4	Stdstds
Red-Mean	33.751	26.227	24.562	20.935	15.280	4.865
Green-Mean	40.982	21.991	20.758	17.901	13.121	3.952
Blue-Mean	35.547	26.452	24.688	20.852	14.882	5.138

Table 2. Coefficients of correlation between six local operators and six location variables (CNA is camera normal angle).

Location variables	WM	Std05	Std1	Std2	Std4	Stdstds
Red channel						
X	0.3821	0.3021	0.288	0.2658	0.2214	0.308
Y	0.4237	0.3363	0.3323	0.3143	0.2541	0.3358
Elevation	0.4475	0.3691	0.353	0.3211	0.2446	0.4237
Slope	0.0292	0.1199	0.1184	0.1163	0.1024	0.0977
Aspect	–0.0132	0.0118	0.0192	0.0342	0.0482	–0.0559
CNA	0.1086	0.0496	0.0564	0.0625	0.0604	0.0122
Green channel						
X	0.3632	0.2944	0.2792	0.2538	0.2055	0.322
Y	0.3803	0.3434	0.3402	0.3219	0.2579	0.3505
Elevation	0.4513	0.3969	0.3812	0.3485	0.2707	0.4493
Slope	0.0932	0.2125	0.2102	0.2016	0.1744	0.189
Aspect	0.0209	0.0533	0.0595	0.0715	0.0895	–0.0339
CNA	0.0927	0.0633	0.0702	0.0748	0.0689	0.0295
Blue channel						
X	0.4142	0.3469	0.3328	0.3106	0.2639	0.358
Y	0.587	0.5212	0.516	0.4931	0.4142	0.5177
Elevation	0.5683	0.4858	0.4694	0.438	0.3576	0.5225
Slope	0.1124	0.2267	0.2247	0.2179	0.1928	0.2047
Aspect	0.0077	0.0556	0.0627	0.0745	0.095	–0.023
CNA	0.2138	0.1591	0.164	0.1632	0.144	0.133

ther divided into the original, non-calibrated local operators and the corrected local operators. By selecting the original, non-calibrated local operators or the corrected local operators from different channels, six data sets for non-calibration and calibration respectively were organized. The selection could lead to many combinations; however, the comparison between channels, and with and without standard deviations was taken into account.

In the combination of the satellite images and digitized aerial photo, the satellite images were first used for pre-stratification of the sample plots and 40 strata were obtained. Within each of the strata, three window means and three standard deviations from three channels were calibrated. The corrected window means and standard deviations were then applied for classification. The classification results are presented in Table 4. For all the data sets above, the 75 permanent field plots were applied to derive the estimates of stand development classes and 488 test plots to assess the classification accuracy.

When the six data sets of the original, non-calibrated local operators from the digitized aerial photo were used, the classification resulted in the overall correct percentage from 39.0 % to 44.2 % and the Kappa value from 0.124 to 0.228. The highest percentage and the largest Kappa value were derived using the first six principal compo-

Table 3. The calibration models of six local operators of green and blue channel using x-, y-coordinate, and elevation for mature stands.

Local operators	Model (local operator = a * x + b * y + c * elevation) a	b	c	Determination coefficient R^2
Green channel				
WM	0.002347	0.027339	0.26134	0.4765
Stds05	0.006852	0.017437	0.49859	0.6210
Std1	0.006178	0.017086	0.44952	0.6105
Stds2	0.005136	0.015159	0.3853	0.5820
Std4	0.002904	0.012239	0.11716	0.3814
Stdstds	0.001722	0.002378	0.16812	0.4403
Blue channel				
WM	0.004053	0.04344	0.207306	0.5671
Stds05	0.010374	0.02906	0.498473	0.6947
Std1	0.009501	0.028209	0.440666	0.6845
Stds05	0.007819	0.024781	0.375406	0.6616
Std4	0.005082	0.019568	0.071247	0.4713
Stdstds	0.002318	0.004306	0.187144	0.5794

Table 4. Comparison of classification accuracy for four development classes with and without calibration of local operators within each of the classes obtained by pre-classification using visual photo interpretation and within each of the strata derived by pre-stratification using satellite images (P = correct percentage, K = Kappa value).

Original, non-calibrated local operators P%	K	Corrected local operators by x-, y-coordinates, and elevation P%	K	Corrected local operators by x-, y-coordinates, elevation, and slope P%	K
Digitized aerial photo					
1 mean (WM_{red}) and 5 standard deviations ($Std05_{red}$, $Std1_{red}$, $Std2_{red}$, $Std4_{red}$, $Stdstds_{red}$) of red channel					
39.0	0.143	49.6	0.313	46.3	0.266
1 mean (WM_{green}) and 5 standard deviations ($Std05_{green}$, $Std1_{green}$, $Std2_{green}$, $Std4_{green}$, $Stdstds_{green}$) of green channel					
39.3	0.124	46.4	0.274	44.4	0.251
1 mean (WM_{blue}) and 5 standard deviations ($Std05_{blue}$, $Std1_{blue}$, $Std2_{blue}$, $Std4_{blue}$, $Stdstds_{blue}$) of blue channel					
40.0	0.159	48.7	0.285	50.0	0.296
3 means only (WM_{red}, WM_{green}, WM_{blue}) from three channels					
39.2	0.150	52.3	0.326	44.8	0.246
3 means (WM_{red}, WM_{green}, WM_{blue}) and 3 standard deviations ($Std05_{red}$, $Std05_{green}$, $Std05_{blue}$) of three channels					
42.4	0.172	56.1	0.390	53.2	0.367
The first 6 principal components of 3 means (WM_{red}, WM_{green}, WM_{blue}) and 6 standard deviations ($Std05_{red}$, $Std05_{green}$, $Std05_{blue}$, $Stdstds_{red}$, $Stdstds_{green}$, $Stdstds_{blue}$) of three channels					
44.2	0.228	55.3	0.358	52.8	0.349
Satellite images only (TM1, TM2, TM3, TM4, TM5, TM7)					
44.1	0.211				
Satellite images first used for pre-stratification, then three window means (WM_{red}, WM_{green}, WM_{blue}) and three standard deviations ($Std05_{red}$, $Std05_{green}$, $Std05_{blue}$) of photo calibrated, and the corrected local operators applied for classification					
		50.2	0.318		

nents of nine stratification variables including three calibrated window means (WM_{red}, WM_{green}, WM_{blue}) from three channels and six calibrated standard deviations ($Std05_{red}$, $Std05_{green}$, $Std05_{blue}$, $Stdstds_{red}$, $Stdstds_{green}$, $Stdstds_{blue}$). However, the results did not significantly differ among the six data sets. The percentages of correctly classified plots were low and according to Kappa values, the classification accuracy was only slightly better than that by a random assignment of plots to classes.

When the local operators from the digitized aerial photo were calibrated using three location variables (x- and y-coordinates, and elevation) having the highest correlation, the overall correct percentage varied from 46.4 % to 56.1 % and the Kappa value from 0.274 to 0.390. The data set consisting of three calibrated window means and three calibrated standard deviations obtained with the smallest block size produced the best classification. Compared to the results derived using the original, non-calibrated local operators, the calibration of the local operators led to a significant classification improvement. The increase in the correct percentage was from 7.1 % to 13.7 % and the relative increase from 18 % to 32 %. The Kappa values were increased by 0.126 to 0.218 and the relative increase varied from 57 % to 126 %.

If the local operators were calibrated using four location variables (x- and y-coordinates, elevation, and slope), the classification results were much better than those obtained using the original, non-calibrated local operators. The accuracy was, however, slightly worse than those derived when the three most important location variables (x- and y-coordinates, and elevation) were used for the calibration of the local operators. On the other hand, adding the slope into the regression calibration models could not further improve the classification.

When one window mean and five standard deviations from a single channel were used for classification, the results were similar among the three channels, and the classification using the corrected local operators was better than that using the original, non-calibrated ones. The accuracy obtained using the original, non-calibrated or corrected three window means only (from red, green and blue channels) were not significantly different from those derived using one window mean and five standard deviations from a single channel. However, the combinations of the window means and standard deviations from different channels resulted in better classification than that using three channel window means only.

The results using the satellite images only were similar to those using the original, non-calibrated local operators from the digital aerial photo, but, much worse than those obtained by the corrected local operators. When the satellite images were first used for pre-stratification, based on which three channel window means and three channel standard deviations from the photo were calibrated, and the corrected local operators were then applied for the classification, the correct percentage and Kappa value were 50.2 % and 0.318 respectively. This combination of the satellite images and digitized aerial photo led to better classification than that using the original, non-calibrated local operators of the photo only, but, the result was not so good as that using the corrected means and standard deviations based on the pre-classification by visual photo interpretation.

An example of the classification matrices using the corrected local operators from the photo is shown in Table 5. The classification matrix was performed using three corrected channel window means and three corrected channel standard deviations based on the pre-classification by visual photo interpretation. The overall correct percentage and Kappa value were 56.1 % and 0.390 respectively. The Kappa value suggested that the classification was significantly better than a random assignment of plots to classes. The best classification was obtained by changing the number of initial strata from 10 to 60 with interval 5 for the K-means algorithm and the final number of initial strata was 40. 426 of 488 test plots were finally classified into four stand development classes and 62 plots were missed because within some strata no field plots were available to derive the estimates. Of 426 plots, 239 were correctly classified into their development classes. The correct percentages of seedling, young and middle-aged stands were higher than 58 %, the highest one was 70 % for the young stands, and compared to these, the correct percentage of ma-

Table 5. An example of the classification matrices derived using the corrected local operators from the digital aerial photo.

Ground truth	Classification result						
	Seedling	Young	Middle-aged	Mature	Total	Correct percentage	Kappa value
Seedling	28	8	2	2	40	70.0	0.053
Young	13	46	17	3	79	58.2	0.077
Middle-aged	6	11	81	26	124	65.3	0.082
Mature	14	13	72	84	183	45.9	0.092
Total	61	78	172	115	281/426	56.1	0.390

ture stands, 45.9 %, was lower. The low Kappa values of individual classes meant that the class performances were only slightly better than a random assignment of plots to classes.

4 Conclusions and Discussion

Central projection of aerial photographs with radial distortions and shadow effects makes the construction of models for classification of sample plots difficult. In this study, a methodology for improving plot classification using digital aerial photograph and corrected local operators was explored. The calibration of the local operators was carried out within each of the stand development classes obtained by pre-classification based on visual photo interpretation and within each of the strata derived by the pre-stratification using satellite images. The results showed that the relative accuracy increase using the corrected local operators varied from 18 % to 32 % for the over correct percentage and from 57 % to 126 % for the Kappa value compared to that using the original, non-calibrated local operators. On the other hand, the calibration of the local operators significantly improved the classification accuracy.

The best Kappa value obtained in this study indicated that the classification of the sample plots into four stand development classes was significantly better than a random assignment of plots to classes. However, the best overall correct percentage, 56.1 %, was quite low. The accuracy was better compared to that derived by Wang (1996) using satellite images, but slightly worse than his result using an expert system. The poor results might be explained partly because the stand development classes were not very well defined and partly because the two samples (one used for deriving the estimates and another for testing the results) were measured in different times. It was thus difficult to classify the sample plots into the classes. In Table 5, for example, 72 of 183 mature stand plots were incorrectly classified into middle-aged class. In addition, tree species were not considered because pine and spruce stands were very dominant in this study area.

The local operators used included a window mean of pixel values, four standard deviations of different size blocks, and a standard deviation of the four standard deviations within a fixed size window of 16 m by 16 m. The window size close to the plot size used was determined according to the previous study related to optimal operational scale in the same area with the same photo scale 1:5000 (Holopainen and Wang, 1998). The window size was assumed to be the optimal operational scale because the aerial photo used in this study was taken at different times and conditions from that applied by Holopainen and Wang.

The variation of pixel values in an optimal size window might be related to stand types. Standard deviations of pixel or block values in the window could thus reveal the characteristics of stand types. As the pixel values were aggregated from finer spatial resolution to coarser resolution, on the other hand, the standard deviations of pixel values decreased (Holopainen and Wang, 1998). However, the degree of the decrease in the standard deviation might depend on stand types. Using the standard deviations of pixel or block values in the fixed window as classification variables, therefore, it was possible to provide the variation information of stand types and to improve the classification for forest stand types especially when one channel such as panchromatic image was only available. The results show that adding the standard deviations slightly improved the classification compared to that using the window means only.

Using regression methods, the original local operators were calibrated to the level of the photo central point. The effect of plot location on the local operators was studied using six location variables including x- and y-coordinates, elevation, slope, aspect, and camera normal angle. The coefficients of determination between the local operators and slope, aspect, and camera normal angle were very low. The three location variables were thus not important as independent variables in the regression calibration models. In fact, the results by adding the slope were not as good as those using x- and y-coordinates and elevation only. This might be explained by the fact that the terrain of this study area slopes gently. In addition, the study area was small and it would thus be valuable to further study the effect of location on pixel values on digitized aerial photos.

In this study, the parameters of the calibration models were estimated using all the sample plots. In fact, the parameters might be satisfactorily derived using the training sample. The size of training sample may vary depending on study areas and stand types, and it would be necessary to study the problem in the future.

The regression calibration models were separately developed within each of the classes obtained by the pre-classification using visual photo interpretation and within each of the strata derived by the pre-stratification using satellite images. On the other hand, the success of this method depended, to some extent, on the pre-classification or pre-stratification. In a small area, it is possible to carry out the pre-classification of sample plots by visual photo interpretation. For classification in a large area, the pre-stratification of sample plots can be made using other auxiliary material such as satellite images. This method can thus be used in practice for forest inventory.

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