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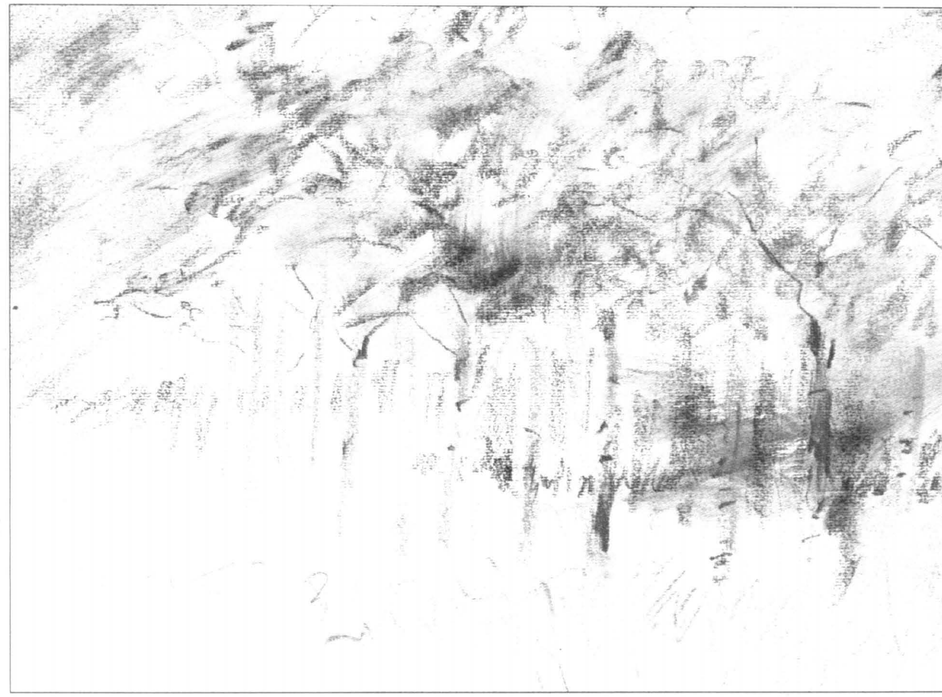

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Change Detection and Controlling Forest Information Using Multi-temporal Landsat TM Imagery

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Editorial Office Unioninkatu 40 A, FIN-00170 Helsinki, Finland
Phone +358 9 857 051, Fax +358 9 625 308, E-mail silva.fennica@metla.fi,
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To be presented, with the permission of the Faculty of Forestry of the University of Joensuu, for public criticism in Auditorium C2 of the University Main Building, Yliopistokatu 2, Joensuu, on 21 November, at 12 o'clock noon.

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Change Detection and Controlling Forest Information Using Multi-temporal Landsat TM Imagery

The Finnish Society of Forest Science — The Finnish Forest Research Institute

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A method was developed for relative radiometric calibration of single multitemporal Landsat TM image, several multitemporal images covering each others, and several multitemporal images covering different geographic locations. The radiometricly calibrated difference images were used for detecting rapid changes on forest stands. The nonparametric Kernel method was applied for change detection. The accuracy of the change detection was estimated by inspecting the image analysis results in field.

The change classification was applied for controlling the quality of the continuously updated forest stand information. The aim was to ensure that all the manmade changes and any forest damages were correctly updated including the attribute and stand delineation information. The image analysis results were compared with the registered treatments and the stand information base. The stands with discrepancies between these two information sources were recommended to be field inspected.

Keywords change detection, satellite image, forest inventory, continuous updating, stand information, radiometric calibration, nonparametric discrimination
Author's address National Forest Inventory, Helsinki Research Centre, Finnish Forest Research Institute, Unioninkatu 40A, 00170 Helsinki, Finland **Fax** +358 9 857 05717
E-mail jari.varjo@metla.fi
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Contents

Preface

This project has been realized as a result of co-operation between the University of Joensuu, the Forest and Park Service of Finland, the Environmental Mapping and Modelling Group at the Ispra Establishment of the Joint Research Centre of the European Commission and the Finnish Forest Research Institute. The study has been supervised by Associate Prof. Jussi Saramäki from the University of Joensuu and Prof. Erkki Tomppo from the Finnish Forest Research Institute. The Forest and Park Service has provided all the necessary material and taken care of all the field work required for controlling the results. I would like to specially thank Mr Arto Tolonen from the Forest and Park Service who has been mainly responsible for the expertise and arrangements involved. The computing facilities have been provided by the University of Joensuu. The Joint Research Centre has provided the facilities needed in analysing the results, and the National Forest Inventory group from the Finnish Forest Research Institute has provided very encouraging environment for finalizing and reporting the work. The manuscript has been read by Prof. Håkan Olsson, Prof. Simo Poso, Ass. Prof. Jussi Saramäki, Prof. Erkki Tomppo, Dr Aimo Hautojärvi and Dr Jukka Heikkonen. Their comments have been very important during the progress of this work. Important comments about the research plan and the work have been provided by Dr Tuomas Häme, Mr Juha Heikkinen, Mr Jaakko Heinonen, Dr Juha Lappi, Mr Väinö Rahunen and Mr Timo Tokola. Especially Mr Tokola's support when planning the work and Mr Heikkinen's comments when finalizing the work have been extremely valuable. Professional help on several important issues during the project has been provided by Mr Matti Huohvanainen, Mr Harri Hyppänen, Mr Veli Kynsijärvi, Mr Kari Pasanen, Mr Tapio Peltoniemi, Mr Janne Soimasuo and Mr Ari Turkia. The language has been kindly and patiently corrected by Dr. Ashley Selby and Ms Heli Mikkelä.

The research project is not only a construction of methods and technical achievements for producing something hopefully new. The human touch is at least as important for generating new ideas and for realising them. If used in a right way the human touch should not violate the objectivity aims of application oriented science but provide resources for accomplishing research tasks. I am afraid my own resources have been limited in this field and I want to give my thanks to my dear wife and to my closest colleagues for their continuous encouragement. Especially, I would like to thank my wife for supporting me on those numerous days during the project when I wanted nothing more than to be a lumberjack again. She, Dr Heikkonen, Dr Paracchini, Ass. Prof. Saramäki, Mr Siitonen and Mr Tokola somehow kept me going on those times.

Joensuu 10 December 1995 / Vantaa 26 August 1997

Jari Varjo, Forest Officer

Terms and Symbols

BA — Basal area, m^2/hectare

Base-line inventory — New forest inventory in which no information from any previous inventories is utilized. In this work a new stand level forest inventory including new stand delineation and assessment of stand attributes by visiting every stand.

Change classes according to the treatment instructions valid during the study period

I Untreated (Unt.) — No man-made changes or catastrophic forest damages, small changes caused by normal growth and possibly by seasonal variation.

II Moderate changes:

Uncommercial thinning (UnÇ. thinn.)
Generally the class consists of treatments of young stands which do not yield commercial timber. The aim of the treatment is to remove poor quality and unhealthy trees and to achieve around 2000 trees/hectare in deciduous dominated stands and 2000–3000 trees/hectare in conifer dominated stands. The class includes all silvicultural treatments which aim to improve a stand, such as cleaning a sapling stand, release cutting and thinning in a sapling stand. Cuttings to improve a young stand by favouring suitable tree species are also included in this class.

Commercial thinning (C. thinn.)
1–3 thinnings during the rotation aimed at increasing both profit and timber quality. Normally, about 30 % of the basal area is removed.

Preparatory cut (Prep. cut)
Thinning of a dense mature stand following a preference to delay treatments aiming at regeneration. Around 20–30 % of the basal area is removed.

Hold over removal (HOR)
Removing the over storey after natural regeneration; drain is 10–50 trees /hectare.

Draining (Drain.)
Improving the growth conditions of a stand by digging new ditches or cleaning existing ditches in order to decrease soil moisture.

III Drastic changes

Treatments aiming at regeneration
* Regeneration cut for natural regeneration (Reg. cut N. or regeneration cut.)
Natural regeneration, only 10–50 seed trees per hectare remain after cut.

* Clear cut
All tree stories are removed. Removals vary between 150 and 300 cubic metres per hectare (m^3/hectare) on the study area.

Soil preparation (Soil prep.)
Harrowing, plowing or scarifying after treatments aiming at regeneration. Harrowing was mainly used in the study area.

Continuous updating — Updating a forest information data base immediately after the treatments and by growth models in untreated areas.

D — Stand mean diameter at breast height (1.3 m).

Δx	Change of variable x
DN	Digital number registered by remote sensing sensor.
Forest stand	The spatial delimitation used in forest inventory and management planning. This is normally about 1–2 hectares in private forest and larger in company and state forest holdings in Finland. It is based on the need for similar future treatments, and it is subjectively based on the homogeneity of tree species composition, age class and soil type within a stand.
Forest holding	Aggregation of several forest stands normally under single ownership which together form an entity for planning forest activities.
FPS	Forest and Park Service, the organization responsible for the management of state owned forests in Finland.
Generic training data	Training data which can be used for nonparametric classification of several image pairs and/or different geographic locations.
Inventory unit	The smallest areal delimitation from which the attribute data are recorded and for which the final results of the inventory are calculated in base-line inventory.
Leverage point	Outlier (see below) in X direction.
M	Mineral soil.
Management planning levels	Operational = 0–1 year Tactical = 1–5 years Strategic = > 5 years.
Me	Mean.
Observation unit	The areal delimitation which is monitored by satellite data in a change detection procedure.
Outlier	An exceptional observation in Y direction which has an erroneously strong influence in the data set.
P	Peat land.
Rapid change	Forest changes due to silvicultural activities or damages, which take place during a couple of weeks. Normal growth or seasonal variations are not considered to be changes in the sense of this study.
Re-lineation	Correction of the areal delimitation of a forest stand because cutting has not followed boundaries lineated in base-line inventory or because of occurrence of a forest damage.
RMSE	Root mean square error.
Sd	Standard deviation.
Treatment information	Record including location and type of man-made treatments implemented during the study period.
Treatment unit	The areal delimitation where the same silvicultural treatment or cutting activity is implemented on the same point of time.

1 Introduction

1.1 The Need for a New Forest Information Updating Scheme

Forest inventories are experiencing rapid changes following the need to decrease the costs of the collection and maintenance of information required for planning the management of natural resources. These changes affect all levels of information needed in forest management planning from the operational level to tactical and strategic planning (Kangas et al. 1992). In Finland, forests are primarily used for timber production (Metsätilastollinen... 1994). Similarly, most of the current forest inventory and management planning routines have been developed for optimising timber production. However, new inventory and planning methods should make it possible to detect areas which may have more value for recreation or as habitat reservations, for example. These new needs should be taken into the consideration in management planning. This places considerable demands on forest inventories and management planning in large forested areas such as Finland and Sweden. It should therefore be possible to gather and maintain the necessary information at a level which enables effective and economic timber production, while recognising all other possible values. This means that new attributes have to be measured in addition to the traditional variables used for timber production planning, and all the information have to be updated often enough to enable required management decisions. New inventory routines will have to be developed for these purposes. This aim is difficult to achieve when inventory costs need to be decreased in same time. In this study, the problem of updating stand level forest information is studied by combining satellite remote sensing with limited field inspections.

The mapping scale used for operational planning in traditional stand level forest inventories has usually been 1:10 000–1:20 000 (Osara 1948, Poso 1983, Nalli and Hyttinen 1992). Aerial photographs have been used for stand delineation purposes. Ocular field inventories combined with some basal area measurements and height measurements have been used for inventorying attribute data (Laasasenaho and Päivinen 1986). The delineation of the stands has been based on the needs of treatment planning and stands have been defined on the basis of future treatments. This has resulted in stands of 1–2 hectares on private forest holdings and larger stands on larger forest holdings. Traditionally, this information has been updated by repeating the base-line inventory at 10–20 year intervals (Korhonen 1990). When considering the new demands of multiple use forest planning, the use of coarser scales or less intensive updating can be considered to be too inaccurate for operational planning. On the other hand, it must be possible to economically gather and update information on large areas at tactical and strategic planning levels. All this information has to be at least as accurate as the traditional stand level information used for timber production planning (Laasasenaho and Päivinen 1986) and up to date to ensure a balanced and sustainable use of natural resources (Kangas et al. 1992).

Updating forest resources data seems to be one of the most essential issues of the management planning of natural resources. All the information required for decision making should be updated often enough, no matter which scale is being considered. This includes both spatial information and attribute information. The present updating schedule of the stand level information appears not always fulfil these requirements. Concerning spatial information, re-lineation is needed due to differences between inventory units and treatment units or due to forest damages. Similarly, updating attribute data is necessary due to normal growth and man-made or natural changes affecting the attributes registered. On large scales, such as stand level forest inventories where a great deal of the necessary information is collected in the field, the demands of cost efficiency create the need to decrease the amount of field work needed for updating. This is because the field work is usually the most expensive phase of an inventory (Ojanen 1978). A considerable amount of field work is required if updating is executed by repeating the base-line inventories. Korhonen (1990) describes three possibilities for updating this kind of stand information:

1) Every stand is re-inventoried every time up to date information is needed.
2) The stands are inventoried once and the information is updated by growth models and by remeasuring stands after every cutting activity.
3) Continuous updating by combining 1 and 2. This means updating by growth models and on the basis of treatment information as long as the errors in the data can be kept at a reasonable level. After this, a new base-line inventory is necessary.

If the amount of repetitive field work in updating can be reduced by employing satellite remote sensing, which is an economic source of repetitive information, the considerable savings may be created without risking the quality of the information (Varjo 1993, 1996). Satellite remote sensing has many benefits as a source of material for updating forest information. Satellite images provide information about the location of interesting patterns and the spectral variations on different channels correlate with the attribute information needed in forest management (e.g. Saatsi 1985, Hopkins et al. 1988). It can also be assumed that the satellite material could, in the best case, fulfil a great deal of the information needs for updating. The large area coverage and thus the low areal costs are also important benefits.

As a result of the need to decrease inventory and updating costs many holders of large forest areas, such as Finnish Forest and Park Service (FPS), have started to use the third possibility, continuous updating, (see previous classes by Korhonen (1990)) for updating forest data instead of repeating base-line inventories. The forest data base is updated after the implementation of treatments and normal growth is predicted by growth models once a year. However, this new approach to updating has created new problems; updating should not reduce too much the quality of the original information. This means ensuring that all man-made activities and any possible natural changes which are severe enough to affect management planning are correctly updated. Controlling the updated information also includes monitoring all the changes in the forest canopy and ensuring that they are correctly updated. Possible bias in the original attribute measurements, or possible bias caused by growth models, can be corrected by applying control field inventories (Laasasenaho and Päivinen 1986). Updating errors due to drastic changes in the case of non-updated treatments or severe forest damages, can be correct only by methods which cover the whole area in question. So far, the accuracy of satellite image based base-line inventories have been too coarse for updating stand information (Päivinen et al. 1993). However, promising methods for satellite image base-line inventories have been presented by Hagner (1990). When new satellites with about 5 m resolution become available this may create new possibilities for updating and controlling attribute information by applying satellite images to base-line inventories (Hyppänen 1994). The Global Positioning System (GPS) may also provide a new and accurate tool for controlling re-lineations (Bergström and Olsson 1993, Hyppänen et al. 1996).

At present, it seems possible to reduce the costs of maintaining the quality of continuously updated forest information by combining traditional field inventories with remotely sensed information (Tomppo 1990, Varjo 1996). Satellite images provide useful material for monitoring large areas both repetitively and economically. This capability is also necessary for controlling possible updating errors and forest damages (Varjo 1996). Updating errors may exist because of human errors or gaps in the information flow. Further, forest damages such as wind breaks are not necessarily noticed and updated in continuous updating procedure without control. Field inventoried data provide accurate but expensive sources of information; it is not economically feasible to achieve required updating intensity by repeating complete field inventories (Varjo 1995). If the advantages of satellite remote sensing and field inventories can be combined with information concerning forest growth, the forest data base would go a long way to fulfil the information needs of forest management. However, this idea requires that the detection of rapid changes in the forest is solved in a cost efficient way. Updating of forest data by growth models and simulation has been possible when there are few tree species and soil type combinations, see Siitonen (1990) for a Finnish example. The resultant accuracy seems to allow 15–30 year updates without the need for new field inventories (Siitonen 1990, Mäkelä and Salminen 1991, Kangas 1997). So far, operational updating applications have not been possible because the accuracy required for change detection has not been achieved. However, promising results have been reported on the use of multi-temporal satellite images for detecting forest changes (Häme 1987, 1988, Olsson and Ericsson 1992, Varjo 1993, Collins and Woodcock 1994, Olsson 1994a).

If changes can be detected from satellite imagery the accuracy of continuously updated attribute information can be then assured by restricting field inventories to suspect stands (Varjo 1993). In addition, promising results have been presented for controlling the delineation errors by satellite imagery (Olsson 1994a). The use of remotely sensed material for updating depends on whether changes in the forest can in fact be monitored by remote sensing (Singh 1989). The use of satellite imagery for detecting forest changes, such as natural damages or human actions, has received attention (Häme 1991, Olsson 1994a, Lambert et al. 1995) and methods to control the quality of continuously updated forest information by remote sensing have been proposed (Häme 1991, Varjo 1995, 1996). It is natural to start this kind of work from the large scale operational level, such as stand level inventory, in order to determine the limits of remotely sensed change detection. It is necessary to examine whether the image data available can fulfil the control needs at the operative level. The same experiences, if acceptable, can later be utilised for smaller scales and different resolution levels.

1.2 Remote Sensing Material for Monitoring Rapid Changes in Forests

1.2.1 Important Characteristics of the Remote Sensing Material

Before the adoption of remote sensing aided updating methods, the best combinations of different materials and methods have to be defined for each case and scale. The balanced combinations of various methods with different materials have to be studied and the technical limitations of the materials have to be understood. At least three different factors have to be considered when evaluating different remote sensing materials for monitoring natural resources. Each factor is related to the properties of the sensors (Mather 1987): 1) spatial resolution affects the size of the smallest separable object; 2) spectral resolution determines the range of the wave lengths which can be analysed and thus affects separability of different phenomena by means of their spectral properties; and 3) radiometric resolution determines the accuracy of the observations within a given channel and thus influences how small changes in intensities that can be separated.

At the operational level, where the accuracy requirement is highest concerning spatial resolution, only high resolution space-borne sensors such as Landsat TM, SPOT HRV, satellite photographs or airborne sensors can be considered. Based on theoretical studies using semivariograms, it seems that the best spatial resolution for monitoring a forest canopy is about 4–5 m (Hyppänen 1996). However, the ability to detect changes is affected by a combination of all the characteristics of the material in question. Limiting factors with satellite or aerial photographs are the control of the image geometry (Holopainen and Lukkarinen 1994) and the partly analogical production of the images. In addition, the spectral resolution of analogical materials is usually lower compared to the Landsat TM sensor, for example. Airborne imaging spectrometers improve spectral and spatial resolution but so far they have mainly been used for research purposes (Mäkisara et al. 1993) and only a few application oriented results have been published. Technology and methodology development in this field may result in new potential tools for change detection. Promising results for detecting changes based for example on the blue shift have been reported from laboratory experiments (Rock et al. 1988, Hoque and Hutzler 1992). However, the sensors available do not provide sufficient spectral and radiometric accuracy to detect this kind of changes in practice. So far, adequate results concerning forest change detection in the boreal forest zone have mainly been based on Landsat TM and SPOT HRV data (Häme 1991, Olsson 1994a, 1994b, Varjo 1996). When considering the radiometric accuracy these data are comparable. However, the lower spectral resolution of the SPOT sensor compared to that of Landsat TM has often reduced the advantages of better spatial resolution (Häme 1991).

In addition to the properties of different sensors, the amount and availability of remote sensing data may also create problems. On many occasions, the sheer amount of remotely sensed data needed to cover a given area can be a limiting factor. Even at the operational level, as in the case of the Landsat and SPOT sensors, the smallest image element, the pixel, can be too small to be used for repetitive monitoring purposes. The amount of data required to cover large entities, such as Europe, is certainly one of the limiting factors. Rapidly improving computing capacity may partly solve this problem. However, the spatial accuracy of the remote sensing materials is improving in same time. In addition, under some circumstances, the availability of the images may be a constraint when considering monitoring systems (Kontoes and Stakenborg 1990). These problems are caused by weather conditions. For example, cloud cover may prevent repetitive acquisition, especially with sensors monitoring the visible and near infra red wavelengths of the electromagnetic spectrum. Radars are not as sensitive to atmospheric disturbances, such as clouds, as optical imagery. However, radar has not been found to significantly improve forest mapping results compared to optical imagery (Koch et al. 1995). One reason may be that radar is very sensitive to the soil and canopy moisture variation (Tomppo et al. 1994). As one possible alternative, the combination of radar and optical imagery for change detecting purposes has been proposed (Guerre 1995).

1.2.2 Observation Units in Forest Change Detection Based on Satellite Remote Sensing

One of the major problems concerning the application of remote sensing to forest change detection is the effect of the size of the observation unit. It is a problem which is closely related to the problem of the quantity of data which can be processed. The smallest originally recorded unit which can be observed by remote sensing is the pixel, and this is determined by the physical properties of a given sensor. In the case of nature resource monitoring satellites, the pixel size varies from the 5×5 m^2 of the IRS 1C panchromatic to the 825×825 m^2 of the Nimbus-7 CZCS sensor. In Finnish forest conditions, such areas will almost always contain several trees. The intensities registered by satellite sensors have also to be related to sample plots or forest stands. In addition to the original pixels, other remote sensing derived observation units can be formed by aggregating or dividing pixels.

Stand and forest holding are logical pixel aggregates for forest applications. However, for purposes of operative change detection, the forest holding is far too coarse a unit to be considered as the observation unit. If the subjectivity related to the definition of a forest stand (Poso et al. 1987, Poso 1994) is accepted, a stand can be considered a suitable observation unit when stand maps are available. The advantages of the forest stand as an observation unit are the good accuracy of base-line stand level data from field surveys (Laasasenaho and Päivinen 1986, Päivinen 1995), especially in combination with remote sensing data, and that the implementation of forest treatments, at least to some extent, follows stand boundaries. Consequently, stand boundaries can be used as prior information creating observation units for change detection. It is obvious that the separability of man-made changes should improve if observation units contain information concerning the location of possible changes (Varjo 1993). The disadvantages of the forest stand as an observation unit are the subjective definition and the lineation of the stands which may result in the need to change stand boundaries (Poso 1994). Together with partial treatments these factors may increase the within-stand variation considerably in

terms of both forest characteristics and spectral response (Poso and Waite 1995).

Artificial observation units can be considered in addition to stands. This is the only possibility if old field information, such as stand delineation, is not available. In this case, the pixel aggregates have to be formed either on the basis of image intensities, or artificially. Automatic segmentation methods based on intensity information have been developed for substituting base-line inventory stand delineation and about 80 % accuracies have been reported compared to base-line delineations (Häme et al. 1988). However, in such cases the problems of increased within-stand variation can be even worse than in stand delineation. This is due to the mismatch between spectral segments and forest stand attributes. Another possibility is to use a completely artificial observation unit such as a quadrant, the sides of which are a multiple of a certain number of pixels, e.g. 2×2 pixels. In this case, the observation unit should be so small that all the necessary areal entities, such as a single clear cut, can be composed by combining observation units to avoid the need for re-lineation after the change detection. The smallest forest stands in Finland are about half hectare in size and can be very narrow in form. New demands related to multiple use and biodiversity seem to result in even smaller stand sizes and a wider variety of stand shapes. In this case, an areal unit not larger than 2×2 pixels with Landsat TM (see Häme 1991) or 3×3 with SPOT XS can be considered. The use of a single pixel as the observation unit would probably be the best solution when considering delineation of forest changes. Another possibility might be a multi-resolution approach where stand or segments and pixels could be used hierarchically.

There are several disadvantages in pixel-level analyses, specially when using multi-temporal data (Mather 1987, Häme 1991). One important point is that registration and rectification errors, i.e. mismatch when overlaying pixels from different acquisitions, increase noise. In a combination with mixed pixels this can easily confuse the detection of real changes by causing several small false changes in the results. These problems could be partly reduced by interpolation to create subpixels for decreasing the original pixel size. However, even the use of Landsat TM at the pixel level may result in too much data for large area applications in change detection when multi-temporal data are considered. This is not necessarily a problem in remote sensing aided base-line inventories because a sampling based approach can be considered (Poso and Waite 1995). However, the whole area under control has to be monitored when developing the quality control method for continuous updating. Otherwise single, non-updated treatments or forest damages would be detected only if they happen to be included in the sample. Compared to problems with mixed pixels, the opposite effect in this context is the reduction of the heterogeneity of spectral classes as the resolution becomes coarser (Markhamn and Townshend 1981). Altogether, noise at the pixel level can easily obliterate spectrally small changes such as those created by silvicultural management activities, and result in false changes being detected (e.g. Peng 1987). This easily leads to the decision that the results of pixel-level change detection have to be reinterpreted by area tresholding or post classification, for example, in order to detect real changes (e.g. Wilkinson et al. 1995).

The decision as to which observation unit should be used depends on the phenomena being monitored. Olsson (1989, 1993, 1994a) tested relative radiometric calibration at both pixel and stand levels and Varjo (1993, 1995, 1996) applied the stand level approach to avoid problems at the pixel level in both radiometric calibration and change detection. If no field information is available concerning the real delineation of the phenomena in question, then the maximum size of the observation unit will depend on the accuracy of the delineation which is considered acceptable for controlling the quality of the spatial forest information. If field information about the stand delineation is available, then the within-stand variation has to be considered. To this end, Häme (1991) used a combination of pixel and stand level change classifications. He first used pixel level change discrimination and then interpreted the results for the stand level based on a within-stand mode class. He proposed the use of 2×2 Landsat TM pixel windows for change detection (Häme 1991). Varjo (1993, 1995, 1996) based stand level change detection on the assumption that at least part of the man-made changes follow the stand delineation. The problem with this approach is that the changing market demand for timber can affect the short-term cutting schedule and thus the stand delineation may be changed as a result of the delineation of treatments. This can be expected to mainly affect those treatments which are producing the largest amount of commercial timber, such as treatments aiming at regeneration. The delineation of the other treatments is determined more by the silvicultural stage of the forest and they do not often result in a need to change the treatment delineation. Stand delineation can therefore be used as spatial information in change detection because a great deal of drastic treatments, as well as most moderate treatments which are difficult to detect from satellite imagery, can be assumed to follow the stand delineation. However, a method is required for relineating those drastic changes which do not necessarily follow the stand delineation.

1.3 Methods for Forest Change Detection Using Multi-temporal Data

The first issue to be considered when analysing rapid changes in the forest canopy using multi-temporal remote sensing data, is the spectral change caused by these changes and the factors which affect the separability of the changes. Remote sensing data are useless if the changes in the forest do not alter the intensities detected by the sensor, or the disturbing factors obliterate the change. The need to detect the obliterating factors as a separate phase depends on the analysis selected and the number of image pairs used. If only one image pair is analyzed, there may be no need for separating changes of interest from other changes (e.g. Häme 1991). It may be assumed that the linear radiometric calibrations could be implicitly included into the change detection procedure (Häme 1991). However, in some cases even the linear radiometric calibration has improved the change detection when it has been used for making the earlier image radiometrically comparable with the later one in difference image analysis by applying relative calibration (Varjo and Folving 1997). The change detection problem may be more easily understood, for example concerning feature selection, if the effect obliterating changes can be decreased.

Several image pairs are required if remote sensed data are to be used for monitoring changes over large areas. If the radiometric calibration is omitted it has to be assumed in the case of supervised approach that the training data can be collected separately for every image pair employed, or that the image pairs are comparable enough without calibration (Varjo 1996). If different image pairs used are not radiometrically comparable, it is necessary to employ radiometric calibration which permits the use of generic training data for several image pairs. In addition, in the case where the selected image analysis neglects the calibration, the acquisitions used should be radiometrically similar with each other in order to make the difference images easily understandable. In the case of unsupervised change classification, uncalibrated data have not given encouraging results compared to change detection using radiometrically calibrated data (Varjo and Folving 1997).

Häme (1988) divided changes detected by remote sensing into two main categories: 1) changes caused by the canopy and 2) other changes. With respect to detecting rapid changes in the forest, there are changes in both categories which can confuse the analysis of the actual phenomenon of interest. Separating the spectral changes caused by local changes in the minority of forest stands from other possible causes of spectral changes can be regarded as a calibration problem (e.g. Olsson 1994a). If radiometric calibration is selected, all the non-object related changes, such as changes in sensor sensitivity (Olsson 1995), changes in atmospheric conditions, as well as variations in viewing and in solar angles (Singh 1989), are determined and corrected, as far as possible, before change detection. In addition, there may be changes in the object, forest, which can disturb the analysis, such as, normal growth (e.g. Nilson and Peterson 1994) or the seasonal cycle. The changes of intensity caused by these factors have also to be considered in calibration (Olsson 1995, Varjo 1996). Further, the sensor differences have to be considered when preparing data for change detection, if the imageries from different sensors are considered (Hall et al. 1991).

Calibration can be considered to have two objectives: 1) to make several images or difference images radiometrically comparable with each other, and 2) to make the phenomenon of interest more easily separable and understandable. There

are two principal approaches to radiometric calibration, relative and absolute calibration (Olsson 1995). In absolute calibration, the image data are scaled in units of reflectance by modelling atmospheric radiative transfer, or measuring empirically the effect of disturbing factors. In relative calibration, images are usually just scaled radiometrically to make them comparable without paying attention to the specific disturbing factors. In atmospheric radiative transfer modelling, information is required concerning the non-object changes, such as those created by weather conditions. Optical properties of the atmosphere may be estimated on the basis of visibility. By using physical models of the atmospheric radiative transfer, the intensities detected on different dates or sensors are adjusted for comparability. If necessary, the changes due to normal growth can be predicted (e.g. Nilson and Peterson 1994) and added in this type of analysis.

There are several methods available for relative calibration depending on the field information available. If no ground information is available, methods such as histogram matching or simple range scaling can be considered (e.g. Franssila et al. 1981, Mather 1987). Selection of the reference data for relative calibration can be based on spectral information or on ground information when available (Hall et al. 1991, Olsson 1994a, Varjo 1996). Good results have been achieved by linear models using separate calibration data especially combined with difference image analysis (Olsson 1993). It can be expected that application of the calibration data with no changes, or when there are only minor variations in the mean canopy intensities will be usable in calibration (e.g. Hall et al. 1991, Varjo 1993).

An important issue when preparing multi-temporal data for change detection is the accuracy of the calibration in relation to the intensity changes caused by activities to be detected. According to Häme's (1991) results, a clear cut causes a 0.02–0.03 increase in red and near infrared reflectance. A clear cut causes one of the largest spectral changes among the man-made forest activities under Finnish conditions (Saukkola 1982, Häme 1991, Varjo 1996). When the change caused by a clear cut is compared to the accuracy of the absolute calibration, it becomes obvious that only this order of change may be detected by comparing absolute calibrated images (Olsson 1995). Calibration errors may obliterate all the other changes (e.g. Muchoney and Haack 1994). The possibilities of detecting changes after calibration seem better when the spectral changes caused by forest activities are compared to the accuracy of relative calibration by statistical methods (Olsson 1994b, 1995, Varjo 1996).

According to literature reviews, a great variety of change detection methods have been tested (Singh 1989, Häme 1991, Varjo 1993, Olsson 1994a). A commonly used method used for image classification is pixel level Maximum Likelihood classification (e.g. Mather 1987, Olsson 1994a). Methods involving the comparison of separate classifications, such as post classification comparison, are problematic because the number of error classes increases rapidly with the number of classes in separate classifications (Lark 1995). There are several problems to be considered when selecting the change detection methodology and none of the traditional methodologies seems suitable for updating and monitoring purposes (Varjo 1993). Recently, the discrimination of multi-temporal data have been proposed, using original spectral bands, difference features or channel transformations as explanatory variables (Häme 1991, Varjo 1993, Olsson 1994a). The selection of the observation unit has a considerable influence on the selection of the actual change detection method.

If a supervised method and the pixel level approach are considered, the intensity distributions (Figs. 1, 2 and 3) of different change classes are difficult to describe accurately by parametric distributions (Varjo 1996). This could be solved by using Wilcoxon's score functions (e.g. Ranta et al. 1989) if the distributions are symmetric. However, this is seldom the case (Figs. 2 and 3).

Another common problem is the construction of balanced training data for change detection. It is often difficult to obtain enough training observations for all the classes of interest because only small fraction of stands per forest holding will be treated annually (Varjo 1993). The only training class which may be assumed to follow a Gaussian distribution is the 'untreated' class (Fig. 1). If an areal unit larger than the pixel is considered and the changes are described by, for example, the central moments of the pixel groups, stands for

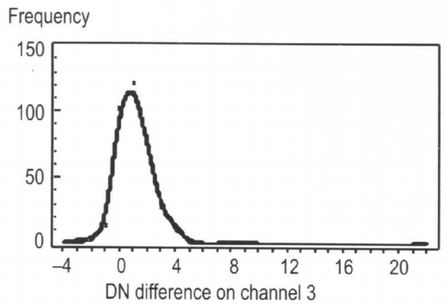

Fig. 1. The DN difference on Landsat TM channel 3 in an untreated stand after regression calibration with a two-year interval between the images, x = observed frequency and solid line = estimated frequency distribution (Varjo 1993).

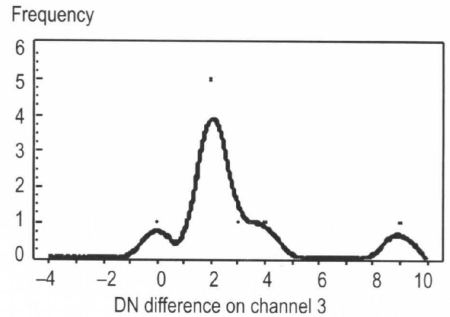

Fig. 2. The DN difference on Landsat TM channel 3 in a thinned stand after regression calibration with a two-year interval between the images, x = observed frequency and solid line = estimated frequency distribution (Varjo 1993).

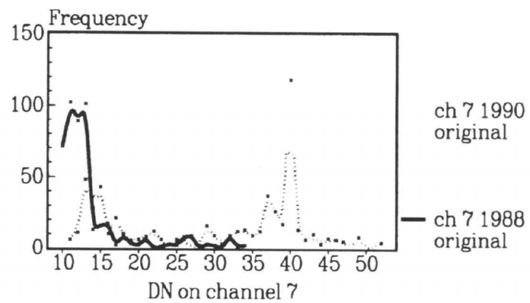

Fig. 3. The 1988 and 1990 Landsat TM channel 7 DN distributions in a partially clear cut stand, x = observed frequency, solid and dotted line = estimated frequency distributions (Varjo 1993).

example, the situation is different. If the sample size is large enough the stand means should, according to the central limit theorem, follow the Gaussian distribution (Ranta et al. 1989). However, this assumption about the Gaussian distribution of the stand means may fail if different change types, such as clear cuts and partial clear cuts, are randomly combined into the same treatment class. It cannot be expected that, for example, the number of different size partial treatments would be normally distributed. In addition, assuming a Gaussian distribution for the mean values would be valid only when there is a large number of observations in every class. This is hard to achieve if several different types of change are differentiated (Varjo 1996). The application of nonparametric discriminant analysis for change detection may be a way to solve many of the above problems (Varjo 1993, 1995). In this approach, the intensity distributions can be multimodal and asymmetric.

While the use of unsupervised methods might solve some of the distribution problems at the pixel level, the pixel level approaches have not been accurate enough for change detection purposes (Varjo and Folving 1997). In addition, the utilization of pixel aggregates has also favoured selection of nonparametric methods for the unsupervised approach (Varjo and Folving 1997). Only treated and untreated pixel aggregates have been separable with usable accuracy by the unsupervised approach (Varjo and Folving 1997). If more accurate causes for change are required, then the nonparametric supervised methods seem more suitable.

1.4 Objectives

The study has two main aims: to develop a cost effective method applying multi-temporal Landsat TM data for detecting rapid changes in the forest canopy, and to control the quality of continuously updated forest data. This includes developing and testing methods for using generic training data in forest change detection and developing a change detection algorithm which is not dependent on distribution assumptions. The possibilities to control that all the human induced forest activities and possible rapid damages are correctly updated with respect to spatial and attribute data is tested for the case of a continuous updating scheme. The control of possible errors in stand characteristics caused by updating normal growth by growth models is not considered. The basic assumption was that by comparing detected changes with the treatment information, the quality of continuously updated forest information could be maintained by inspecting a small number of stands in the field (Varjo 1996).

The study falls into three sections: 1) calibrating the multi-temporal Landsat TM image pairs radiometrically to achieve comparability under different situations; 2) detecting changes from multi-temporal Landsat TM data; and 3) estimating the effectiveness of the whole system for controlling the quality of continuously updated forest data.

In the first section, the main issue is the calibration of multi-temporal Landsat TM images for change detection. The first task is to determine how the time and type of the changes affect intensities within one image pair and how relative radiometrical calibration affects the analysis of the single difference image. The second task is to determine the possibility of generating generic training data in such a way that training data from earlier difference images covering the same location could be used for classifying new image pairs. The third calibration problem to be examined is whether the training data from different locations can be adopted for the classification of changes in a new difference image. The objective of the first section is to provide multi-temporal imagery which would allow the use of generic training data for change detection.

In the second section, the accuracy of change detection based on Landsat TM difference images produced in the first section is tested by further developing a promising nonparametric approach proposed by Varjo (1995). The classification accuracy is evaluated in three situations: 1) the training data are from the difference image under classification; 2) the training data are from a separate difference image from the same area; and 3) the training data are from a totally different area. The results of a nonparametric classifier are compared to those of Maximum Likelihood method (Mather 1987). In addition, a simple method is presented for relineating changes when the area of change differs from the stand delineation used as prior information in the change detection.

In the last section, the methods are tested for controlling continuous updating in five subareas from the forest district of Hyrynsalmi. The change classification is compared to the treatment information, and the need for field work for controlling the quality of continuously updated forest information is evaluated for these five subareas. The suitability of the methods for decreasing the amount of field work necessary for maintaining the accuracy of forest information for management planning purposes is assessed. It has become obvious in the FPS, at least during the transition period between repetitive inventories and continuous updating, that continuously updated forest information needs to be controlled because of human errors in the updating process, changes in stand delineation and possible damages. The costs of the method proposed are compared to the costs of previous updating methods in which the baseline inventories were repeated.

2 Material

2.1 Study Area and Stand Information

The main study area is located in Hyrynsalmi forest district of the Finnish Forest and Park Service (FPS) in the municipality of Hyrynsalmi, Eastern part of Central Finland (location of the study area centre: long. 28°30'E, lat. 64°30'N). In addition to the Hyrynsalmi area, data from Varjo's (1996) study, based on a test site at Nurmes, were used for comparison purposes. The Nurmes site is located about 100 kilometres south of the Hyrynsalmi site. (Fig. 4.).

In the Hyrynsalmi area, the mean stand size is 6.0 hectares. The Hyrynsalmi study area is divided to 17 subareas according to the division used by the FPS (Fig. 5). The mean effective temperature sum (threshold +5 °C) of the thermal growing season during 1961–1990 in the region varies between 900 and 1000 d.d. The mean annual precipitation varies between 320 and 340 mm from May to September and the difference between precipitation and evaporation varies from +10 to +50 mm (Metsätilastollinen... 1994). The forests are dominated by conifers; Norway spruce (*Picea abies*) is the most common on rich soils and Scots pine (*Pinus sylvestris*) on poor soils. The two species often form mixed stands. Pure stands of deciduous species are rare. Sometimes birch (*Betula pendula* and *Betula pubescens*), aspen (*Populus tremula*) and alder (*Alnus incana*) may form single species stands but more often they are mixed with each others and conifer species. The mean growing stock volume in the area of Kainuu Forestry Board District was 71 m³/ha in 1992, being 63 m³/ha in pine dominated stands, 124 m³/ha in spruce dominated stands and 60 m³/ha in birch dominated stands. The mean annual volume increment was 2.68 m³/ha between 1987 and 1991 (Metsätilastollinen... 1994).

Three data sets for 1) radiometric calibration, 2) training the change detection algorithm, and 3) testing, were formed for the Hyrynsalmi area. In addition, all the proposed change stands from the test data were visited in field to verify the change analysis results. The data set used for radiometrical calibration of the satellite acquisitions consisted of subareas 4074, 6115, 6121 and 6134 totalling 4311 ha (Fig. 5). In addition, they formed the 'untreated' class in the training data. The calibration data consisted of 390 stands on mineral soils and 321 stands on peat land. There were no treatments or reported forest damages in those subareas during the study period 21st June, 1990–31st July, 1993. The rest of the training data consisted of the stands where the treatment history was known. They were selected by the responsible district officer from subareas 1027, 3052, 3056, 3061, 3063, 4081, 4083, 5103, 6113, 6123 and

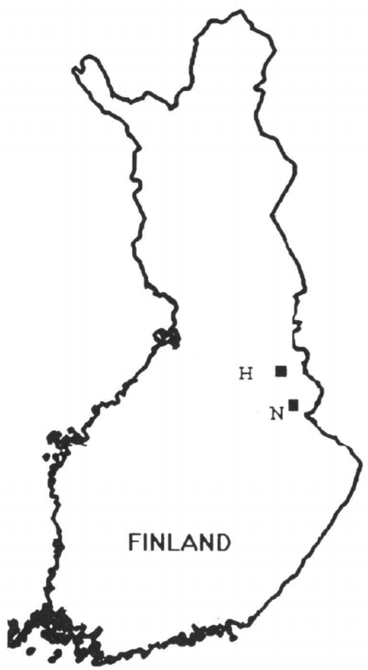

Fig. 4. Location of the test areas, H = Hyrynsalmi and N = Nurmes.

Table 1. Mean stand attributes in Hyrynsalmi training data according to the stand register, mineral soil.

Treatment	BA pine, m²/ha Mean/*Sd*	BA deciduous species, m²/ha Mean/*Sd*	BA spruce, m²/ha Mean/*Sd*	Age of the main storey, years Mean/*Sd*	Mean height, m Mean/*Sd*	Mean diameter, cm Mean/*Sd*
Unt	6.9	1.6	4.8	65.3	10.1	15.2
	6.8	*2.8*	*7.3*	*52.6*	*5.4*	*7.7*
UnC. Thinn.	0.2	0.1	0	12.4	2.1	4.0
	0.6	*0.3*	*0*	*5.1*	*1.5*	*1.7*
C. Thinn.	8.4	2.1	2.6	53.4	10.8	13.8
	5.6	*5.8*	*4.6*	*28.5*	*3.4*	*4.8*
Prep. cut	19.1	0.5	0.4	111.6	17.7	24.6
	7.1	*1.0*	*0.8*	*21.9*	*2.4*	*4.3*
HOR	*	*	*	*	*	*
Clear cut	*	*	*	*	*	*
Reg cut	*	*	*	*	*	*
Soil prep.	*	*	*	*	*	*

*data base partially updated, class means and deviations useless for describing the whole class.

Table 2. Mean stand attributes in Hyrynsalmi training data according to the stand register, peat land.

Treatment	BA pine, m²/ha Mean/*Sd*	BA deciduous species, m²/ha Mean/*Sd*	BA spruce, m²/ha Mean/*Sd*	Age of the main storey, years Mean/*Sd*	Mean height, m Mean/*Sd*	Mean diameter, cm Mean/*Sd*
Unt	4.1	0	0.9	44.1	5.9	8.9
	4.6	*0*	*2.7*	*34.2*	*3.2*	*4.9*
UnC. thinn	2.2	*0*	*0.3*	23.3	4.4	6.0
	1.8	*0*	*0.5*	*2.9*	*1.5*	*2.4*
C . thinn.	1.4	*0*	*0.4*	38.0	9.4	11.2
	2.2	*0*	*0.9*	*8.4*	*3.7*	*4.2*
Prep. cut	19.0	*0*	*0.6*	96.7	16.3	20.7
	11.9	*0*	*1.2*	*29.4*	*4.1*	*5.4*
Clear cut	15.7	*0*	*0.7*	134.0	18.6	23.8
	10.6	*0*	*1.6*	*16.7*	*2.3*	*5.1*
Drain.	0	0	0	40	3.3	3.6
	0	*0*	*0*	*14*	*0.5*	*0.5*

6133 (Fig. 5, Tables 1 and 2). The basal area and forest type distributions were sufficiently representative to describe the variation in the study area and in all of the three data sets used. The stand level age distribution was uneven throughout the whole region because of few observations from the middle aged stands. The basal area, forest type and age distributions were comparable in all the three data sets (Figs. 6, 7 and 8).

There were nine treatment classes in the training data: 1) no damage or man-made change (untreated, Unt.), 2) uncommercial thinning (UnC. thinn.), 3) commercial thinning (C. thinn.), 4) preparatory cut (Prep. cut), 5) hold over removal (HOR), 6) regeneration cut for natural regeneration (Reg. Cut N./regeneration cut), 7) clear cut, 8) soil preparation (Soil prep.), and 9) draining (Drain.). Drained stands only existed on peat land. Altogether in the training data, there were 500 stands on mineral soils and 351 stands on peat land. The majority of the treatments in the training data were implemented between 1990 and 1992 (Table 3).

The FPS selected five subareas for testing the methods: 1026, 3056, 3061, 5101 and 6133 totalling 6133 ha. The test data consisted of 593 stands

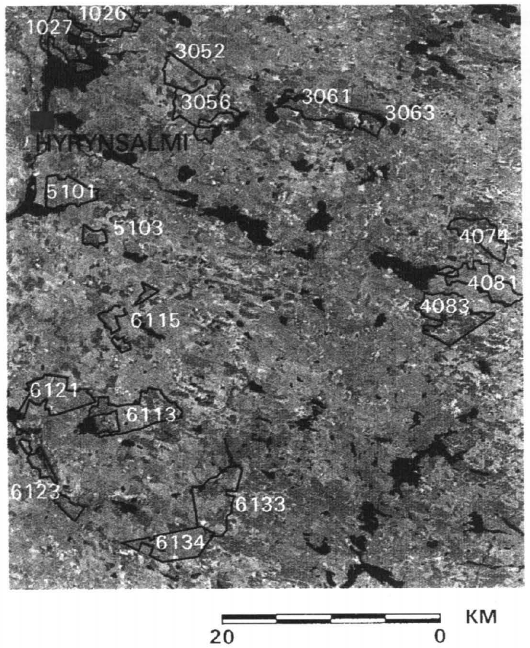

Fig. 5. The Hyrynsalmi test area. Copyright of the background satellite image belongs to: ©ESA, 1992, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

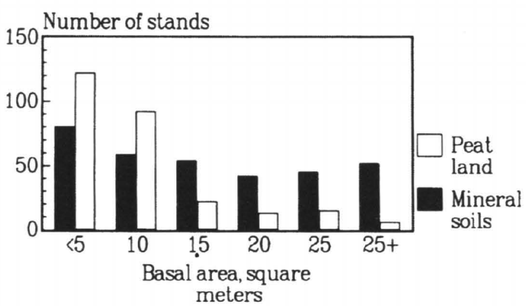

Fig. 6. The basal area m²/ha distribution in the calibration data.

on mineral soils and 123 stands on peat land. They were selected because a range of forest management activities had taken place on those subareas during the study period.

The stand delineation and stand level attribute data were available from the last base-line inventory in 1989. It had been a normal stand level inventory after which the treatments and normal growth had been updated continuously. The stands

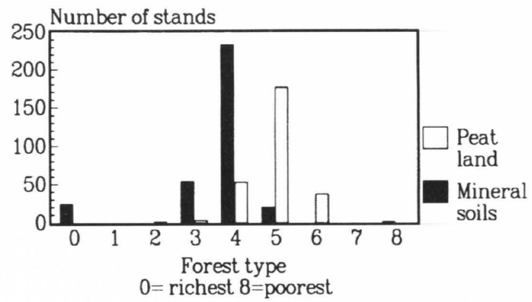

Fig. 7. The forest type distribution in the calibration data, the forest types are presented according the classes used by FPS (Suunnittelun ... 1991).

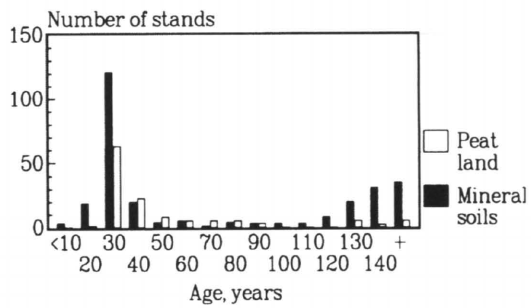

Fig. 8. The age distribution in the calibration data.

had been initially delineated from aerial photographs and the delineation had been controlled in the field. Storeywise attribute data had been collected by ocular field inventory assisted by some basal area, height and diameter measurements in every stand (e.g. Osara 1948, Suunnittelun... 1991). Stand delineation was transformed into the Finnish uniform coordinate system at each digitized point. In addition to continuous updating, the treatment information was available based on the salary book keeping. This information was interpreted for this work by the district officer responsible for forest management in the study area.

The accuracy of the attribute information had been controlled by inspecting 30 randomly selected sites which together included 90 stands. Control measurements had been carried out by measuring a grid of relascope sample plots for each selected stand; altogether 1186 relascope plots had been measured. The reference information for a stand had been created as a mean of relascope plot attributes belonging to the stand.

Table 3. Frequency and timing of the treatments in the training data.

Year of implementation	UnC. thinn. M	UnC. thinn. P	C. thinn. M	C. thinn. P	Prep. cut M	Prep. cut P	HOR M	HOR P	Reg. cut N. M	Reg. cut N. P	Clear cut M	Clear cut P	Soil prep. M	Soil prep. P	Drain. M	Drain. P
90–91	12	4	2		3				7		4		5			
91–92	1	2	10	5	13	1			4		18		6			4
92–93			3	1	10	7	4		2		6	6				

M = mineral soil, P = peat land

Table 4. The Landsat TM quadrants used.

Test site	Name used	Time of the acquisition	Track/row/ quadrant	Combined registration and rectification error in original pixels (30 × 30 m)
Hyrynsalmi	H90	21.06.1990	188/15/b	0.51
Hyrynsalmi	H92	10.06.1992	188/15/b	0.44
Hyrynsalmi	H93	31.07.1993	188/15/b	0.51
Nurmes	N88	08.06.1988	187/15*	0.45
Nurmes	N90	23.06.1990	186/15*	0.32

b=north-east quadrant, *=floating quadrant

Based on a comparison with the operational data base in use, there was no systematic error in the attribute information at the 10 % risk level (Leskinen 1993).

2.2 Remote Sensing Information

Three Landsat TM acquisition quadrants were acquired from the Hyrynsalmi test site and two were available from the Nurmes test site (Varjo 1996) (Table 4). The details of the Nurmes test site are presented by Varjo (1993, 1996). The quadrants from the Nurmes test site had first been registered together after which they had been rectified into Finnish uniform coordinate system (Häme 1991, Varjo 1996). For the Hyrynsalmi test site, the image from 1992 was first rectified into the Finnish uniform coordinate system, and the other images were registered on to the rectified 1992 image. First order polynomial was used for registration and rectification for the Hyrynsalmi site and second order for the Nurmes site. For both test sites, images were resampled into 20×20 m² pixel size by the nearest neighbour method. The ground control points were selected independently for registration and rectification. Combined registration and rectification errors varied from 0.32 to 0.51 pixels when the registration and rectification errors were considered to be independent (Varjo 1996) (Table 4). The quadrants used in Hyrynsalmi were completely cloud free on the selected test areas. In order to reduce the effect of mixed pixels along roads, lakes, and river sides, 20 m wide patches adjacent to such features were given null DN values.

In addition to Landsat TM images, two aerial photographs were acquired covering subarea 3061. They were false colour infrared photos taken at a scale of 1:30 000 and orthogonally corrected and magnified to 1:10 000 for final use. Visual interpretation suggested that the precision of the orthogonal correction with these two images was insufficient for using the aerial photographs as reference information for change delineations. Every reference delineation digitized from the photographs was first corrected into the Finnish uniform coordinate system based on tie points located around the change object under delineation. It was estimated that by employing this procedure, the location errors in reference delineations were less than 5 m.

3 Methodology

3.1 Processing Multi-temporal Landsat TM Data for Forest Change Detection

3.1.1 Regression Calibration and Image Differencing for One Image Pair

For making two overlaying Landsat TM scenes radiometrically comparable, the earlier acquisition in each image pair was calibrated to the level of the later acquisition by robust regression (Olsson 1993, Varjo 1996). Stand means of intensity values were regressed between TM images for each channel (Equation 1); i.e. the first order differences in intensities between the images caused by differences in atmospheric conditions, observation and sun angles, normal growth, possible seasonal differences and changes in sensor properties were explained by regression. This was achieved by using the calibration data in which no known rapid changes existed (Olsson 1993). There were two types of phenomena which were supposed to be loaded into the regression coefficients: 1) changes in the sensor properties and growth of trees were dependent on time and 2) the other affecting phenomena, which were just different realizations of conditions existing on the time of image acquisition. All these intensity changes between two acquisitions were assumed to be linear. The calibration and the whole analyses were executed separately for peat lands and mineral soils because of their different spectral responses (Saukkola 1982).

When estimating the parameters at Equation 1, the inverse of within-stand variance of intensity from earlier image was used as weight (Varjo 1996). Homogeneous stands therefore were given more weight in the parameter estimation. The weighting reduced the effect of mixed border pixels typical to small stands and the registration and rectification errors. The parameters of the model were estimated twice. After the first estimation, outliers and leverage points were detected and excluded from the calibration data before the estimation of the final calibration parameters (Varjo 1996). By detecting outliers and excluding them from the calibration data, the effect of possible unknown forest damages, undetected clouds and cloud shadows were reduced from the calibration (Varjo 1996).

$$y_{i,n} = \beta_{0,i,n} + \beta_{1,i,n}x_{i,n} + \beta_{2,i,n}x_{i-1,n} + \beta_{3,i,n}x_{i+1,n} + \beta_{4,i,n}x_{i-2,n} + \varepsilon_{i,n} \qquad (1)$$

where

$\beta_{p,i,n}$ = parameters of the model (p = 0, 1, 2, 3, 4),
$\beta_{2,i,n}$ = 0 when $i \neq 4$,
$\beta_{3,i,n}$ = 0 when $i \neq 3$ and
$\beta_{4,i,n}$ = 0 when $i \neq 6$

$y_{i,n}$ = mean DN value of a stand on channel i on the dependent image

$x_{i,n}$ = mean DN value of a stand on channel i on the independent image taken n years before the dependent image

n = time interval between dependent and independent image, n = 1, 2, 3 years

i = Landsat TM channel 1 = 1, 2, 3, 4, 5, 6, 7

$\varepsilon_{i,n}$ = error term

An observation was considered to be an outlier if the difference between the stand mean feature and estimate of it from Equation 1.

$$y - \hat{y}$$

was statistically significant at 5 % risk level (e.g. Varjo 1996) according to the Student's t-test. The test was made separately for each band. Similarly, an observation was considered to be a leverage point if Cook's distance was greater than 1 (Weisberg 1985, Rousseeuw and Leroy 1987 p. 227). Cook's distance indicates the change of the parameter estimate if the parameters of the calibration model are estimated without the single observation (Rousseeuw and Leroy 1987). If the change is too strong the observation has erroneously strong influence on the parameter estimates (Rousseeuw and Leroy 1987).

Based on the relative calibration of the earlier image, the stand level DN differences ($\Delta M_{DN(m)}$) mean (m = 1), standard deviation (m = 2), skewness (m = 3), 25 % quartile (m = 4) and 75 % quartile (m = 5) were calculated for every TM channel and for every single image pair (Varjo 1996) (Equation 2).

$$\Delta M_{DN(m)i} = y_{(m)i} - \hat{y}_{(m)i} \qquad (2)$$

where

$y_{(m)i}$ = feature m calculated from the DN values of a stand on channel i at time t

$\hat{y}_{(m)i}$ = feature m calculated from the DN values of a stand on channel i at time $t - n$ after regression calibration by Equation 1

In addition the difference of within stand central moments, the Angular Second Moment (ASM) texture measure was computed using 3 × 3 pixel window (Haralick et al. 1973) for Landsat TM channels 3 and 4 (Equation 3). The difference of ASM values were calculated as presented in equation 2. All these features ΔM and ΔASM were considered as spectral indicators and explaining variables of forest change. They were supposed to correlate with the change of stand properties due to damages or human induced actions (e.g. Saukkola 1982, Häme 1991, Olsson 1994a, Varjo 1996). In this study, the mean ASM for stands was formed as a mean of four directions (Equation 3) (Haralick et al. 1973, Hyppänen 1994). The ASM is a measure of the homogeneity of intensities within a stand, and it varies from 0 to 1. For a spectrally homogeneous stand, the ASM is close to one and for a strongly heterogenic stand it is close to 0 (Haralick et al. 1973). The ASM was selected based on the assumption that under normal conditions treatments such as thinning from below tend to make a stand more homogeneous. This is because the main tree storey and the most fertile trees are favoured in these treatments.

$$\mathrm{ASM} = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng}\left(\frac{P(i,j)}{R}\right)^2 \qquad (3)$$

where

P = relative frequencies in co-occurrence matrix (Haralick et al. 1973) in which two neighbouring cells are having DN values i and j respectively

Ng = number of quantized DN classes

R = number of DN value pairs

3.1.2 Studentization of Regression Calibrated Differences

The regression calibrated stand level differences ($\Delta M_{DN(m)i}$) in the training and the test data were studentized (in the sense of Weisberg 1985) to enable the use of generic training data for several image pairs. Regression calibration gives all the DN difference images unique scaling of the dependent image (see Equation 1) (Olsson 1994a). These explanatory candidates ($\Delta M_{DN(m)i}$) were studentized to make them more independent of this image pair specific scaling (Weisberg 1985, Olsson 1994a) (Equation 4). When the studentized changes were used for discrimination, it was assumed that spectrally exceptional untreated stands would not be as easily misclassified as without studentization because the scaling factor becomes larger compared to average observations.

$$\Delta M_{(m)i} = \frac{\Delta M_{DN(m)i}}{\mathrm{RMSE}_i\sqrt{1+\mathrm{lev}_i}} \qquad (4)$$

where

$\Delta MDN_{(m)i}$ = DN difference of stand level feature m on channel i with scaling of the dependent image

$\Delta M_{(m)i}$ = unitless studentized difference of stand level feature m on channel i

RMSE_i = root mean square error on channel i in Equation 1

lev_i = leverage of an observation on channel i (Weisberg 1985, Olsson 1994a)

3.1.3 Range Scaling of the Regression Calibrated and Studentized Differences

Range scaling presented by Franssila et al. (1981) (Equation 5) was used in the cases where studentized differences $\Delta M_{(m)i}$ between image pairs were not comparable because of a different range in corresponding training classes (for an empirical example see Appendix 3A).

$$y_i = \frac{\mathrm{Sd}_i^z}{\mathrm{Sd}_i^w} \cdot x_i^w + \left[\overline{x_i^z} - \overline{x_i^w} \cdot \frac{\mathrm{Sd}_i^z}{\mathrm{Sd}_i^w} \right] \quad (5)$$

where

y_i = $\Delta M_{(m)i}$ on channel i in the difference image w scaled according to the difference image z

x_i^w = $\Delta M_{(m)i}$ on channel i in difference image w

Sd_i^z = standard deviation of $\Delta M_{(m)i}$ value on channel i in difference image z

Sd_i^w = standard deviation of $\Delta M_{(m)i}$ value on channel i in difference image w

$\overline{x_i^z}$ = $\Delta M_{(m)i}$ value on channel i in difference image z

$\overline{x_i^w}$ = $\Delta M_{(m)i}$ value on channel i in difference image w

The combination of the three radiometric calibration steps are presented: stand level regression, studentization of the regression calibrated stand level DN differences, and range scaling of the studentized DN differences when the studentization by some reason did not produce comparable ranges. These methods were also tested separately and the effect of the calibration with respect to change detection was analysed. The presented radiometric calibration was assumed to enable the use of training data from a totally different period when image pairs cover each other, or even from totally different areas as long as a similar type of forest is analysed.

3.2 Method for Detecting and Re-lineating Rapid Forest Changes Using Multi-temporal Landsat TM Data

The results of Olsson (1994a) and Varjo (1993, 1996) were combined when selecting the change detection methodology for this work. The above calibration approach was selected to enable the use of generic training data for detecting rapid forest changes (Varjo 1993, 1996, Olsson 1994a). Olsson (1994a) proposed a studentization method for making separate difference images more comparable. Varjo (1996) used a two stage stand level nonparametric change classification. In this two stage approach, changes were first classified by nonparametric discrimination mainly based on intensity difference between two Landsat TM acquisitions. In the second stage, possible change areas were re-examined by using a measure of spectral change, available forest attribute data and knowledge of possible treatments in certain conditions using the rule based expert system (Varjo 1996). The measure of spectral change used in the second phase was Kolmogorow-Smirnov's D and its occurrence point (Varjo 1996). In this work, the change classification was accomplished in one phase by replacing the second stage of Varjo's (1996) approach with the studentized variables of spectral change proposed by Olsson (1994a) in the classification procedure used by Varjo (1993, 1996). The Kolmogorow-Smirnow's D for spectral change on Landsat TM channels was also replaced by studentized differences used as an explaining variable in the discrimination. The explanatory spectral variables for the change discrimination were selected on the basis of results from previous studies (Häme 1991, Varjo 1996), as well as from the results of stepwise parametric discrimination (Ranta et al. 1989). The rule based expert system of Varjo (1993, 1996) was replaced by the use of the experience of local forest management officer instead of general rules.

A nonparametric stand level discrimination (SAS... 1989, Varjo 1993, 1996) was also employed for detecting changes. The selection was based on the assumption that the stand level difference features used to describe the treatment classes do not accurately enough follow any parametric distribution. Even the distribution of the stand means belonging to a class can be multimodal or non symmetric. There are several obvious reasons for these problems. It is difficult to collect enough training observations for all the treatment classes. Treatments in certain classes, such as uncommercial and commercial thinnings, are sometimes implemented only in dense parts of the stands. Another example are the drastic changes which only occur in a part of a stand. When such stands are present in any given class, they make the class distributions very complicated to describe by a parametric distribution and a nonparametric solution becomes the most appropriate one (Varjo 1996).

The explaining stand level variables in each class of interest in the training data were described by Kernel functions (Equation 6) (Silverman 1986, SAS... 1989). Similar approach has resulted good accuracy in detecting forest changes (Varjo 1993, 1995, 1996). The normal distribution form of the single Kernel function was used. As in the calibration, the stand delineation was used as prior information for forming units, stands, for change detection. A Kernel density estimate was calculated for every stand under classification for assigning stands to their treatment class (Equation 6). The difference between this method and the traditional Maximum likelihood (ML) classification is that in this method the Mahanalobis distance is calculated between every stand within the training class and the stand under classification. The density estimates assigning a stand to a training class are formed as a mean of the all the distances between an stand under classification and all stands in the training class (Equation 6). In ordinary ML classification, an stand under classification is compared only with training class means (Mather 1987). The robustness of the method was analysed by the Jackknife method (Ranta et al. 1989).

$$f_c(\mathbf{x}) = \frac{1}{l_c} \sum_{i=1}^{l_c} K_c(\mathbf{x} - \mathbf{y}_i) \quad (6)$$

where

$f_c(\mathbf{x})$ = kernel estimate of density of explaining variables given that the stand belongs to the class c

l_c = number of stands in the training class c

$\mathbf{y}_i$ = stand i in the training class c

$$K_c(\mathbf{z}) = \frac{1}{(2\pi)^{\frac{p}{2}} h^p |\mathbf{S}|^{\frac{1}{2}}} e^{-\frac{1}{2}\mathbf{z}' \mathbf{S}^{-1} \frac{\mathbf{z}}{h^2}}$$

p = dimension

h = window parameter for smoothing

$\mathbf{S}$ = pooled variance-covariance matrix of explaining variables

A stand is classified into class c according to the highest posterior probability (Equation 7). The prior probabilities were also set equal to decrease the risk of misclassifications of changes such as forest damages which can be expected to have equal occurrence probability, for example, in all the age classes.

$$p(c|\mathbf{x}) = \frac{f_c(\mathbf{x})}{\sum_{c=1}^{l} f_c(\mathbf{x})} \quad (7)$$

where

$p(c|\mathbf{x})$ = posterior probability that the stand x belongs to the class c

l = number of classes in the training data

The change classification in the test data was controlled by inspecting all the proposed change sites in the field. The change type was labelled in the field and if it differed from the change class proposed by the method, the stand attribute information was inventoried according the traditional stand level ocular inventory procedure of the FPS for further analysis. The 'untreated' class was controlled by sequential sampling (Loetsch and Haller 1973, Varjo 1996).

The overall percentage of correct classifications was used to describe the classification accuracy. This was because the overall accuracy directly affects the amount of field work needed to control the discrepancies between image analysis and treatment information. It was considered the most important component of the accuracy for this application (Lark 1995). The percentage of correct classifications is calculated by dividing the sum of the numbers in diagonal at the confusion matrices by the total number of observations. The mean of the class specific correct classification percentages (Mather 1987) was not used because all the change classes found from ground inspection in the test data were not present in the training data. In these classes, classification into any of the change classes present in the training data was considered to be correct because they should be noticed when comparing the change classification results with the treatment information. The robustness of the classification accuracy was evaluated by estimating the lower edge of the 95 % confidence level for the overall percentage of the correct classification (Equation 8) (Jensen 1986). In the evaluation, the overall percentage of the correct classification was expected to follow Gaussian distribution. Accuracy assessments based on the χ^2 distribution, such as χ^2-test, were not considered because of the assumptions required for using the χ^2 distribution (Ranta et al. 1989). This is because with several change classes the number of observations should be quite high to ensure that the expected values in confusion matrix will be high enough (Ranta et al. 1989).

$$s = P - \left(z\sqrt{\frac{PQ}{n}} + \frac{50}{n} \right) \tag{8}$$

where
s = lower confidence limit
P = correct classification percentage
Q = 100 – P
z = critical value in Student's t-test
n = sample size

In addition to the assessment of stand level accuracy of the change detection, there is a need to control the delineation of the detected changes. Possible differences are due to the differences in the size of inventory units, stands, and actual treatment units. In addition, possible forest damages can not be expected to follow stand boundaries. Utilisation of the procedure proposed for change detection is too heavy to be used at the pixel level and that is why it was not directly tested for change delineation. Other methods are therefore needed for checking the delineation of the detected changes.

The possibility to delineate changes was demonstrated by screen digitizing visible changes from single Landsat TM and difference images, and comparing them with reference data from aerial photographs. In addition, the present stage of the operational stand boundary information after application of continuous updating was studied by comparing the stand boundary data base to the reference data. This was assumed to indicate the actual need for correcting the boundaries of the stands in which changes were detected.

3.3 Applying the Presented Methods for Controlling Continuously Updated Forest Information

The application of the methods presented to the case of the FPS consisted of three main parts. In the first part, the Landsat TM images were geocorrected and radiometrically calibrated for forest change detection. The available field information was combined with the satellite imagery (Fig. 9). The first part consisted of six steps:

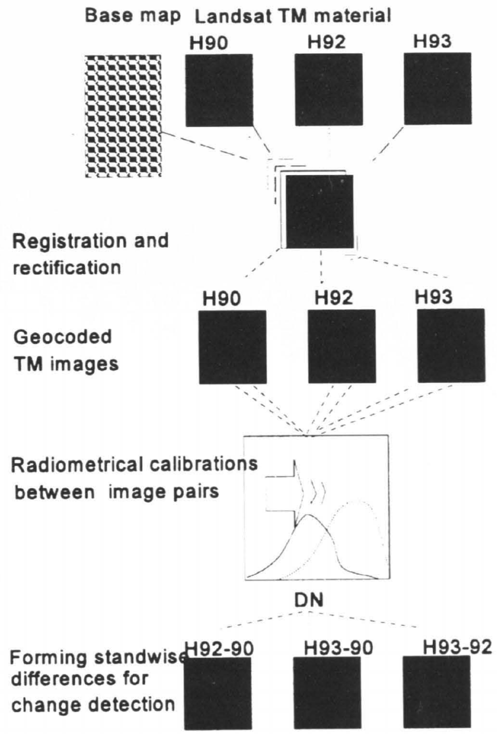

Fig. 9. Producing the multi-temporal TM data for forest change detection.

1) registration and rectification of the images
2) combining digital stand maps with imagery
3) radiometric relative calibration of the image pairs by regression
4) calculating stand level difference features used in the subsequent analysis
5) studentization of the difference features
6) range scaling the studentized difference in the cases where studentization failed to bring training and test data into comparable range.

In the second part, rapid changes in the forest were detected from Landsat TM data and, in the third part, the changes detected from satellite images were compared to the recorded man-made changes. Based on the comparison, the stands showing discrepancies between treatment information and image analysis were recommended for field updating (Fig. 10). The third part included also a cost comparison between presented continuous updating with satellite image aided con-

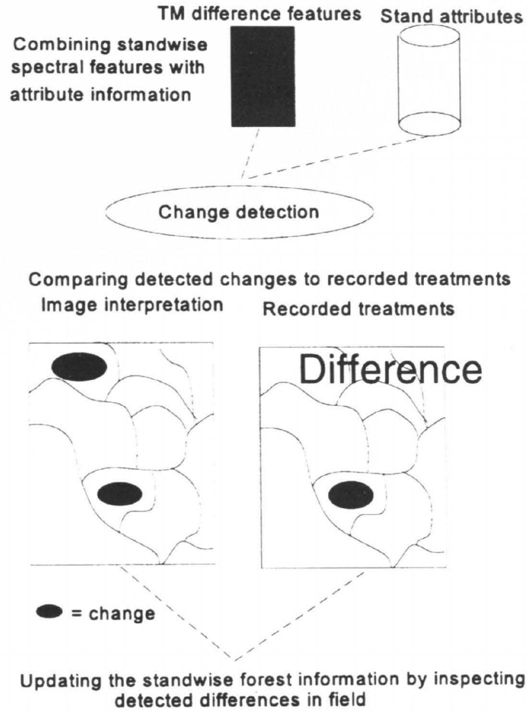

Fig. 10. Detecting changes form multi-temporal TM data and updating the stand information.

trol and traditional updating by repetitive base-line inventories.

The second part consisted of three steps:

1) selecting spectral difference features for change detection
2) combining the old field attribute information with spectral features for change detection
3) detecting stand level changes using nonparametric classifier.

The third part consisted of three steps:

1) the local forest management officer compared the detected changes with the stand treatment records
2) the stands showing considerable discrepancy from previous information sources were recommended for field inspection
3) the applicability of the method for controlling the quality of continuously updated forest information was evaluated by comparing the costs of the methods presented with the old updating by repeating the base-line inventories.

4 Results

4.1 Radiometric Calibration of Multi-temporal Landsat TM Images

Altogether in the three difference images, 93 stands were detected as outliers and three stands as leverage points on mineral soils, and 100 stands as outliers and five stands as leverage points on peat land in the calibration data (Table 5). On mineral soils, 23 % of the detected outliers were young stands of low basal area and all the leverage points were low density pine stands. On peat land, 47 % of the outliers were open bogs and all the leverage points were small stands of low density (Table 5).

Simple regression models were estimated for Landsat TM channels 1, 2, 5, and 7, while for channels 3, 4 and 6 multiple regression was used (see Equation 1) (Table 6). After excluding the outliers and leverage points, the root mean square errors of the final calibration models varied from 0.2280 to 0.9471 (Table 6, Appendix 1, Fig. 11). The coefficient of determination varied from 0.59 to 0.94 with multiple regression and from 0.66 to 0.93 with simple regression. The coefficients of determination should not be interpreted literally because of outlier exclusion. However they are indicative because the same procedure were applied for all the image pairs. Generally, the coefficients of determination were at the same level for H92–H90 and H93–H92 but slightly weaker for H93–H90.

The usefulness of the training data in which treatments were implemented in different years within difference image was examined by Student's t-test with respect to differences of stand means between different treatment classes and the 'untreated' class. The longest time interval, image pair H93–H90, was selected for this comparison. Simple t-test was selected analyse the first order explaining power of different TM channels (Appendix 2). Statistically significant differences were most often found on TM channels 2, 3, 5 and 7. In the case of drastic changes in mineral soil stands, the differences were significant in almost all the TM difference channels except channel four (Appendix 2A1–3, Fig. 12). The only exception was a soil preparation which took place between 1990 and 1991. This was separable only on channel 4 and without any calibration. In the case of majority of moderate changes, the difference was significant at least on one of the difference channels (see Appendix 2A1–3). This indicated that it should be possible to separate at least the treated and untreated stands in the training data on mineral soils on the basis of spectral in-

Table 5. Characteristics of the outliers and leverage points excluded from the calibration data.

	Number	Mean area ha	Sd of area ha	Mean BA m^2/ha	Sd of BA m^2/ha	Outliers H92–H90 D I	D S	Outliers H93–H92 D I	D S	Outliers H93–H90 D I	D S
M outliers	93	5.9	12.4	16.5	8.9	23	27	23	21	33	25
P outliers	100	5.6	8.2	8.2	7.5	37	26	23	16	26	20
M lev. points	3	1.0	0.4	6.3	1.5						
P lev. points	5	1.7	0.9	4.4	2.9						

D 1 = detected from one channel only, D S = detected from several channels.

Table 6. RMSE of the calibration models.

Landsat TM channel	Parameters β_0	β_1	β_2	β_3	β_4	RMSE H92–H90 M	P	RMSE H93–H92 M	P	RMSE H93–H90 M	P
1	*	*				0.4014	0.3089	0.2824	0.2377	0.3828	0.2934
2	*	*				0.4402	0.4005	0.3400	0.3459	0.4068	0.3908
3	*	*		*		0.4226	0.5341	0.3523	0.2695	0.3893	0.3031
4	*	*	*			0.3536	0.2479	0.4979	0.5043	0.4578	0.4164
5	*	*				0.4185	0.6176	0.2648	0.3359	0.3356	0.3546
6	*	*			*	0.8757	0.9471	0.3731	0.4562	0.3036	0.4476
7	*	*				0.5007	0.5331	0.2280	0.2364	0.2999	0.3107

* Effective in Equation 1, M = mineral soils and P = peat land.

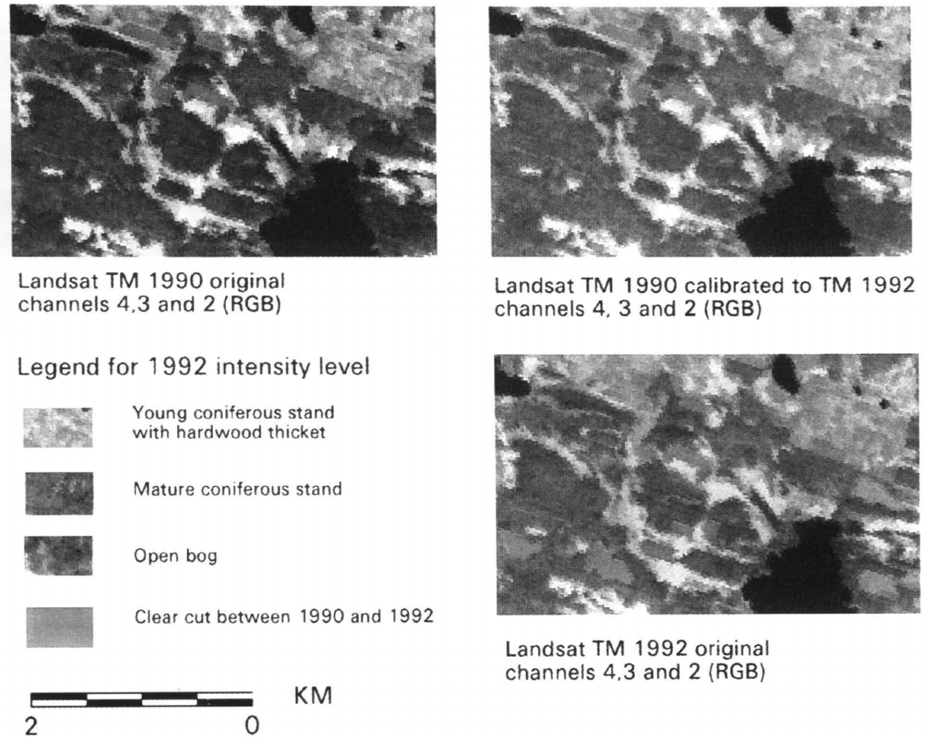

Fig. 11. Radiometric calibration by robust regression, an example from sub-area 3061 on mineral soils. Copyright of the satellite images belong to: ©ESA, 1990 and 1992, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

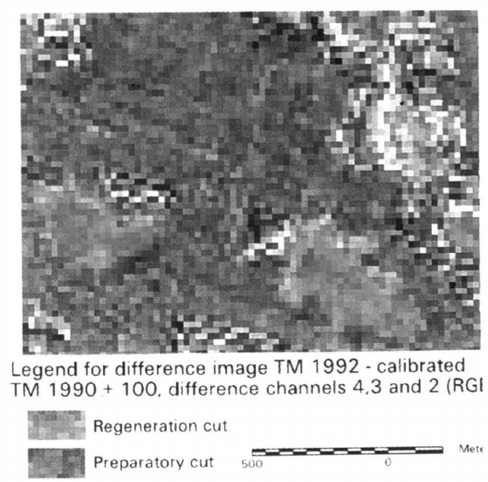

Fig. 12. The regeneration cut and preparatory cut in the regression calibrated difference image. Copyright of the satellite images belong to: ©ESA, 1990 and 1992, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

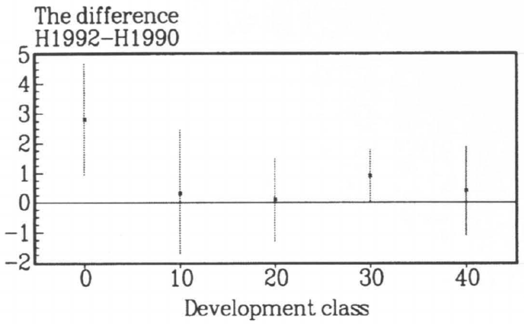

Fig. 13. The stand level mean differences and the standard deviations of the differences at the calibrated and studentized situation on mineral soil in the 'untreated' class on Landsat TM channel 3, H92–H90.

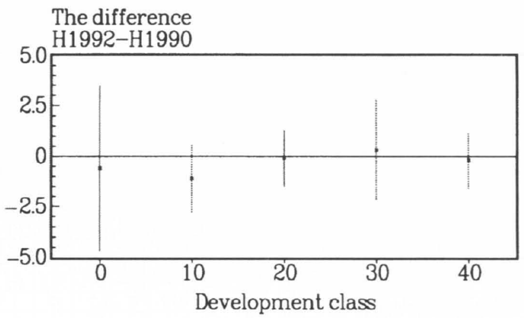

Fig. 14. The stand level mean differences and the standard deviations of the differences at the calibrated and studentized situation on mineral soil in the 'untreated' class on Landsat TM channel 7, H92–H90.

formation (Appendix 2A1–3). On peat land, only the drastic changes were separable on the basis of spectral information (Appendix 2B). The separability of the change classes was not dependent on the implementation time within the three-year interval (Appendix 2). The results of the Student's t-test should be interpreted keeping the multi-comparison problem and the distribution violations in mind.

The effect of the regression calibration and studentization was initially studied by the difference of stand means in different development classes on mineral soils in the 'untreated' class. The development classes used were: 0 = thicket, 10 = young forest 7 cm < D< 17 cm, 30 = moderate age forest D ≥ 17 cm and 40 = mature forest. After the regression calibration and studentization, the image pair H92–H90 showed no statistically significant intensity changes at 5 % risk according to the t-test in any of the development classes in the 'untreated' class (Figs. 13 and 14).

Secondly, the effects of the proposed steps of the radiometric calibration process were tested by comparing the separability of the stand means between the 'untreated' class and the treatment classes after each step. The image pair H93–H90 was used for comparisons on mineral soils (Appendix 2A1–3). There were some differences in the separability of certain treatment classes depending on the calibration. The 'uncommercial thinning' class was more separable in the uncalibrated situation compared to the calibrated data. In the 'commercial thinning' class, the separability was of the same order after all the calibrations. However, TM channel 7 was more important in the uncalibrated situation compared to the calibrated data in the both thinning classes. In the 'preparatory cut' class there were no differences dependent upon the calibration, but the uncalibrated data worked best in the 'hold over removal' class. In the most drastic change classes, i.e. 'clear cut' and 'regeneration cut for natural regeneration', there were no differences dependent upon the calibration. The only exception was in the 'soil preparation' class. None of these changed stands were clearly separable with the uncalibrated data, although, a later soil preparation could be identified based on calibrated data (Appendix 2A1–3). Altogether there were only marginal differences between regression calibrated, and regression calibrated and studentized data.

The possibilities of using generic training data for several separate image pairs was analysed by comparing the differences of the stand mean intensities between regression calibrated and studentized image pairs (Appendix 3). The analysis based on stand means was selected because the difference of the stand mean intensities alone described the used change classes quite accurately (see classification results chapter 4.2). The change classes detected from different difference images on mineral soils in the Hyrynsalmi area showed a similar spectral response on all the Landsat TM channels. The only exceptions were channels 5 and 7 in the 'uncommercial thinning' class, channel 4 in the 'commercial thinning' class, and all the channels in the 'preparatory cut' class. In the 'commercial thinning' class on mineral soils, the image pair H93–H90 showed an increase in TM channel 4 whereas commercial thinning decreased TM channel 4 intensities in all the other difference images. The 'uncommercial thinning' class showed increase in the image pair H93–H90 but decrease in the image pair H92–H90 on channels 5 and 7. A preparatory cut resulted increased intensities in all the channels but the magnitude of change varied between the image pairs (Appendix 3A).

Despite the studentization, spectral changes were different between the Nurmes and Hyrynsalmi areas on mineral soils for almost all the change classes on all the channels. In the 'commercial thinning' and 'clear cut' change classes studentized spectral changes were smaller in the Nurmes test data on all the channels. In the 'HOR' class, changes were larger on all the channels except on channel 4. This may have been because there were only few observations for both test sites specially in the 'HOR' class. The 'untreated' class in the Nurmes test data showed greater differences compared to the Hyrynsalmi test data (Appendix 3A). Without scaling into comparable range, comparisons between the Nurmes and Hyrynsalmi test sites were meaningless (Appendix 3). The range scaling method proposed by Franssila et al.. (1981) (Equation 5) was applied for scaling the studentized training data from different locations.

On peat land, the studentized means H93–H92 showed lower intensity changes compared to H93–H90 from the Hyrynsalmi test site (Appendix 3B). A comparison between Nurmes and Hyrynsalmi was not useful for peat lands because there were so few observations.

4.2 Change Detection

The difference of stand mean intensities, standard deviations, skewness, 25 % and 75 % quartiles for all the TM channels were used for feature selection applying the backward stepwise discriminant analyses (SAS ... 1989). The original DN values were not included because of the need to limit the number of explaining variables and because stand attribute information was available for separating the same types of spectral changes occurring in different forests. In the beginning of the analysis all the previous spectral variables were included in the discrimination model. In each step the explanatory variable which had the lowest squared partial correlation with the change classes was removed until the discrimination model was no longer improved. This was done for each of the three intervals on both mineral soils and peat land using studentized training data. The results of these analysis were combined with Varjo's (1993) selection of explaining variables. The difference variables which had been selected at least three times out of the four analyses, were selected to be used as explaining variables in change detection (Table 7). The only exceptions were the differences of channel 1 and 2 means which were accepted on peat land though they had been selected only twice. All the selected spectral features were studentized according the calibration error and the leverage in the test and in the training data respectively for the test and train-

Table 7. Spectral explanatory variables used in the change discrimination.

Explanatory variable	Landsat TM channel 1		2		3		4		5		6		7	
	M	P	M	P	M	P	M	P	M	P	M	P	M	P
DM_{mean}		*	*	*	*	*	*	*	*	*	*	*	*	*
DM_{Sd}		*		*	*			*	*	*	*			*
$DM_{Skewness}$							*							*
$DM_{25\%\ quartile}$									*		*			
$DM_{75\%\ quartile}$						*							*	

* used as explanatory variable in the change discrimination

ing observations. In addition to spectral information, the old field information employed were the basal area of pine, spruce and birch, and the age of the main storey. According to the stepwise discrimination, the selected texture measure ΔASM on channels 3 and 4 had so low explanation value that it was excluded from the explanatory variables. Consequently, only the change of standard deviation was used as a measure of texture.

The window parameter for discrimination (h in Equation 6) was based on the standard deviation of stand mean differences on Landsat TM channel 3 and number of stands (Varjo 1996). Silverman's (1986 p. 45) approximation was used in the estimation. The window parameters varied from 0.221 to 0.621 (Table 8).

In the discrimination analysis, applying regression calibrated and studentized difference images from Hyrynsalmi area, the correct classification percentage in the training data for all the intervals was 100 on both mineral soils and on peat land. For the image pairs H92–H90 and H93–H92, a part of the training observations were from other difference images (Table 3). When the classification in training data on mineral soils was tested for the image pair H92–H90 using only the differences of stand means from TM channels 2–7 as explanatory variables, the percentage of correct classifications was 96.7. Because of the overlap of the training and the test data consisting of 46 stands, mainly uncommercial thinnings, could not be avoided, the robustness of the method was studied by the Jackknife analysis. The overlap was due to the low number of observations. In the Jackknife analysis the training data were classified by dropping out observations one by one from the analysis and classifying the observation excluded as an independent observation. This test was applied only to the difference images of two- and three-year intervals because with a one-year interval there were too few change observations within the period and it was necessary to avoid the possibility of error caused by using training data from other intervals. The results were almost the same as for the generic training data, i.e., the percentage of correct classifications was 100 except in one case; concerning a two-year interval on peat land there were probably too few observations available in the 'preparatory cut' class. Because of this, seven untreated stands (2.0 %) were classified into the 'preparatory cut' class. The proposed nonparametric change discrimination was compared to a traditional ML solution employing a two-year interval on mineral soil.

Table 8. Window parameters used in the discrimination.

The image pair	Window parameter Mineral soil	Peat land
H92–H90	0.355	0.414
H93–H92	0.221	0.434
H93–H90	0.621	0.600

Table 9. Jackknife change classification results in the training data using the traditional ML classifier with the image pair H92–H90 on mineral soils .

Treatment in the training data	Image analysis by the Jackknife method Unt.	UnC. thinn.	C. thinn.	Prep. cut	Reg. cut N.	Clear cut	Soil prep.	Total	%
Unt.	357	6	8	17			2	390	82.2
UnC. thinn.	1	12						13	2.7
C. thinn.	3		7	1	1			12	2.5
Prep. cut	1			15				16	3.4
Reg. cut N. & soil prep.			1	2	6	1	1	11	2.3
Clear cut & soil prep.	1	1		2	1	17		22	4.6
Soil prep.		1					10	11	2.3
Total	363	20	16	37	8	18	13	475*	100.0
%	76.4	4.2	3.4	7.8	1.7	3.8	2.7	100	89.3

* 25 changes that occurred within H93–H90 are excluded to make sure that possible preparatory actions for 1993 treatments before H92 image, such as opening forwarding tracks or temporary forest roads, do not affect the result.

Table 10. Change discrimination results for the Hyrynsalmi test data using the image pair H92–H90 on mineral soils. Results using the ML classifier are presented in italics*.

Field check	Image analysis Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Total	%
Unt.	436	11	1	8	4		2	1	463	78.1
UnC. thinn.	21	19							40	6.7
	16	*24*								
C. thinn.		1	4	2					7	1.2
	2	*1*	*4*							
Prep. cut	1			9					10	1.7
	2		*1*	*7*						
HOR				1					1	0.2
				1						
Reg. cut N.			2	1		15	1		19	3.2
& soil prep.			*1*	*1*		*15*	*1*			
Clear cut	2		3			1	16	6	28	4.7
& soil prep.			*9*	*5*			*10*	*4*		
Partial clear cut	4		5	3	1		1		14	2.4
or Reg. cut N.	4		1	2			1		8	1.3
	9	*2*	*7*	*4* (combined)						
Soil prep.										
Drain.	2								2	0.3
	2									
Wind damage				1					1	0.2
	1									
*Total	470	31	16	27	5	16	21	7	593	100
%	79.3	5.2	2.7	4.6	0.8	2.7	3.5	1.2	100	86.7

*Summary information concerning the ML classification is not presented because of the lack of information for the 'untreated' class.

With the above mentioned Jackknife classification of the training data, the ML classifier resulted in 89.3 % correct classification (Table 9).

The effect of studentization was studied by classifying the Hyrynsalmi training data without studentization. As could be expected based on the analysis during the calibration, the results were exactly the same as with the studentization. The usability of the studentized training data was tested by dividing the training data into two parts; changes were detected from H93–H92 using the training data from H92–H90. On the mineral soil, the percentage of correct classification was only 1.7 percentage unit lower compared to the situation including the training data from H93–H92. (Table 11, Appendix 4B and 5A). Concerning peat lands, omitting the training observations from H93–H92 seemed to slightly improve the results. This may, however, result from the differences in the standard deviations between the H93 and other Landsat TM images from the Hyrynsalmi area as well as from the uneven distribution of the peat land training observations at different intervals (Table 11, Appendix 4E and 5B).

In the test data, the percentage of correct classifications when using studentized explainers varied from 55.3 % on peat land to 86.7 % on mineral soils depending on the interval between the images (Table 10 and 11, Appendix 4). The ML classifier was compared to the selected nonparametric classifier by classifying the changed stands in the test data on mineral soils. Unchanged stands could not be used because all the stands which were found to be changed by the ML classifier could not any more be inspected in the field. When classifying the changed stands only, the correct classification for the ML classifier was 56.2 % and 60.0 % for the selected nonparametric classifier. If any change classified to a change class was considered to be correct in this test, the percentage of correct classification was 75.4 % using ML and 73.8 % using the selected nonparametric classifier (Table 10).

To examine the possibility of using generic training data from geographically different locations, the Hyrynsalmi training data were classified by using the training data of Nurmes (Varjo 1996) and vice versa. For these experiments the explaining variables were studentized stand level differences of means for TM channels 3–7, difference of skewness for TM channel 7 and differences of standard deviations for TM channels 2, 3, 6 and 7 and the basal area (Varjo 1996). It became obvious that the ranges of the regression calibrated and studentized difference images were different between these test areas (Appendix 3A). These $\Delta M_{(m)i}$ were smoothed by range scaling the studentized differences into the same mean and variance (see Equation 5). The training observations from the area not covered by the difference image under classification seemed to perform quite nicely after the range scaling. At least, when broad change classes such as employed in the Nurmes data are accepted, a useable accuracy can be achieved (Table 11, Appendix 6).

4.3 Change Detection Errors

4.3.1 Change Class Labelling Errors

The classification errors which occurred with the nonparametric classifier for the Hyrynsalmi test data were analysed on the basis of the stand register and the observations made during the field checking. (Tables 12 and 13). The accuracy of the classification in the 'untreated' class was controlled by a sequential sampling. According to the sequential sampling scheme, the stands classified into the 'untreated' class were untreated at 5 % risk. The aim was to find possible reasons for classification errors or to determine common denominators which could possibly permit the omission of part of the unchanged stands which were classified as changed out from the field inspection (Fig. 15). Only the error classes including at least two stands were analysed. In addition, errors with partial treatment, soil preparation and uncommercial thinnings on peat lands were not included in Tables 12 and 13 because they were obviously caused by timing problems and unclosed canopy. The most serious error was the classification of a changed stand as 'untreated'. There were only two clear reasons for this error. A high proportion of deciduous species caused some stands to be classified into the 'untreated' class although they really belonged to the 'preparatory cut' class. Such stands were not present at the training data

Table 11. Correct classification percentages with different combinations of the training and test data.

Test data	Training data	Number of classes training/test	Correct classification % In training data	In test data	95 % confidence level
N90–N88 Mineral soil	N90–N88 (Varjo 1993)	4/4	100.0	*98.3	97.4
N90–N88 Peat land	N90–N88 (Varjo 1993)	4/4	97.9	*91.1	88.9
H92–H90 Mineral soil	H92–H90, H93–H92	8/12	100.0	86.7	84.3
H93–H92 Mineral soil	H92–H90, H93–H92	8/12	100.0	75.2	72.2
H93–H90 Mineral soil	H93–H90	8/12	100.0	78.2	75.3
H92–H90 Peat land	H92–H90, H93–H92	9/12	100.0	71.5	64.4
H93–H92 Peat land	H92–H90, H93–H92	9/12	100.0	74.0	67.1
H93–H90 Peat land	H93–H90	9/12	100.0	55.3	47.5
H93–H92 Mineral soil	H92–H90	7/6	100.0	73.5	68.3
H93–H92 Peat land	H92–H90	5/4	100.0	74.9	69.8
H93–H90 Mineral soil	N90–N88	4/8	100.0	*85.4	84.6
N90–N88 Mineral soil	H93–H90	4/4	99.8	*80.2	76.6

* Changes grouped according to (Varjo 1993): untreated, moderately changed and drastically changed.

Table 12. Properties of completely erroneously classified stands on mineral soil stands in the Hyrynsalmi test data.

Field inspection	Image interpretation	BA pine m²/ha Mean/*Sd* 92–90	93–92	93–90	BA deciduous species m²/ha Mean/*Sd* 92–90	93–92	93–90	BA spruce m²/ha Mean/*Sd* 92–90	93–92	93–90	Age of the main storey years Mean/*Sd* 92–90	93–92	93–90	Mean height m Mean/*Sd* 92–90	93–92	93–90	Mean diameter cm Mean/*Sd* 92–90	93–92	93–90	Classification probability to correct class* Mean/*Sd* 92–90	93–92	93–90
UnC thinn.	Unt.	2		1	1		1	0		0	22		23	4		4	6		5	0		.1
		3		*2*	*1*		*2*	*1*		*0*	*10*		*9*	*2*		*3*	*3*		*2*	*.1*		*0*
C thinn.	Unt.			14			2			2			60			11			16			0
				6			*2*			*5*			*42*			*4*			*5*			*0*
Prep. cut	Unt.			6			8			3			60			10			12			.1
				8			*7*			*3*			*34*			*4*			*5*			*.1*
Clear cut	Unt.	6			2			5			59			15			27			0		
		8			*3*			*8*			*65*			*7*			*3*			*0*		
Damage	Unt.			2			0			0			130			19			26			
				0			*0*			*0*			*0*			*1*						
Unt.	UnC thinn.	2	0	2	1	0	0	1	0	1	23	12	20	5	3	4	8	6	8	0	0	.2
		4	*1*	*2*	*1*	*1*	*1*	*3*	*1*	*4*	*25*	*10*	*26*	*4*	*2*	*3*	*6*	*3*	*4*	*0*	*.1*	*.2*
Unt.	C thinn.		11	10		2	1		3	1		64	39		10	8		16	13		0	.2
			5	*5*		*2*	*4*		*4*	*1*		*46*	*38*		*5*	*4*		*9*	*7*		*.1*	*.2*
Unt.	Prep. cut	20	18	20	2	1	21	1	2	3	106	111	113	16	16	17	24	25	25	0	0	.1
		7	*6*	*6*	*2*	*2*	*2*	*2*	*3*	*2*	*34*	*34*	*25*	*4*	*3*	*2*	*7*	*6*	*4*	*0*	*0*	*.2*
Unt.	HOR	2	1	2	1	0	0	1	0	0	25	14	16	6	3	4	8	6	6	0	0	.1
		2	*1*	*3*	*2*	*1*	*0*	*1*	*0*	*0*	*17*	*7*	*14*	*1*	*2*	*3*	*3*	*2*	*4*	*0*	*0*	*.2*
Unt.	Clear cut	6	6		1	1		2	2		75	57		13	11		21	16		0	0	
		7	*8*		*1*	*1*		*5*	*2*		*87*	*62*			*7*		*2*	*10*		*0*	*0*	
Unt.	Reg. cut N.		8			3			4			145			16			23			0	
			8			*3*			*4*			*23*			*4*			*6*			*0*	

*See equation 7.

(compare Tables 1 and 12). Furthermore, on peat lands the obvious reason for errors in the 'commercial thinning' class was the greater proportion of deciduous species than in the training data (compare Tables 2 and 13). All the damaged stands were not recognized as having changed, but they did not exist in training data; neither did drainings occur in the mineral soils' training data. The misclassification from the 'soil preparation' class to the other change classes were probably due to the fact that there was often no information available in either the training data or the test data to separate the spectral responses from treatments aiming at regeneration and soil preparations.

The reasons were more obvious for the classification errors in the opposite direction, i.e. in the cases when unchanged stands were classified into the change classes. In the training data, the 'uncommercial thinning' class was represented only by the cleaning of sapling stands, while in reality various different treatments, such as the clearing of a felling area, had spectral responses close to this training class. In addition, the cleaning of a sapling stand was often done in such a way that only the most dense parts of the stand were treated. In such a case, the spectral response from the whole stand changed less than when the whole stand was treated. Another reason decreasing the separability of this class may be the larger variation on young untreated stands compared to the older ones (see Fig. 13). On mineral soils in the 'commercial thinning' and 'preparatory cut' classes, the possible reason for misclassification was again the greater proportion of deciduous species than in the training data, especially with respect to the 'preparatory cut' class. The 'HOR' class was sometimes confused with improvement cuttings, and this was obviously caused by the sparse density of the growing stock and thus spectral response from ground vegetation.

Errors in the 'clear cutting' class were surprising and no obvious reasons for them were found. One possibility may be that in some stands the attribute data were already updated according to the situation after the clear cut while in the others it was not. However, the clear cut classifications were not affected when the classification was tested without using basal areas and age as explaining variables.

Table 13. Properties of completely erroneously classified stands on peat land stands in the Hyrynsalmi test data.

Field inspection	Image interpretation	BA pine m²/ha Mean/*Sd*			BA deciduous species m²/ha Mean/*Sd*			BA spruce m²/ha Mean/*Sd*			Age of the main storey years Mean/*Sd*			Mean height m Mean/*Sd*			Mean diameter cm Mean/*Sd*			Classification probability to correct class** Mean/*Sd*		
		92–90	93–92	93–90	92–90	93–92	93–90	92–90	93–92	93–90	92–90	93–92	93–90	92–90	93–92	93–90	92–90	93–92	93–90	92–90	93–92	93–90
C thinn.	Unt.	2	2	1	11	11	0	0	0	0	30	30	*	12	12	*	13	13	*	0	0	0
		0	*1*	*1*	*2*	*1*	*0*	*0*	*0*	*0*	*15*	*12*	*	*2*	*1*	*	*1*	*1*	*	*0*	*0*	*0*
HOR	Unt.	*			*			*			*			*			*			0	.1	1
																				0	*.1*	*.2*
Unt.	C thinn.		11	8		1	2		1	4		65	66		9	10		13	14		0	.1
			3	*6*		*1*	*3*		*1*	*6*		*21*	*40*		*3*	*4*		*3*	*5*		*.1*	*.1*
Unt.	Prep. cut	1	3	2	0	1	0	0	0	0	12	19	16	6	6	5	7	8	7	.1	.1	.1
		2	*4*	*3*	*0*	*2*	*1*	*0*	*1*	*0*	*18*	*22*	*19*	*2*	*3*	*2*	*3*	*4*	*3*	*.1*	*.2*	*.2*
Unt.	Drain.			1			0			0			33			4			7			0
				2			*0*			*0*			*32*			*2*			*3*			*0*

* No information recorded
**See equation 7.

On peat land, the reasons for errors in the 'uncommercial thinning' class were similar to those for mineral soils. Untreated sparse and low volume stands were sometimes classified into the change classes such as 'commercial thinning' or 'preparatory cut'. In such cases, the tree canopy may not have been the main reflecting element, and differences in moisture, and consequently in the ground vegetation, may have caused spectral changes which were misinterpreted. Another reason may be the rapid growth in young stands which may affect the detected intensities especially concerning the treatments from the beginning of the analysis interval. Such stands can be left out of the field inspection without risking the quality of the continuously updated stand information.

4.3.2 Change Delineation Errors

When the delineation of the man-made changes was examined by comparing the clear cut and regeneration cut for natural regeneration areas, which were clearly visible, to the existing stand delineations it was obvious that several errors existed (Fig. 16). Two new aerial photographs corrected to orthogonal projection and covering sub-area 3061 were used for studying the delineation errors and the possibilities for a more precise re-lineation. The reference delineation for clear cut and regeneration cut for natural regeneration areas was made from these aerial photographs. Two types of errors could be identified by comparing the screen digitized delineations from TM images and the present delineation from the map base with the reference delineation. The error types were commission errors, i.e., untreated areas, which had been delineated as treated areas, and omission i.e., where treated areas had been delineated as untreated areas (Table 14). The change discrimination algorithm presented was not tested with respect to the change delineation as it was not applicable at the pixel level. As an alternative approach, screen digitization from single and difference image were tested for correcting the errors in the delineations of drastic treatments. It was demonstrated that the change delineation errors concerning drastic change classes can be improved by screen digitization from Landsat TM data (Table 14, Fig. 17).

Table 14. Possibilities to correct delineation errors from Landsat TM data.

Examined delineation	Correct delineation area %	Commission error area %	Omission error area %
Present delineation	54	25	21
Clear cut and reg. cut N. delineation from H92	85	14	1
Clear cut and reg. cut N. delineation from H92–H90	77	17	6
An example of one screen digitized preparatory cut H92–H90	69	13	18

4.4 Costs of the Methods Presented

The estimated decrease of field work with continuous updating controlled by the proposed method was compared to the old updating method using repetitive base-line inventories. The need for field inspections in the test data were estimated for a hypothetical ten-year-control period by assuming that the level of the changes from one- to three-year control periods remain constant during the whole ten-year period. The final costs were estimated for a thirty-year period by multiplying the ten-year period costs by three. The thirty-year period was supposed to be the maximum interval for the applicability of the available growth models and thus the maximum interval between two base line inventories when applying continuous updating.

The district officer responsible for the treatments in the area compared the presented change classification results with treatment information and present attribute data. Based on this comparison, all the stands from the test data were divided into three decision categories according to the need for further field inspection (Varjo 1996):

a) No need for field inspection; no differences between image analysis and recorded treatments.
b) No need for field inspection although the change detected from satellite images differed from the

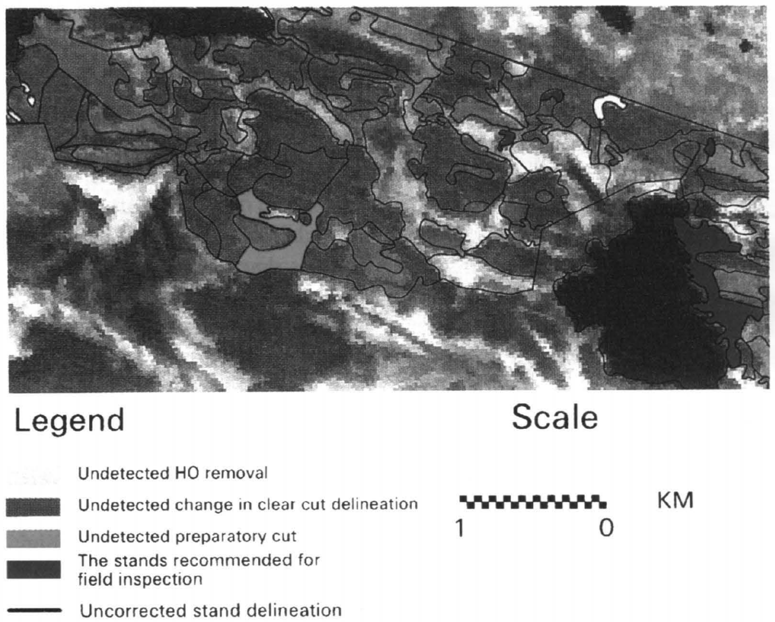

Fig. 15. The change classification errors in sub-area 3061. Copyright of the background satellite image belongs to: ©ESA, 1993, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

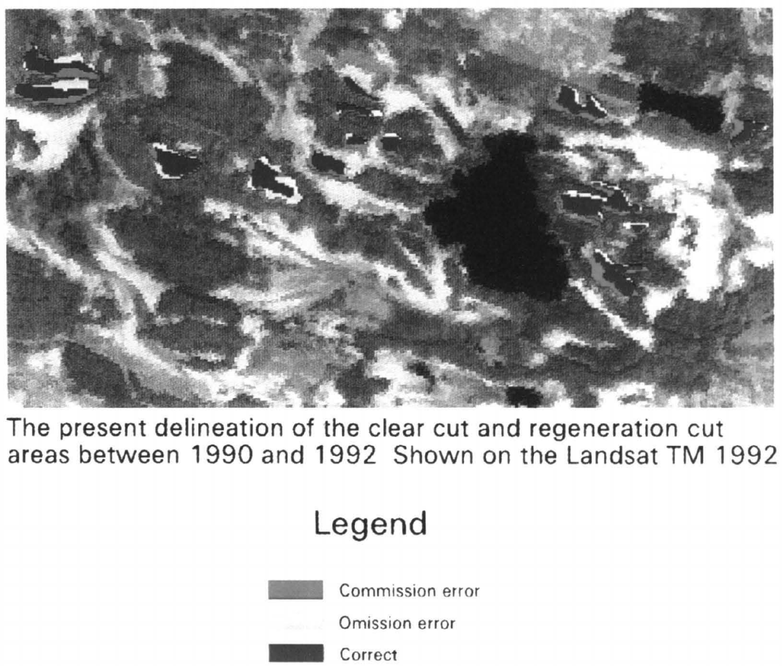

Fig. 16. The change delineation errors in the existing stand delineation with drastic changes in sub-area 3061. Copyright of the background satellite image belongs to: ©ESA, 1992, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

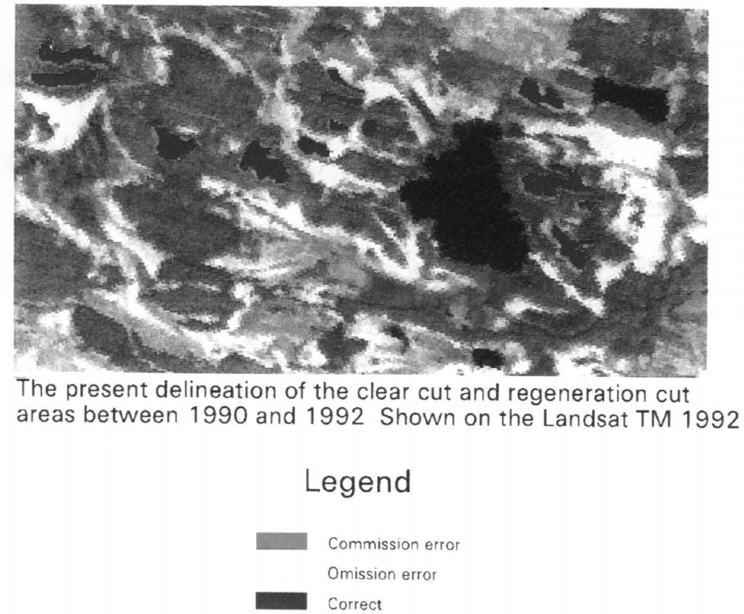

Fig. 17. The change delineation errors with drastic changes after correction by screen digitizing. Copyright of the background satellite image belongs to: ©ESA, 1992, EURIMAGE, National Land Survey of Finland/Satellite Image Centre.

recorded treatment. The difference was not considered to affect the planning of future treatments and thus a field inspection was not recommended. For example, commercial thinning in the treatment list was labelled as a preparatory cut in the change detection.

c) Field inspection is recommended; the image analysis differed considerably from the registered treatment or the existing stand attribute data.

From the stands which were labelled as changed, 27 to 39 % belonged to the category c within one image pair, depending on the time interval between the images (Table 15).

The distribution of the stands into decision categories was used to estimate the need for field inspection during a ten-year inventory period. The proportion of all the stands recommended for field inspection varied from 34.5 % on mineral soils with 5 TM image pairs to 100 % with 3 image pairs on peat land and with 10 image pairs on mineral soils (Table 16).

The costs of the method presented were estimated based on costs of the geo-corrected Landsat TM data on mineral soils. The costs of the image analysis were assumed to be part of the fixed costs as great deal of the proposed system can be automatized. The image analysis costs were assumed to be unchanged between different intervals applied. The effective cover of the TM image for the FPS for the Hyrynsalmi test area was 40 % and the price of a geo-corrected Landsat TM quadrant with value add tax in Finland was 26 474 FIM. The costs of the field inspection were estimated to be 50 FIM per hectare. With these parameters, the image costs varied from 0.27 FIM to 0.80 FIM per hectare for a ten-year-period varying according to the number of images needed (Table 17).

Several aspects should be considered when evaluating the results from a financial point of view. First, the updating is missing or erroneous for only a small proportion of the treated stands. Similarly, the proportion of the stands in which there has been significant damages, is small. According to the comparison of the treatment information and image analysis, the joint proportion of these kinds of stands varied between 1.5 % for

Table 15. The distribution of the detected changes into decision categories according to the need for field inspection.

Control period	Number of proposed changes	Decision classes a, % M	a, % P	b, % M	b, % P	c, % M	c, % P
H92–90	146	35	3	22	6	27	7
H93–92	216	8	4	40	6	38	4
H93–90	284	22	3	16	7	39	13

Table 16. Percentages of stands recommended for field inspection in different image intervals.

Control period	Stands recommended for field inspection between two images on mineral soil, %	on peat land, %	Stands recommended for field inspection within a hypothetical ten-year-period with 3–10 Landsat TM images on mineral soil, %	on peat land, %
H92–H90	6.9	8.9	34.5	44.5
H93–H92	13.8	8.1	*	81.0
H93–H90	18.7	30.1	62.3	*

* According to the results, all the stands should be reinventoried.

Table 17. Image costs of the proposed satellite image analysis.

Lenght of the control period years	Number of acquisitions needed	Cost of one acquisition, FIM/ha	Estimated costs for a 10-year-period, FIM/ha	Percentage of stands recommended for field inspection within a 10-year-period on mineral soil
1	10	0.08	0.80	100
2	5	0.08	0.40	34.5
3	3.3	0.08	0.27	62.3

a tree-year control period to 2.5 % for a one-year control period on mineral soils in the test data. The largest proportion of updating for the shortest control period was due to errors in the 'soil preparation' class and delays continuous updating procedure for the treatments. When the proportion of incorrectly updated stands was combined with the proportion of serious errors in the change classification as a whole, the maximum proportion of erroneously updated stands was under 1 % after the proposed control on mineral soils. On peat land the proportion of erroneously updated stands after the control was 2–3 %. These figures can be considered as rough accuracy estimate of the stand level attribute information after continuous updating controlled by training data from the same geographical area and with the information subjected to quality control. This estimate does not include the possible errors caused by growth models for long updating periods between base-line inventories.

Because of the great number of classification errors between change classes in the one-year-interval, only two- and three-year-intervals on mineral soil were included in the cost estimation. Only mineral soil stands were included because the amount of peat land test data was low. The 'soil preparation' class could be separated only from the latest one-year-interval and there were several errors in the classification from this class to the other change classes. In this situation it was supposed that the cost estimation would give too negative results for one-year-interval.

The image costs varied from 0.27 FIM per hectare with a three-year image interval to 0.4 FIM per hectare with a two-year image interval for the

ten-year hypothetical control period. With the same intervals, the percentage of stands recommended for field inspection respectively were 62.3 and 34.5 % in all stands on mineral soil. This means that for two-year control periods, every stand would be field inspected about once in every thirty-year-period. By a very rough estimation, to be economic, the costs of controlling the quality of continuously updated field information should be lower for a thirty-year-period compared to three repetitive base-line inventories within this period; assuming that both methods were started in a situation where the base-line inventory had just been accomplished before the beginning of the period. It is assumed that for the whole period, stands are field inspected separately, i.e. without any information from field inspections during the previous two- or tree-year-interval.

The costs of the controlling the quality of information by satellite images with a two-year-interval between the images would be 1.2 FIM per hectare for a thirty-year-period. This has to be summed with the costs of the field inspection required which is 1.035 (i.e. 3 × 0.345) times the total base-line inventory for the thirty-year-period, totalling 52.95 FIM per hectare. When these costs are compared to the costs of base-line field inventories (approximately 50 FIM per hectare multiplied by three for the thirty-year-period) the final costs of the traditional system for a thirty-year-period are 150 FIM per hectare. With a three-year-interval, the image costs for the proposed method would be 0.80 FIM per hectare, and the costs of field inspecting 1.869 (i.e. 3×0.623) times the total base-line inventory costs, totalling 94.25 FIM per hectare. On the other hand, the inventory costs using a traditional stand level inventory were estimated to be much lower for the FPS mainly because of the large average stand size in the test area. The estimated costs per hectare were 24 FIM under these circumstances. The comparison would then result in 72 FIM/ha for the traditional repetitive inventory and 26.04 FIM/ha and 45.66 FIM/ha for continuous updating controlled by the remote sensing method proposed with two- and three-year-intervals respectively between the images.

The cost estimation can be questioned because the field inspection of only a few stands revealing possible change would increase the costs per hectare compared to normal base-line inventory. However, in practice the inspection can be combined with other necessary work such as delineation of cutting areas or monitoring the cutting work, and so the cost estimates are probably indicative; even though they must not be considered absolutely accurate. In addition, the costs of the remote sensing data, such as Landsat TM in this study, are very low compared to the costs of field work. This may enable the economical use of the method proposed, even in the case of a lower effective cover than 40 % or with somewhat higher control inspection costs. If the effect of changes in the effective cover or field inspection costs are estimated on the basis of the current costs of TM images in image pairs for two-year intervals for a thirty-year period, the costs of the proposed method, continuous updating with control, remain lower in all the combinations compared to updating by repetitive inventory (Figs. 18 and 19). This indicates that the change detection would be economic for controlling continuous updating also on peat land at least with two-year image interval.

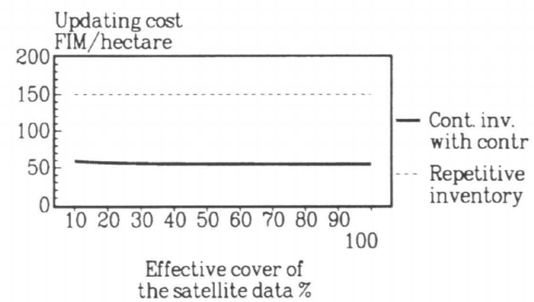

Fig. 18. Total updating cost as a function of effective cover % of satellite data over a thirty-year-period.

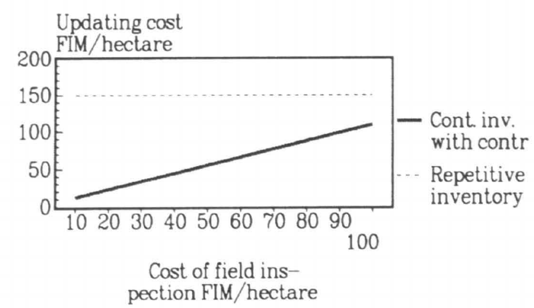

Fig. 19. Total updating cost as a function of field inspection cost over a thirty-year-period.

5 Discussion

5.1 Calibration for Producing Generic Training Data

The results of the regression calibration were satisfactory when the root mean square errors (RMSE) of the calibration models were compared to the magnitude of the changes to be detected. On mineral soils, the smallest statistically significant change between stand mean intensities in the two calibration alternatives was 0.8 DN on Landsat TM channel 2 for the 'uncommercial thinning' class after regression calibration (Appendix 2A3). Generally, this class caused the smallest change in stand mean intensities. The RMSE of the calibration for channel 2 varied from 0.3 to 0.4 DN, which should not prevent the detection of this magnitude of change. The results of the calibration matched those of previous results (Chavez and MacKinnon 1994). The RMSEs of the calibration models were of the same magnitude as Varjo's (1996) and Olsson's (1993, 1994a). Significant differences in RMSEs or coefficients of determinations were not detected when the multiple regression results from channels 3, 4 and 6 were compared to simple regression on other channels. The multiple regression was used only with channel pairs: 3, 4 and 6. For other channels, multiple regression was not found to improve results in a way which would have favoured the use of it.

The number of outliers detected in this study was greater than in Varjo's (1996) study. Sparse stands where soil and under storey vegetation effect the detected spectral response were easily detected as outliers. This was because the spectral changes were partly caused by changes in the understorey. In addition, many of the outliers were one-channel specific. Nonetheless, detecting and excluding outliers based upon strict rules seems to be feasible. If only the most exceptional observations were excluded, the risk of existence of hidden outliers could still affect the calibration (Rousseeuw and Zomeren 1990). Naturally, extensive exclusion of observations can only occur where there are enough observations to represent variability of all the age and forest type classes in the calibration data. Such was the approach in this investigation where 24 % of the observations were excluded from the calibration of mineral soils and 31 % on peat land. If the exclusion by the rules presented would have resulted in an insufficient number of observations, the weighting of the outliers instead of their exclusion could have been considered (Olsson 1993).

T-tests showed only little difference in the separability between treatment classes and the 'untreated' class between the regression calibrated difference images, the regression calibrated and studentized difference images and the uncalibrated difference images based on stand means over a three-year-interval (compare Häme 1991). The spectral changes caused by different treatments after regression calibration corresponded well to those estimated by absolute calibration (Nilson and Peterson 1994, Muinonen 1995). TM channel 4 was found to show a varying spectral response, e.g. after thinning (Häme 1991, Olsson 1994a). Olsson (1994a) has proposed this to be due to decreasing proportion of deciduous trees in cutting. In this work the effect of removing deciduous trees was noted clearly later as change detection errors in mixed species stands which were not present in the training data.

Based on empirical results the applicability of the proposed linear calibration in the case of a single image pair does not seem very clear. The calibration affects the change detection and improves the results in some cases. However, the detected differences between a calibrated and an uncalibrated single image pair were minor; but analysing and labelling the different change types has been shown to be easier from calibrated than from uncalibrated data (Chavez and MacKinnon 1994, Varjo and Folving 1997).

When studying the effect of the time of change within a three-year-interval from the studentized image pair H93–H90, the changes from the middle of the period generally caused smaller spectral responses compared to the changes at the beginning of the period with respect to the commercial thinning and preparatory cut classes. It was expected that normal growth would tend to cover any changes from the beginning of the interval making them more difficult to detect. However, on the basis of the stand means, thinnings from 1990–1991 were separated more easily than thinnings from 1991–1992. This is obviously because of the low number of observations. Concerning more drastic change groups, the time of the changes had no effect on the separability of the changes. A regeneration cut for natural regeneration between 1992–1993 caused a smaller spectral response than earlier observations with all the three calibration alternatives used. This was probably because there were only two observations available from this period. Generally, the results of the statistical tests concerning both the separability and the time of the changes should not be interpreted literally because of a small number of observations in some classes.

The calibration results were fairly good when applying training data from the same geographic location, but from different image pairs. This indicates a possibility of employing such a generic training data which was aimed in this study. However, the change ranges were too different when the Hyrynsalmi and Nurmes data were employed. This may indicate that studentization does not work if training data from different geographical locations are used or the difference images applied are not similar enough (Appendix 3). A possible reason for this effect may be the phenological changes between the images: the earlier image from Nurmes was from early spring unlike the two Hyrynsalmi images employed in this test. On peat land, the comparison between Hyrynsalmi and Nurmes data was not usable because of the sparsity of observations. One possibility to overcome these problems could be robust studentization, i.e., excluding or giving smaller weight to the observations with most exceptional residuals in the studentization (Olsson 1994a).

5.2 Change Detection by Remote Sensing for Controlling Continuously Updated Forest Information

The ASM texture measure which had a reasonable explanation value for describing within-stand variation with mono-temporal data (Hyppänen 1994) had a low explanation value when used for change detection. One reason for this might be that the analysis window used (3 × 3 pixels) may not have been the best scale for detecting stand level changes. Another possible explanation might be that the assumption concerning the increase of spectral homogeneity after silvicultural treatments can be made in only a few cases; even in the training data where, for example, partial treatments were not present. In this case, the measure of homogeneity, such as ASM, is not useful as a texture measure for change detection. The selection of other spectral variables for detecting change produced results similar to those from previous studies (Häme 1991, Varjo 1993, Olsson 1994a). Compared to Varjo's (1996) results the only exception was that in some cases the quartiles used in the present work replaced the central moment, which was selected in the earlier study. In addition to the selected explaining variables the original stand level DN values might have some explanation value. They could help the separation of the change classes with similar spectral response but in different age forest and thus from different operation for example. However, in this work they were excluded because of the need to keep the number of explaining variables low enough and because the old field information was available for above described separation of changes in different forests.

The analysis of the explanation values of the TM difference channels revealed that channel 7 had considerable explanatory power in change detection (Olsson 1994b, Lambert et al. 1995). The use of TM channel 4 seems problematic because while it may have certain explanatory power in change detection, the direction of the change of intensity is unstable and varies within some of the given change types (Häme 1991). Channel 4 might work better in unsupervised approaches to change detection. An examination of the ability to detect changes using only the differences of stand means as explanatory variables with the training data gave correct classification results which were 3.3 percentage units lower compared to the discrimination with all the selected explanatory variables for a three-year-interval. The difference is not great in terms of percentage units, but when considering the traditional ten-year-inventory cycle it is obvious that an additional 10 % error is not acceptable because of the increasing need for field inspection. Consequently, changes cannot be detected accurately enough for control purposes by using only the differences of stand means.

The window parameters for change discrimination were selected by Silverman's (1986) approximation, based on the stand mean differences on Landsat TM 3 and the number of observations. The window parameter had the highest values with the longest interval. A possible reason for this is that the spectral change due to treatments becomes smoother as the time interval increases. This may partly explain the fact, discussed above, that the changes described by differences of stand means are not always sufficient, especially over short intervals where violations such as nonsymmetricity in parametric distributions become most obvious.

When the results of the change classification based on the test data using two-year-interval were compared to those of Varjo (1993, 1996), the percentage of correct classifications was about 10 percentage units lower on mineral soils and about 20 percentage units lower on peat land in the current work. The lower percentage of correct classifications was obviously due to the increased number of change classes with more accurate labelling of the change type (e.g. Lambert et al. 1995). This could be expected, especially as several spectrally weak change classes such as 'uncommercial thinning' or 'draining' were included (e.g. Muchoney and Haack 1994). The correct classification percentage varied according to the interval by almost ten percentage units on mineral soils and almost twenty percentage units on peat land.

It was not expected that the best accuracy would be achieved for mineral soils with a two-year-interval rather than a one-year-interval. There were at least two reasons for this. The first was the separability of the 'soil preparation' class which was often confused with the other change classes in the case of one-year-interval. The soil preparations could only be separated from the latest image pairs by field inspection. In earlier image pairs, soil preparations were combined with treatments aiming at regeneration and were consequently not erroneously classified. The second was the unequal distribution of the training data between the various intervals. In addition, the differences in standard deviations, especially between H93 and other images from Hyrynsalmi, may have had some effect. In the regression calibration, the standard deviation of the regression calibrated image can be expected to be lower compared to the original image. This is because the regression will always smooth the results. Consequently, there may be small additional artificial changes in the differences of standard deviations due to the regression calibration.

The useability of the studentized generic training data was tested by classifying the changes in the test data without studentization. As expected, there was no difference in the results when using the image pair H93–H90 with and without studentization. However, detecting the changes between H93–H92 using only the training data from the image pair H92–H90 slightly decreased the correct classification percentage on mineral soils (Appendix 5A). This may indicate that having at least some training observations from the image pair being analysed for changes improves the results and may explain the superiority of the two-year interval in this work. On peat land, excluding the training observations from the period 1993–1992 seemed to slightly improve the change classification, but this must be due to the insufficient amount of available data. When it was possible to use training data from a totally different area by using Varjo's (1996) broad change classes, the result was acceptable; but only if these change classes were considered to be accurate enough for controlling purposes. Jackknife analysis confirmed that the change classification results presented were reliable even though there was some overlap between the training and test data concerning single treatment observations. Jackknife analysis was selected to allow partial overlap for keeping the amount of the training observations at reasonable level with all intervals.

The selected nonparametric classifier was compared to the traditional parametric ML classifier by means of the Jackknife discrimination of the training data. The percentage of correct classifications was about ten percentage units lower when using the ML classifier than the result with selected nonparametric classifier. However, when only the change classes from the test data were classified by the ML classifier, or only treated and untreated stands were separated, the differences were smaller compared to the results with the nonparametric classifier. This indicates that with the ML classifier, problems caused by mixing between the 'untreated' class and the 'moderate change' classes, and especially within the 'moderate change' class, are even greater than in the case of the nonparametric classifier.

Because of the stand level approach, the accuracy of the delineation of the treatments aiming at regenerations was studied by comparing the new screen digitized boundaries and boundaries from the operational database with reference delineation from aerial photographs. The comparison showed that despite updating the delineation, the realized treatments differed from the lineation in the database. The obvious reason for this was that stand delineations made for management planning purposes, even for as short as a ten-year period, are not flexible enough for the short-term planning of harvesting. To enable management planning boundaries to be followed when realizing cuttings, the stand size should be so small that any combination of amounts and assortments of timber could be formed by combining these small stands. So far, this has been impossible because of inventory costs and technical problems related to the handling and locating of very small stands. However, promising results have been presented to decrease the size of the observation unit down to the plot level in a base-line forest inventory and monitoring (Hagner 1990, Tomppo 1992). If it became operational, such a system could reduce the need for the re-lineation of changes. In the present situation, however, it has to be accepted that stand delineation is sometimes changed because of the demand for certain timber assortment or simply because the stand delineations on a map and those made in field do not completely match. Such errors have to be corrected, at least with treatments aiming at regeneration which form the basis for forest generations and consequently define new stands.

This study has shown that at least existing delineations can be corrected by simple screen digitizing to the level where 85 % of the regeneration and clear cut areas were delineated correctly. As an alternative to manual delineation good results have been introduced with spatially more accurate images. Olsson (1994b) achieved over 90 % re-lineation accuracy in clear cut areas and over 80 % accuracy in thinning cut areas by applying image segmentation and discriminant analysis to multi-temporal SPOT images. With the manual approach in the present work, most of the errors after correction were due to the fact that too large an area was delineated to be treated. This commission error can possibly be decreased by personnel training. It was surprising that the delineation accuracy achieved with the difference image was slightly lower compared to that with single images. This may be due to the effect of the mixed pixels on the difference image. Another possible reasons may be the non optimal look up table setting and unfamiliarity of the personnel with difference images. The delineation of lighter treatments such as thinnings was not normally a problem compared to treatments aiming at regeneration. This was because, for example, thinnings yielded much less commercial timber and thus there was no need to relineate thinning areas because of changing market demands. If delineation errors existed with treatments such as thinnings, they were mostly due to inaccuracies between stand maps and the delineation of the thinning area in the field.

The percentage of stands with changes recommended for field inspection was only half of that found by Varjo (1996), but this was because a more accurate treatment information was available for the Hyrynsalmi test site. The percentage of category '*c*' stands from all stands in the best case with a two-year period on mineral soil was 6.9 %, totalling 34.5 % for a hypothetical ten-year period. However, in the worst cases, all the stands were recommended for field inspection. The superiority of the two-year control period was not expected. According to Olsson (1994a), for example, the diminishing spectral response of the changes due to time should not be very radical; at least during the first 3 years between images. The main reasons for the strength of the two-year period were the unequal distribution of the training data between different image pairs and different standard deviations on the H93 image compared to the two earlier images. Based on the results of this study the two-year period might be suitable for monitoring rapid forest changes. The effect of possible phenological changes between the image pairs, for example, may effect the results and thus more material is needed for further testing.

6 Conclusions and Future Outlooks

Radiometric calibration proposed for one TM image pair works well with the 1–3-year intervals applied in this work. The results suggested that even longer calibration intervals should be tested. Olsson's (1994a) results show that the calibration interval can be extended up to at least 5–6 years. The construction of generic training data for successive image pairs by studentization was successful in this work. However, the time interval did not exceed three years and only one image pair was available for each interval. It was estimated that if the calibration works for longer periods, it might be possible to construct generic training data for a longer period than three years. In addition to the required combarability of the change observations between image pairs it is necessary to have a set of untreated observations for calibration when aiming the generic training data. This seems possible to be achieved based on the outlier and leverage point detection before calibration if such an information as in this work is not available for separating untreated areas.

The use of generic training data was supported by the fact that the timing of the changes within the control period did not necessarily affect the detectability of changes under the conditions of the test area when the intervals used were not longer than three years. The differences between change observations in different regions were so great that range scaling was necessary after studentization. However, the possibility of using generic training data between different geographic locations seems promising, but further testing with more accurate change classes are needed before estimating the final accuracies in such an approach. It also has to be remembered that only forest observations were used in the calibration. If a broader classification scheme, such as land use classification, was to be applied it can be expected that the calibration accuracy would decrease.

In change detection the results showed that the change classification accuracy decreases as the interval between images increases. The only exception was the one-year interval on mineral soil but it has to be considered to be due to insufficient data as discussed in previous chapter. The overall change classification accuracy was generally higher compared, for example, to the results obtained by Häme (1991). The differences in these two works may be partly due to the greater mean size of the stand in the present study. Other reasons may be the use of the nonparametric change classifier instead of, for example, Maximum Likelihood classifier. The results would suggest that the applied nonparametric approach is more robust with unbalanced training data than the traditional Maximum Likelihood classifier. The differences might be smaller if balanced training data concerning all the treated classes and the class 'untreated' could be constructed. However, due to the small area of man-made annual forest treatments compared to untreated areas this is impossible as long as the methods proposed are not applied in practice. If applied they would continuously create new training data via field inspections.

The method for change classification proposed in this study also requires training data from all the classes and from all the forest types involved. In particular, the existence of broadleaved species in some stands in the test data confused the change detection process. A problem arose with mixed stands. If the broadleaved trees were removed, the consequent decrease of intensities was sometimes offset by the increase caused by the treatment. When it was not possible to collect complete training data, the problem could partly be reduced if broad change classes can be accepted in the change detection (Varjo 1996). This was especially the case when detecting damaged or partially treated stands. With broad change classes, such as 'untreated', 'moderately changed' and 'drastically changed' (Varjo 1996), the damages and partial treatments were mostly classified into the 'moderate change' class. In the current work, damages were more often misclassified as 'untreated'. In addition to classification errors, it was clear that re-lineation is needed in the case of a stand level approach.

Under the conditions of the FPS, controlling continuously updated forest attribute information by multi-temporal Landsat TM satellite image seems to be profitable when using a two-year interval between images especially on mineral soil. The results were at same level compared to those presented by Varjo (1996). Estimates based on a one-year interval were probably too pessimistic because of the unfavourable distribution of the training observations. However, no advantages were found in using one-year instead of two-year intervals except for securing the updated information every year and a reduction of serious errors. The two-year interval seemed superior in terms of economy and accuracy compared to the three-year interval. Before final conclusions, it has to be remembered that only few image pairs were available in this work and the result should be verified with larger data.

When calculating the costs of quality control for continuous updating using satellite images, only the material costs were taken into consideration. This was because it was assumed that many parts of the methodology used could be automated (e.g. Eckhardt et al. 1990) by using a generic training information base. The technical facilities are already available for the automatic preprocessing of the multi-temporal satellite images needed for the change detection system under discussion. Automatic and semi-automatic methods have been described for registering satellite images together and rectifying them on map coordinate systems (Holm et al. 1994). The relative radiometric calibration system can be automated by developing outlier and leverage point detection so that changes in the calibration data will automatically be excluded. The change detection phase can be semi-automatized for generating the training data base by accepting new observations for the generic training data base derived from field checks on the category 'c' changes previously detected. The necessary re-lineation of the drastic changes can also be done automatically with the stand level approach (Olsson 1994a). In addition, the development of automated mapping systems such as GPS for recording stand delineation already planned to be cut or during cutting may replace the need for separate treatment delineation.

When estimating the costs the fact has to be noted that the satellite image obtained for controlling continuously updated forest information may also serve other purposes. In addition to monitoring rapid changes with long updating periods, it may also be necessary to control the updating of the slowly changing larger part of a forest area. The base-line forest inventory methods which employ satellite remote sensing have been continuously improving, and possibly the most severe errors caused by updating the normal growth can be corrected from satellite imagery. The current methodology and satellite imagery allows accurate estimation of forest attributes for large areas such as forest districts or possibly the subareas used in this work (Tomppo 1992, Päivinen et al. 1993). Good examples of this kind of applications are provided by the reference sample plot method for the regionalisation of national forest information (Kilkki and Päivinen 1987, Kilkki 1988, Tomppo 1990, 1992). Several new satellites and sensors will also be available in the next few years which will increase the spatial resolution to the 2–10 meters. This may improve both the separability of rapid changes and the possibilities for satellite image aided base-line inventories.

In addition to the reduced costs compared to the old repetitive inventory system, the advantage of continuous updating controlled by remote sensing is that the forest data base is more often up to date. Error levels of less than 1 % on mineral soils and 2–3 % on peat land have been estimated after the proposed control. From the point of updating control these are conservative estimates because they are based on the assumption that the errors between repetitive two-year control periods are independent. However, it can be expected that repetition of the control several times in same the area would increase the information concerning the most likely sources of errors. Repeated errors in very similar, or even in the same stands, once understood would relieve the stand from further field inspection. Another factor affecting to the applicability of the proposed controlled continuous updating is the error caused by growth simulation. It may set even stronger limits to the maximum period between base line inventories than the updating of treatments (Kangas 1997). The combined affect of growth model errors and conservativeness of control error estimate is difficult to estimate but they can be expected to offset each other at least up to some extent.

The only comparison made was between the old repetitive inventory system and a continuous updating system aided by satellite images. It is more difficult to compare cost and risks for continuous updating with inadequate quality control methods. It seems obvious that some quality control is necessary, at least in the beginning when employing a new system. During the implementation of continuous updating in the FPS, it became obvious that all the treatments had not been updated and also that there were significant errors in the delineation. Two of the main issues when deciding upon a suitable method for quality control are the accuracy necessary for updating attribute information and the accuracy required for stand delineation. It has been demonstrated that both can be improved by the presented methods. The resulting level of the serious updating errors after the proposed control is low. In addition, the stand delineation can be improved by satellite remote sensing in the case of treatments aiming at regeneration at the end of one forest generation. It is obvious that if, for example, aerial photographs are used for delineation, then the results will be more accurate than the satellite remote sensing such as used in this investigation.

Landsat TM data, especially at two-year intervals, would appear to be both accurate and economical for the task of controlling the quality of continuously updated forest information in the conditions prevailing in the state owned forest properties in Central Finland (Varjo 1993, 1996). Nonetheless, future research will need to address at least two problems. First, for multi-national purposes, the possibility to detect changes in natural resources by using coarser data than Landsat TM has to be considered. Which types of change and how small an area of change can be detected from the data which can be economically applied repetitively for the global level also requires attention. The results achieved by coarser remote sensing data will certainly include more errors, but the main function at this level is to guide further and more accurate investigations concerning potential areas of interest, for example, forest damages or areas of over exploitation. Second, scales larger than have been applied in this work also require attention. On these scales, more accurate remote sensing data such as aerial photographs, airborne scanners or satellite images with better spatial resolution, have to be considered. Longer intervals and the detection of smaller changes may reduce some of the problems which have arisen in this work. In addition, an increased spatial accuracy may permit the construction of more complete training data by dividing observations. Another advantage is that geometrically more accurate data may permit the direct measurement of interesting variables, such as the change in crown diameter or number of trees, instead of estimating the change on the basis of spectral responses. On the other hand, the cost of satellite remote sensing data, even with a low effective cover, is very small compared to the costs of field inspections. This may allow the combination of different multi-temporal data sets such as radar and visible wave length images if this improves the accuracy of change detection.

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Appendix 1A. Parameters of the calibration models on mineral soils.

Control period / parameters		Landsat TM channel 1	2	3	4	5	6	7
H92–H90	β_0	21.247	8.864	9.884	8.964	8.638	10.479	3.330
n=2	β_1	0.725	0.701	0.736	0.793	0.830	1.060	0.825
	β_2	0	0	0	0.198	0	0	0
	β_3	0	0	–0.043	0	0	0	0
	β_4	0	0	0	0	0	–0.022	0
H93–H92	β_0	8.368	4.005	4.119	–21.675	2.467	84.774	2.866
n=1	β_1	0.688	0.639	0.521	1.101	0.718	0.236	0.518
	β_2	0	0	0	0.627	0	0	0
	β_3	0	0	0.015	0	0	0	0
	β_4	0	0	0	0	0	–0.004	0
H93–H90	β_0	22.945	90.490	9.688	–8.438	6.905	82.691	4.268
n=3	β_1	0.499	0.454	0.393	0.840	0.629	0.293	0.439
	β_2	0	0	0	0.840	0	0	0
	β_3	0	0	–0.020	0	0	0	0
	β_4	0	0	0	0	0	–0.025	0

Appendix 1B. Parameters of the calibration models on peat land.

Control period / parameters		Landsat TM channel 1	2	3	4	5	6	7
H92–H90	β_0	15.692	5.457	5.599	11.005	–2.627	17.403	–2.551
n=2	β_1	0.834	0.859	0.927	0.747	1.098	1.034	1.208
	β_2	0	0	0	0.202	0	0	0
	β_3	0	0	–0.027	0	0	0	0
	β_4	0	0	0	0	0	0.093	0
H93–H92	β_0	17.353	4.402	5.902	–9.848	9.214	77.909	4.557
n=1	β_1	0.535	0.620	0.456	0.982	0.556	0.276	0.421
	β_2	0	0	0	0.414	0	0	0
	β_3	0	0	0.008	0	0	0	0
	β_4	0	0	0	0	0	0.024	0
H93–H90	β_0	25.621	6.115	8.208	0.730	6.494	78.732	3.193
n=3	β_1	0.449	0.607	0.420	0.760	0.566	0.331	0.519
	β_2	0	0	0	0.595	0	0	0
	β_3	0	0	–0.001	0	0	0	0
	β_4	0	0	0	0	0	–0.032	0

Appendix 2. The effect of timing of the treatments on the difference image 1993–1990.

The hypothesis for the 'untreated' class was

$$H_0: Me = 0$$

The test used for this class was

$$t = \frac{Me}{SD\sqrt{\frac{2}{n}}}$$

For the other classes the hypothesis was

$$H_0: Me_{\text{class } x} = Me_{\text{class 'untreated'}}$$

Variances of the different treatment classes and the 'untreated' class could not be assumed to be equal. For instance, thinnings make a stand more homogeneous which can be assumed to affect to the variance of these treatment classes. The t-test used was (e.g. Ranta et al. 1989, Snedecor and Cochran 1989).

$$t = \frac{Me_1 - Me_2}{\sqrt{\frac{Sd_1^2}{n_1} + \frac{Sd_2^2}{n_2}}}$$

The degrees of freedom were solved for each tested pair from the following equation (Ranta et al. 1989).

$$\frac{1}{df} = \frac{\left[\dfrac{\frac{Sd_1^2}{n_1}}{\frac{Sd_1^2}{n_1} + \frac{Sd_2^2}{n_2}}\right]^2}{n_1 - 1} + \frac{\left[1 - \dfrac{\frac{Sd_1^2}{n_1}}{\frac{Sd_1^2}{n_1} + \frac{Sd_2^2}{n_2}}\right]^2}{n_2 - 1}$$

Appendix 2A1. Regression calibrated and studentized changes in training data for the image pair H93–H90 for mineral soils.

Treatment	Realized	Landsat TM channel 1		2		3		4		5		6		7	
		Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd
Unt.		–.3	2.2	.2	1.3	–.1	2.0	0.5	5.6	–.3	6.8	–.2	1.4	–.2	3.2
UnC.Thinn.	90–91	1.0	1.7	**1.9**	**1.5**	**2.9**	**2.2**	–1.8	2.7	**6.0**	**6.1**	**3.0**	**3.1**	**5.0**	**3.8**
C. Thinn.	90–91	8.6	2.8	**3.2**	**0.2**	10.0	1.38	8.6	3.8	66.4	17.3	6.2	17.3	23.9	9.5
	91–92	5.7	6.6	4.6	4.4	7.8	8.0	4.4	7.1	**32.8**	**28.3**	**6.3**	**5.0**	17.4	16.4
	92–93	8.93	2.8	**6.4**	**0.8**	12.7	3.3	8.6	5.0	57.3	11.5	10.4	2.2	31.7	6.2
Prep. cut	90–91	6.7	2.3	**5.9**	**0.2**	9.5	0.8	–2.0	1.2	34.9	10.3	5.6	3.2	23.6	0.6
	91–92	**3.1**	**3.1**	**2.6**	**1.2**	**4.1**	**2.2**	1.1	4.1	**20.7**	**14.3**	**3.3**	**3.4**	**10.4**	**5.8**
	92–93	**10.9**	**10.3**	**6.4**	**5.2**	**11.1**	**8.8**	2.2	4.9	**35.3**	**28.1**	**4.3**	**4.3**	**18.9**	**15.9**
HOR	92–93	2.0	2.8	4.3	1.4	5.5	2.4	9.6	7.9	17.9	10.9	1.5	2.7	10.1	5.7
Reg. cut N.	90–91	**14.2**	**5.5**	**8.0**	**3.6**	**16.1**	**6.3**	2.6	4.6	**79.0**	**27.1**	**10.8**	**3.0**	**50.7**	**14.3**
	91–92	**17.3**	**2.3**	**9.4**	**0.9**	**21.2**	**2.4**	–.1	1.5	**86.7**	**3.3**	8.9	1.8	**56.0**	**2.5**
	92–93	10.5	0.8	7.9	0.6	17.7	1.9	10.8	1.5	75.4	7.6	13.8	3.5	34.8	4.9
Clear cut	90–91	**20.1**	**4.3**	**10.5**	**2.9**	**22.9**	**5.6**	0.2	4.1	**84.1**	**13.5**	**9.3**	**0.9**	**54.8**	**6.8**
	91–92	**18.5**	**7.7**	**10.8**	**4.4**	**21.6**	**8.9**	1.9	6.9	**82.4**	**36.8**	**10.9**	**5.5**	**52.8**	**21.7**
	92–93	**12.7**	**3.9**	**7.7**	**3.2**	**15.7**	**6.4**	4.7	4.3	**69.1**	**20.0**	**7.6**	**4.0**	**27.1**	**15.0**
Soil prep.	90–91	15.3	9.3	9.9	6.1	18.8	10.5	–.2	6.6	73.0	49.5	5.2	7.2	40.8	24.0
	91–92	8.5	5.8	**6.1**	**2.5**	**11.7**	**5.9**	–13.3	10.6	**41.9**	**25.6**	5.0	3.2	**33.7**	**12.0**

Statistically significant differences at 1 % risk based on two-way Student's t-test are in bold face

Appendix 2A2. Uncalibrated changes in the training data for the image pair H93–H90 for mineral soils.

Treatment	Realized	Landsat TM channel 1		2		3		4		5		6		7	
		Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd	Me	Sd
Unt.		**–3.1**	**1.7**	**–2.3**	**1.1**	**–3.1**	**2.0**	.2	3.8	**–10.5**	**4.8**	**–4.6**	**2.6**	**–5.6**	**2.8**
UnC. Thinn.	90–91	**–4.8**	**1.5**	**–3.1**	**.7**	**–5.1**	**1.3**	**2.3**	**2.2**	**–16.0**	**2.0**	**–8.8**	**1.4**	**–8.7**	**2.1**
C. Thinn.	90–91	1.9	1.0	1.5	.8	3.5	1.9	2.4	1.6	16.9	7.6	1.5	3.4	5.4	4.5
	91–92	–.5	2.8	–.2	2.0	.4	3.4	1.8	4.0	**2.0**	**10.0**	–.7	3.5	**.8**	**5.4**
	92–93	1.2	0.9	**.9**	**.3**	2.9	1.3	4.3	2.4	10.0	4.3	.7	2.0	**4.7**	**1.3**
Prep. cut	90–91	.3	1.2	**.4**	**.1**	1.5	.7	.5	.2	3.5	3.5	–1.3	.7	3.0	.6
	91–92	**–1.3**	**1.6**	**–.8**	**.8**	**–.3**	**1.4**	.2	2.1	**–1.8**	**5.6**	**–1.9**	**2.0**	**–1.3**	**2.3**
	92–93	**2.1**	**4.0**	**.9**	**2.2**	**2.9**	**3.9**	.2	3.1	**4.6**	**9.2**	**–.2**	**1.4**	**2.2**	**4.6**
HOR	92–93	–6.0	1.7	–2.5	0.9	–5.5	1.4	**12.1**	**3.7**	–15.1	4.7	**–10.8**	**1.9**	–11.6	2.5
Reg. cut N.	90–91	**3.4**	**2.6**	**1.6**	**1.7**	**4.6**	**2.9**	.8	1.8	**19.2**	**10.2**	**1.8**	**2.2**	**11.7**	**4.5**
	91–92	**4.7**	**1.0**	**2.3**	**.5**	**7.0**	**1.1**	–1.0	.8	**22.8**	**1.7**	.9	1.6	**14.0**	**1.2**
	92–93	2.2	.6	1.9	.6	5.6	.9	4.4	1.0	17.9	3.5	3.8	1.1	6.7	1.7
Clear cut	91–92	**5.5**	**1.9**	**2.5**	**1.4**	**7.1**	**2.6**	–.5	2.2	**20.9**	**5.2**	**.9**	**1.2**	**12.3**	**2.8**
	91–92	**4.9**	**3.7**	**2.8**	**2.3**	**6.8**	**4.6**	.6	2.1	**20.6**	**14.1**	**2.2**	**4.2**	**12.2**	**7.6**
	92–93	**2.8**	**1.5**	**1.4**	**1.3**	**4.8**	**2.5**	.8	2.2	**16.3**	**6.8**	**1.5**	**1.6**	**4.9**	**4.5**
Soil prep.	90–91	2.2	5.8	1.4	3.4	3.0	7.3	**3.1**	**1.1**	12.5	23.2	–3.8	7.2	5.2	11.2
	91–92	–2.0	3.9	–1.2	2.1	–2.1	4.8	–.4	4.0	–2.7	13.8	–5.7	4.1	–.7	7.2

Statistically significant differences at 1 % risk based on two-way Student's t-test are in bold face.

Appendix 2A3. Regression calibrated DN changes in the training data for the image pair H93–H90 for mineral soils.

Treatment	Realized	Landsat TM channel 1 Me	1 Sd	2 Me	2 Sd	3 Me	3 Sd	4 Me	4 Sd	5 Me	5 Sd	6 Me	6 Sd	7 Me	7 Sd
Unt.		–.1	1.0	**.1**	**.5**	.0	.8	.2	2.6	–.1	2.3	**–.1**	**.5**	–.1	1.0
UnC. Thinn.	90–91	.4	.7	**.8**	**.6**	**1.1**	**.9**	–.8	1.3	**2.0**	**2.1**	**1.2**	**1.2**	**1.5**	**1.2**
C. Thinn.	90–91	3.3	1.1	2.6	0.1	3.9	0.6	4.0	12.7	22.4	5.9	4.5	0.6	7.2	2.9
	91–92	2.2	2.5	1.9	1.8	3.0	3.1	1.9	3.2	**11.0**	**9.5**	**2.5**	**2.0**	5.2	4.9
	92–92	3.4	1.1	**2.6**	**0.3**	5.0	1.3	4.0	2.3	19.3	3.9	4.1	0.9	9.5	1.8
Prep. cut	90–91	2.6	.9	2.4	.1	3.7	.3	–.9	.6	11.7	3.5	2.2	1.3	7.1	0.2
	91–92	**1.2**	**1.2**	**1.1**	**.5**	**1.7**	**.9**	.5	1.9	**6.9**	**4.8**	**1.3**	**1.4**	**3.3**	**1.8**
	92–93	**4.2**	**3.9**	**2.6**	**2.1**	**4.3**	**3.4**	1.0	2.2	**11.9**	**9.4**	**1.7**	**1.7**	**5.7**	**4.8**
HOR	92–93	.8	1.1	1.7	.6	2.2	.9	4.5	3.7	5.8	3.7	.6	1.0	3.0	1.7
Reg. cut N.	90–91	**5.5**	**2.1**	**3.2**	**1.5**	**6.3**	**2.5**	1.2	2.1	**26.5**	**9.1**	**4.3**	**1.2**	**15.2**	**4.3**
	91–92	**6.6**	**.9**	**3.8**	**.3**	**8.3**	**.9**	.0	.7	**29.1**	**1.1**	**3.5**	**.7**	**16.8**	**.8**
	92–93	4.0	0.3	3.2	.2	6.9	.7	5.0	.7	25.4	2.5	5.5	1.4	10.5	1.5
Clear cut	90–91	**7.8**	**1.6**	**4.3**	**1.2**	**8.9**	**2.2**	.1	1.9	**28.2**	**4.5**	**3.8**	**.3**	**16.5**	**2.0**
	92–93	**7.1**	**2.9**	**4.4**	**1.8**	**8.4**	**3.5**	.9	3.2	**27.7**	**12.4**	**4.3**	**2.2**	**15.9**	**6.5**
	92–93	**4.9**	**1.5**	**3.1**	**1.3**	**6.1**	**2.5**	2.2	2.0	**23.3**	**6.8**	**3.0**	**1.6**	**8.2**	**4.5**
Soil prep	90–91	5.9	3.5	4.0	2.5	7.3	4.1	–.1	3.1	24.6	16.6	2.1	2.8	12.3	7.2
	91–92	3.3	2.2	**2.5**	**1.0**	**4.6**	**2.3**	–6.1	4.9	**14.1**	**8.6**	2.0	1.3	**10.1**	**3.6**

Statistically significant differences at 1 % risk based on two-way Student's t-test are in bold face.

Appendix 2B. Regression calibrated and studentized changes in the training data for the image pair H93–H90 for peat land.

Treatment	Realized	Landsat TM channel 1 Me	1 Sd	2 Me	2 Sd	3 Me	3 Sd	4 Me	4 Sd	5 Me	5 Sd	6 Me	6 Sd	7 Me	7 Sd
Unt.		–.3	2.3	.2	1.4	.5	2.2	.3	5.9	–1.7	8.7	–.5	5.0	–.4	4.0
UnC. Thinn	90–91	1.8	1.8	**1.4**	**0.4**	2.0	1.6	0.0	5.2	**12.4**	**2.6**	2.4	4.3	4.8	2.0
	91–92	.4	.7	–.1	.9	1.1	1.0	–3.5	5.3	–3.8	5.3	–.2	1.0	–.5	2.7
C. thinn.	91–92	2.3	5.6	1.6	4.1	3.9	6.5	–.2	3.2	20.3	22.1	4.0	7.3	10.2	15.3
Prep. cut	92–93	10.7	11.7	6.1	5.3	9.1	7.1	–2.6	3.7	**22.8**	**10.8**	1.9	1.8	**12.3**	**4.9**
Clear cut	92–93	**12.1**	**3.9**	**8.1**	**3.2**	**16.0**	**6.2**	1.2	4.1	**68.2**	**19.8**	**7.3**	**3.9**	**26.9**	**14.8**
Drain.	91–92	3.1	1.7	3.1	1.4	5.8	2.1	–2.9	7.1	**31.5**	**8.2**	5.1	3.2	**16.6**	**4.7**

Statistically significant differences at 1 % risk based on two-way Student's t-test are in bold face.

Appendix 3A. Regression calibrated and studentized differences of the stand means in the different image pairs for mineral soils.

TM	Image pair	Unt. Me	Unt. Sd	UnC. thinn. Me	UnC. thinn. Sd	C. thinn. Me	C. thinn. Sd	Prep. cut Me	Prep. cut Sd	HOR Me	HOR Sd	Reg. cut N. Me	Reg. cut N. Sd	Clear cut Me	Clear cut Sd	Soil prep. Me	Soil prep. Sd
1	H92–H90	.0	3.3	1.4	2.8	6.1	5.2	4.2	4.7			16.4	6.2	15.3	6.5	17.4	8.4
	H93–H92	–.6	2.6			7.0	6.4	13.9	13.8	1.6	2.1	14.4	.9	16.9	4.2		
	H93–H90	–.3	2.2	2.1	4.5	6.8	5.6	6.3	7.6	2.0	2.8	14.4	4.8	17.6	7.0	11.8	8.0
	N90–N88	1.0	2.0			1.9	2.1			7.9	2.5			7.9	3.7		
2	H92–H90	.3	1.6	.2	1.4	3.6	3.6	2.8	2.6			8.4	3.1	8.1	3.9	9.5	5.2
	H93–H92	–.2	1.5			4.9	2.8	7.8	5.3	3.2	1.3	9.8	.2	10.4	3.9		
	H93–H90	.2	1.3	2.8	3.7	5.3	3.6	4.3	3.8	4.3	1.4	8.3	2.8	10.1	4.1	7.8	4.7
	N90–N88	.8	2.1			1.2	1.8			4.9	1.4			4.3	2.6		
3	H92–H90	.4	2.6	1.1	3.3	8.5	7.3	5.1	4.4			20.2	5.7	20.0	9.2	18.2	11.4
	H93–H92	–.4	1.9			10.1	6.7	12.6	8.8	5.4	3.0	20.1	2.2	18.4	6.8		
	H93–H90	–.1	2.0	4.9	7.5	9.2	6.8	7.3	6.4	5.5	2.4	17.6	5.3	20.6	8.3	14.9	8.7
	N90–N88	.8	1.8			2.5	3.1			9.5	2.8			9.5	5.4		
4	H92–H90	1.1	5.9	–9.0	5.0	–1.8	7.8	.2	6.3			0.2	7.2	6.7	11.4	–5.8	10.0
	H93–H92	–.7	5.6			–1.2	14.8	2.3	3.3	3.7	3.8	9.2	1.6	5.2	3.4		
	H93–H90	.5	5.6	–5.6	14.2	5.7	6.4	1.6	4.5	9.6	7.9	3.3	5.1	2.2	6.1	–7.4	11.0
	N90–N88	.6	2.7			–3.2	3.2			–2.4	4.0			2.7	6.5		
5	H92–H90	.3	6.9	–3.2	8.4	30.1	24.3	18.8	12.4			67.4	7.2	67.7	29.9	52.6	40.4
	H93–H92	–1.5	8.6			38.7	39.0	44.4	34.5	24.5	13.5	89.7	9.2	86.9	24.7		
	H93–H90	–.3	6.8	7.7	8.7	42.9	27.2	27.3	21.0	17.2	10.9	80.3	20.6	79.9	31.5	56.2	39.7
	N90–N88	2.1	4.8			6.2	9.0			24.6	15.4			30.2	15.3		
6	H92–H90	–.3	1.6	2.4	2.4	5.9	5.5	5.1	3.7			13.6	2.4	13.4	5.7	3.7	6.8
	H93–H92	.0	1.4			7.9	4.4	5.1	4.7	3.4	2.0	13.9	4.1	8.1	4.1		
	H93–H90	–.2	1.4	2.8	3.1	7.1	4.4	3.8	3.6	1.5	2.7	10.8	3.0	10.0	4.9	5.1	5.1
	N90–N88	1.1	2.0			4.1	3.1			7.7	9.8			10.6	6.2		
7	H92–H90	.2	3.3	–1.0	5.0	11.3	8.8	8.3	6.7			35.2	8.9	29.8	12.5	29.7	17.2
	H93–H92	–1.1	3.8			31.7	11.8	24.5	20.5	14.0	6.4	43.8	5.4	35.8	19.1		
	H93–H90	–.2	3.2	7.4	9.5	21.4	14.7	14.6	11.5	10.1	5.7	49.4	12.9	47.8	21.6	36.9	17.8
	N90–N88	1.2	2.9			4.3	5.7			17.2	5.4			16.5	6.7		

Appendix 3B. Regression calibrated and standardized differences of the stand means in the different image pairs for peat land.

TM	Image pair	Unt. Me	Unt. Sd	UnC. thinn. Me	UnC. thinn. Sd	C. thinn. Me	C. thinn. Sd	Prep. cut Me	Prep. cut Sd	Clear cut Me	Clear cut Sd	Drain. Me	Drain. Sd
1	H92–H90	–.0	.9	1.3	1.2	1.6	2.8					3.2	.8
	H93–H92	–.1	.7					4.0	4.5	4.6	1.3		
	H93–H90	–.3	2.4	1.4	1.6	2.3	5.6	9.4	11.4	12.1	3.9	3.1	1.2
2	H92–H90	.2	.6	.3	.8	.6	1.8					2.3	.6
	H93–H92	.1	.6					2.7	2.1	3.6	1.4		
	H93–H90	.2	1.4	.9	.9	1.6	4.1	5.6	5.2	8.1	3.2	3.1	1.4
3	H92–H90	.1	1.1	1.1	1.0	2.8	3.1					4.1	.9
	H93–H92	–.0	.7					3.6	2.8	6.3	2.4		
	H93–H90	.5	2.2	1.8	1.4	3.9	6.5	8.3	7.0	16.0	6.2	5.8	2.2
4	H92–H90	.2	1.8	–2.7	1.6	–1.6	2.1					–2.0	1.0
	H93–H92	–.4	2.7					–1.5	1.7	.5	1.6		
	H93–H90	.3	5.9	–1.1	5.0	–.2	3.2	–1.9	4.0	1.2	4.1	–2.9	7.1
5	H92–H90	1.4	4.7	2.5	3.3	9.9	12.8					20.6	4.4
	H93–H92	–1.6	4.2					7.0	3.7	22.5	6.7		
	H93–H90	–1.8	8.7	7.1	8.8	20.3	22.1	20.5	11.9	68.2	19.8	31.5	8.2
6	H92–H90	.0	1.6	2.3	1.7	5.3	5.9					4.9	1.3
	H93–H92	–.1	1.9					1.3	0.8	3.2	1.5		
	H93–H90	–.2	5.0	1.6	3.6	4.0	4.2	1.9	1.7	7.3	3.9	5.1	3.2
7	H92–H90	0.0	2.3	1.1	1.4	5.2	7.3					10.6	2.1
	H93–H92	–.2	1.3					3.4	1.3	7.9	4.4		
	H93–H90	–.4	4.0	3.0	3.4	10.2	15.3	10.9	5.9	29.9	14.9	16.6	4.7

Appendix 4A. Change discrimination results using the image pair H93–H90 in the test data for mineral soils.

Field check	Image analysis								
	Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Total	%
Unt.	350	23	4	26	15				418	70.5
UnC. thinn.	6	26	1	4	6		1		44	7.4
C. thinn.	5	1	2						8	1.3
Prep. cut	2		2	12					16	2.7
HOR	1		2		1				4	0.7
Reg. cut N. & soil prep.			1	2		17	6		26	4.4
Clear cut & soil prep.	1		4	1	1	2	22	5	36	6.1
Partial clear cut	3	1	5	2		1	4		16	2.7
or reg. cut N.	2		2	4	2		2		12	2.0
Soil prep.								1	1	0.2
Drain.					2				2	0.3
Wind damage	2		1	3		1	3		10	1.7
Total	372	51	24	54	27	21	38	6	593	100.0
%	82.2	8.6	4.0	9.1	4.6	3.5	6.4	1.0	100.0	78.2

Appendix 4B. Change discrimination results using the image pair H93–H92 in the test data for mineral soils.

Field check	Image analysis								
	Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Total	%
Unt.	406	40	11	25	4	3	9	1	499	84.1
UnC. thinn.		3			1				4	0.7
C. thinn.			1						1	0.2
Prep. cut				6					6	1.0
HOR		1	1		1				3	0.5
Reg. cut N. & soil prep.				3		4			7	1.2
Clear cut & soil prep.		1	1			4	2		8	1.3
Partial clear cut			1				1		2	0.3
or reg. cut N.		1	1	1	1				4	0.8
Soil prep.	3	1	4	1	1	16	16	8	50	8.4
Drain.										
Wind damage			3	1		4	1		9	1.5
Total	409	47	23	37	8	31	29	9	593	100
%	69.0	7.9	3.9	6.2	1.4	5.2	4.9	1.5	100	75.2

Appendix 4C. Change discrimination results using the image pair H93–90 in the test data for peat land.

Field check	Image analysis									
	Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Drain.	Total	%
Unt.	50	12	5	6					2	75	61.0
UnC. thinn.	2	6		6					1	15	12.2
C. thinn.	4	1	2	3			1			11	8.9
Prep. cut			1							1	0.8
HOR		1		1						2	1.6
Reg. cut N. & soil prep.				1						1	0.8
Clear cut & soil prep.	1		1				1		1	4	3.3
Partial clear cut			3				1			4	3.3
or reg. cut. N.	1									1	0.8
Soil prep.											
Drain.	1		1	1						3	2.4
Damage	1	1		3						5	4.1
dried											
beaver				1						1	0.8
Total	60	21	13	22			3		4	123	100.0
%	49.5	17.1	10.6	17.1			2.4		3.3	100	55.3

Appendix 4D. Change discrimination results using the image pair H92–H90 in the test data for peat land.

Field check	Image analysis									
	Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Drain.	Total	%
Unt.	79	2	1	4					1	87	70.7
UnC. thinn.	9	5	1							15	12.2
C. thinn.	2	2								4	3.3
Prep. cut											
HOR	2									2	1.6
Reg. cut N. & soil prep.			1							1	0.8
Clear cut & soil prep.	1		2							3	2.4
Partial clear cut	2		2							4	3.3
or reg. cut N.			1							1	0.8
Soil prep.											
Drain.											
Damage	4			1						5	4.1
dried											
beaver	1									1	0.8
Total	100	9	8	5					1	123	100.0
%	81.3	7.3	6.5	4.1					0.8	100	71.5

Appendix 4E. Change discrimination results using the image pair H93–H92 in the test data for peat land.

Field check	Image analysis									
	Unt.	UnC. thinn.	C. thinn.	Prep. cut	HOR	Reg. cut N.	Clear cut	Soil prep.	Drain.	Total	%
Unt.	88	9	3	11						111	90.3
UnC. thinn.											
C. thinn.	2		2	2			1			7	5.7
Prep. cut	1									1	0.8
HOR											
Reg. cut N. & soil prep.											
Clear cut & soil prep.							1			1	0.8
Partial clear cut or reg. cut N.											
Soil prep.											
Drain.				2			1			3	2.4
Total	91	9	5	15			3			123	100.0
%	74.0	7.3	4.1	12.2			2.4			100	74.0

Appendix 5A. Change discrimination results for the image pair H93–H92 using the training data only from H92–H90 for mineral soils.

Field check	Image analysis								
	Unt	UnC. Thinn.	C. Thinn.	Prep. cut	Reg. cut N.	Clear cut	Soil prep.	Total	%
Unt.	148	6	17	13	1		1	186	88.3
C. Thinn.					1	1	1	3	1.4
Prep. cut	1	2		4	2	1		10	4.7
HOR	1	2					1	4	1.9
Reg. cut N. &soil prep.							2	2	0.9
Clear cut & soil prep.	4	1		1				6	2.8
Total	154	11	17	18	4	2	5	211	100.0
%	73.0	5.2	8.1	8.5	1.9	0.9	2.4	100	73.5

Appendix 5B. Change discrimination results for the image pair H93–H92 using the training data only from H92–H90 for peat land.

Image analysis	Field check							
	Unt.	UnC. Thinn.	C. Thinn.	Prep. cut	Clear cut	Drain.	Total	%
Unt.	161	7	19	12		2	201	93.4
C. Thinn.	1						1	0.5
Prep. cut	4		3				7	3.3
Clear cut & soil prep.	5	1					6	2.8
Total	171	8	22	12	0	2	215	100
%	79.6	3.7	10.2	5.6	0	0.9	100.0	74.9

Appendix 6.A. Change discrimination results for Hyrynsalmi H93–H90 training data using Nurmes N90–N88 as training data for mineral soils.

Image analysis	Field check					
	Unt.	C. Thinn.	HOR	Clear cut	Total	%
Unt.	377	11	2		390	78.0
UnC thinn.	7	3	1	2	13	2.6
C. thinn.	9	2		4	15	3.0
Prep. cut	18	7	1		26	5.2
HOR	4				4	0.8
Reg. cut N. & soil prep.	3	1		9	13	2.6
Clear cut & soil prep.	5	7		16	28	5.6
Soil prep. (no partial)	3			8	11	2.2
Total	426	31	4	39	500	100
%	85.2	6.2	0.8	7.8	100	85.4

Appendix 6B. Change discrimination results for Nurmes N90–N88 training data using Hyrynsalmi H93–H90 as training data for mineral soil.

Image analysis	Field check					
	Unt.	C. Thinn.	HOR	Clear cut	Total	%
Unt.	281	20	33	6	340	93.7
C. Thinn.	4			3	7	1.9
HOR	1			2	3	0.8
Clear cut & soil prep.	1	2		10	13	3.6
Total	287	22	33	21	363	100
%	79.1	6.1	9.1	5.7	100	80.2

Class thinning is assumed to represent classes: uncommercial thinning, thinning and preparatory cut
Class clear cut is assumed to represent classes: regeneration cut for natural regeneration, soil preparation and clear cut

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