Effects of data uncertainty on dynamic treatment units

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Supervisor: Renats Trubins, Southern Swedish Forest Research Centre, SLU

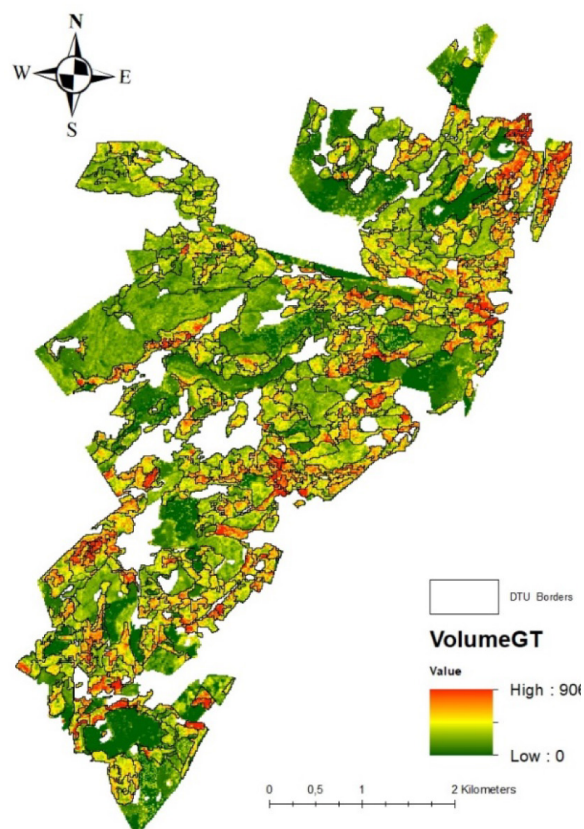# Effects of data uncertainty on dynamic treatment units

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Abstract

The purpose of this thesis was to study the effects of uncertainty in the pixel level estimates concerning the potential benefits of dynamic, pixel-based treatment units compared to traditional stand-based treatment allocation. Because of automatic stand delineation having benefits resulting in the possibility to be more commonly used in forest industry. In thesis assumption is made that the original ALS-dataset exactly represents the "Ground truth".

The study area is a part of the Östad foundation (Östad "stiftelse") located in Southern Sweden. The property is owned by Östad foundation and is mainly used for industrial and education purpose. The analysis area is comprised of 1 848 ha. The forest is managed in the traditional Scandinavian clearcutting regimes.

The results shows that uncertainty effects potential incomes in all cases, especially on the stands where traditional stand delineation was used. Target harvest volume (share of harvested pixels) also has an impact on the potential losses. When the target volume goes from 60 000 m^3 to 80 000 m^3 the financial trend is changing and the potential losses per m^3 is decreasing. Due to this phenomenon the biggest potential loss in SEK per m^3 is reached at the target volume of 60 000 m^3. In terms of dynamic treatment units (DTU) the difference per m^3 between the "Ground truth" and created rasters are relatively low, in some cases less than -1 SEK/m^3. The results concerning the average difference between DTU and "Original borders" variants with simulated dNPV in all cases favor the DTU's. In all tested cases DTU had an economical advantage over the planning within existing boundaries. Even with target volume of 20 000 m^3 results improve by -3.2 SEK/m^3 in average between DTU and "Original borders". The largest difference between simulated dNPV data of DTU and "Original borders" is - 5.9 SEK/m^3, this result is achieved by 60 000 m^3 as the target harvest volume. The conclusion is drawn that DTU planning is more efficient than forest management planning based on "Original stand" borders even when the effect of volume data errors is considered. The data errors have larger effect on the planning results within the framework of original borders that within the DTU framework. Highest difference was achieved in case of minimum segment size 0.5 ha and target harvesting volume 60 000 m^3 where, the difference was -6.9 SEK/m^3.

Key words: DTU, dynamic treatment units, ALS, Airborne laser scanning, tactical planning, final felling, RMSE, relative mean square error, segmentation

Contents

Abbreviations

ALS - airborne-laser scanning,

AVCC - avoided value change plus costs,

CHM – canopy/crown height model,

CIR - color-infrared

DBH - diameter at breast height,

dNPV - change of NPV,

DTM - digital terrain model,

DTU - dynamic treatment units,

GT - Ground truth,

H - Mean tree height,

MINS - minimum segment size,

NOK - Norwegian krone,

NPV - net present value,

RMSE - root mean square error, relative mean square error,

SCD - spectral detail,

SEK – Swedish krone,

SI - site index,

SPD - spatial detail.

1. Introduction

To maintain sustainable flow of forest resources, management is a vital process. To provide high and even flow of forest products for the forest owners, information about forest stands are important. The conventional way of collecting data for the forest management proposes is based on field inventories. Of course, thru the decades the method of how field inventories are performed has changed to become increasingly efficient, but they are still mainly man driven by manual measuring in the field. However, manual forest field inventories as well as subsequent stand delineation is time consuming and requires professional knowledge with manual labor. Nevertheless, the inventory is done professionally the forest owner cannot avoid that stand delineation are partially subjective. Consequently, several studies concerning automatic stand delineation methods based on the aerial images, remote sensing such as clustering methods with digital terrain or crown high model are developing.

Since Holmgren and Thuresson (1997) presented their article about using satellite imaginary in forest management. Remote sensing has developed rapidly. Because of errors in the data of airobe-laser scanning inventory, the economical aspect of decision based on remote sensing is still questionable. Inaccurate airborne-laser scanning data (with high level percentage of error) may lead to incorrect decisions which ultimately leads to financial loses for the forest owners. Forest inventories based on the ALS data might change the understanding of forest stands due to the boundaries changing depending on the used criteria.

1.1. The stand concept

In the traditional way stands are delineated subjectively, to represent the area with common attributes, for example yield, and wood density, age distribution, site fertility (index), tree species composition, in other words, conditions that distinguish the area from the surrounding forest. According to Gunnarsson et al., (1998) there is no indication that the stand delineation may change far in the future (Packalén et al., 2011). Stands as discrete treatment units were described long time ago. For example, Ström (1829) described the idea to delineate subjects into units based on homogeneity with respect to variables such as age distribution, standing volume etc.

All forest data are collected and recorded as values per defined unit and organized during the planning process. This approach of processing spatial data is still the major method used to administrate forest (Gunnarsson et al., 1998). Information about the surface of study area is obtained from forest inventories which is more than simple forest data collection. Because of the forest inventory is possible to extract a lot of information, collected data helps distinguished stands and make responsible forest management decisions. Since one of the main criteria to delineate stands is homogeneity, understanding of traditional stands concept is both an inventory unit and a treatment unit. As previously mentioned, a forest stand is described by many variables, this information is used to create a dataset for forest management operation units in forest area.

1.2. Methods of stand delineation

For forest management planning purposes division of areas into more uniform treatment units are necessary. In the process of creating stands only minor deviation in age and species composition is accepted. In general, within bigger sections or land circuit greater deviations is allowed. The preciseness of division of forest into forest stand can be achieved in a variety of ways.

However, since inventories is time consuming assumptions about the homogeneity of stand conditions and stand boundaries are constant over the time potentially the information about stands are misleading due to generalizations. For example, Ståhl (1992) research shows that young stands from the beginning may seem homogenous but over the time the structure most likely will change. Such permanence is more present in the near-natural growth forest than in managed stands. Nevertheless, manual forest stand delineation is subjective those simplifications which helps the forester to manage data combining and scheduling treatments in the simplest possible way to reduce labor costs as well as working hours (Holmgren and Thuresson, 1997). According to Heinonen, et al. (2007), the main advantage for using dynamic treatment units (DTU) is that forest owners might be more efficient at utilization of forest resources than by using the fixed compartments.

Automatic stand delineation have the potential to become more commonly used in forestry. Meanwhile, ALS is gaining popularity as the realization that the inventory and treatment unit does not necessarily need to be connected. So, the inventory units would be in pixels while the treatment units would be constructed from aggregated pixels. In this case the treatment units are not more stable because the layout is determined by certain criteria, Net-preset value of future harvest for instance (NPV). There exist several studies that compare new delineation methods with traditional human-interpreted stand borders, two of the main stand delineation methods occurs in the studies of Wu et al. (2013), Pekkarinen (2001), Packalén et al. (2011), Mustonen, et al. (2008) and other similar studies. The methods are:

1. Human-interpreted stand delineation
2. Automatic stand delineation

1.2.1. Human-interpreted stand delineation

The conservative way to interpreted stand delineation is based on previous treatments, merge the stands with similar growth conditions, tree species composition, size, tree age etc. Manual stand delineation method is also by using color-infrared orthophotography (CIR). It can be done on paper or on a computer screen in office or using a mobile device on field. For this approach of delineation not only colour-infrared orthophotography is used, but also any other type of orthophotography. The approach has been developed in several commercial research projects (Pekkarinen 2001, Sell 2002, Leckie et al., 2003). Human-interpreted approaches main disadvantage is lack of information about the specific canopy height, but the strength is the data concerning the visual tree species variation, especially comprehending differences between hardwood and conifers (Wu et al., 2013, Mustonen et al., 2008).

1.2.2. Automatic stand delineation

Automatic stand delineation uses different types of remote sensing data such as CIR orthophotography, ALS, satellite images or combinations of them. Stand automatic delineation

are created by applying a segmentation algorithm on the relevant data. Different types of data have different capacity to capture a variety of properties concerning the tree cover. Due to this, the choice of data will affect the method applied. Before the introduction of ALS, the infrared orthophotographs with simple algorithm were the most common type of data. Distinguishing deciduous tree species from conifers is the strength of this method. For that reason, infrared orthophotographs data gives the opportunity to casually follow the forest dynamics from a distance, including species variation. This method main disadvantage is lack of specific information about the tree height. (Wu et al., 2013, Leppänen, et al., 2008)

Leppänen, et al. (2008) presented approaches for stand delineation using automatically interpreted stand delineation, with a segmentation algorithm based on a Digital Terrain Model and using a Crown Height Model (CHM). Mustonen, et al. (2008) compared two methods, the traditional stand delineation and segmentation method, where the second method is less subjective to generalize the treatment units. In the article authors conclude - automatic segmentation method using the CHM for creating treatment units is less expensive and less time-consuming compared to traditional forest stand delineation. For segmentation Mustonen, et al. (2008) use algorithms introduced by Baatz and Schäpe (2000). Mustonen (2008) presented a segmentation method using ALS-derived vegetation height. Diedershagen et al. (2004) showed an approach to stand delineation using commercial (*"FOGIS"*) software and high-resolution ALS data combined with multispectral data. The main advantage of this approach is to use high-resolution digitized vegetation height model and high-resolution data into the segmentation algorithm as an input (Wu et al., 2013).

Hybrid segmentation approach introduced by (Wu et al., 2013) is based on three-band image containing tree height, density and information of composition, from raw ALS data in the study two popular image segmentation methods is combined, mean shift and spectral clustering algorithm. Mean shift algorithm is used to segment an image to create raw stands, which are refined by spectral clustering (Wu et al., 2013).

1.3. Towards dynamic treatment units

Treatment unit is a geographically confined forest area that is according to the tactical plan scheduled for a forest management operation. It could be thinning, final felling, planting etc. Usually, the stands boundaries have been fixed a long time ago based on physical and measured conditions. Peter Holmgren and Tomas Thuresson in 1997 introduce the concept of "Dynamic treatment units" (DTU) (Holmgren and Thuresson, 1997). The authors suggest to take into account, not only internal factors, such as spatial variation of volumes, soil condition, tree species growth, but also the external factors, such as timber price in the market. The concept of DTU is capable to consider all preparatory logistical costs for the operation. To start working with DTU's is not an easy task because this approach does not consider stands as stable forest inventory units over time. The treatment units are formed to prescribe treatments, after which they are not used any more. Since different authors Holmgren and Thuresson, (1997), Packalén, et al., (2011) Öhman (2001) and others use different criteria to organize the segments, it seems that the biggest challenge is to define common criteria and implement it in an algorithm. As a principle of forming DTU more specific, treatment related criteria, can be set including economic aspects, in contrast to the general homogeneity and size criteria used for

defining stands in traditional forest inventory (Holmgren and Thuresson, 1997, Packalén, et al., 2011).

Traditionally, delineating stands has been a part of the forest inventory process. From the human-interpreted stand delineation point of view it made sense not to have more inventory units than the treatment units which are necessary for planning, as it would keep the inventory costs low. Remote sensing-based forest inventory allows the most essential forest resource data such as mean height, basal area, and stand volume to be collected. The forest variable estimates can be obtained for smaller inventory units at no extra costs using ALS data (e.g., Næsset 1997, Packalén and Maltamo 2007). In recent years, ALS has become the most commonly used remote sensing technique for forest inventory purposes. Considering the inventory possibilities offered by remote sensing the use of DTU in forest management become more possible, because the inventory provides wall-to-wall coverage of growing stock estimates with resolution equal to the smallest unit used in calculations (raster cells, hexagons, and microsegments). High resolution also enables the possibility to use remote sensing data for the traditional stand and micro-stand delineation (van Aardt et al. 2006, Mustonen, et al., 2008, Pascual et al. 2008, Packalén, et al., 2011).
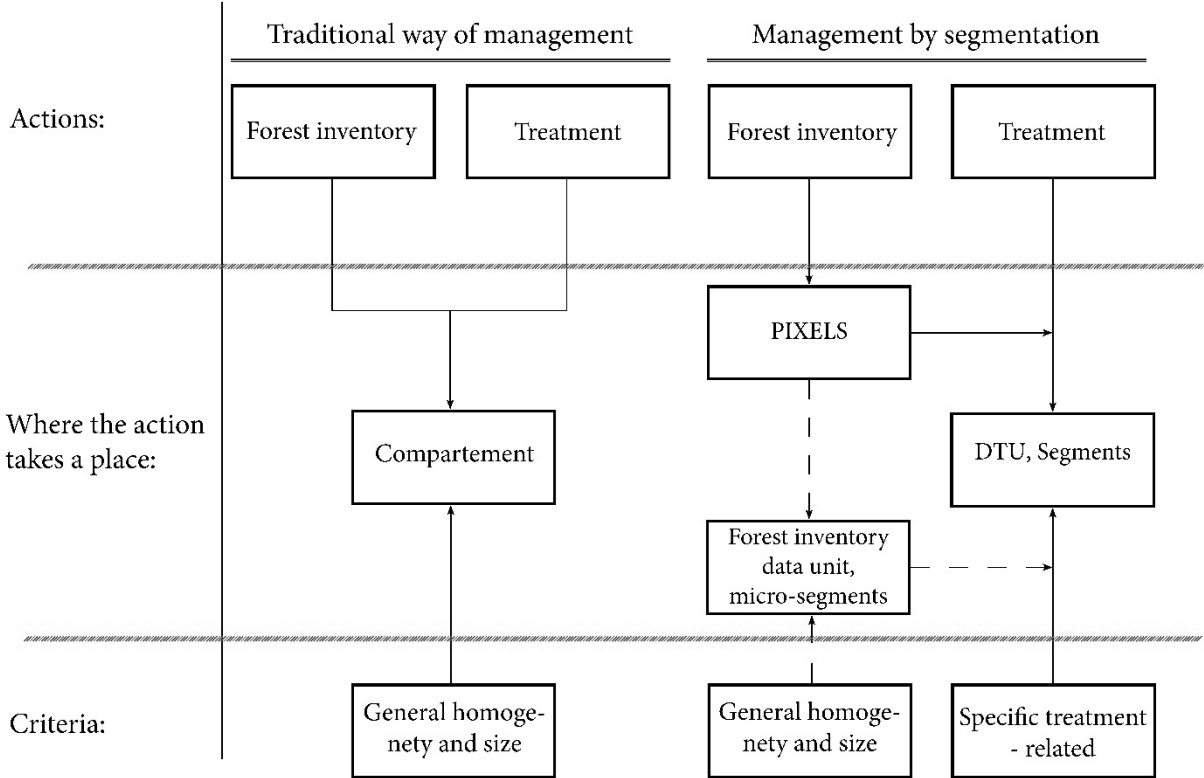

Figure 1. Potential relationships between forest inventory units and treatment units.

The complexity of the DTU forming is affected by the number of the input spatial units. It is possible to simplify the problem by preparing intermediate size units as it is presented by Pukkala et al. (2014) segmentation approach – called diffusion method to aggregate cutting

operations referred as "micro-segments". The main idea is aggregating pixels based on general homogeneity criteria and size. Figure 1 illustrates possible relationships between forest inventory units and treatment units. Traditional way of management assumes that before the targeted treatment takes place the owners need to have an information about the stand. Restrictions and criteria about the treatments are set by the tactical plan and legislation. In this management approach inventory and treatment units are highly related to each other. Since inventory provide with field information within the stand borders and based on this information owners make their decisions about the treatments. Alternative approach is to use remote sensing as an inventory unit in that case inventory units are pixels provided by ALS data. To increase efficiency of forest operation it is necessary to combine pixels together in segments - DTU. Pixel based inventory also has opportunity to implement some specific related treatment criteria such as NVP of future harvest. In case of forest management being done by pixel segmentation inventory and treatment units are not related. Pixels fulfill the inventory unit purpose, but pixel segments are treatment units. Pukkala et al. (2014) has another approach to inventory units, where they instead of using pixels uses pixel segments. They also states that DTU are created by combining pixel inventory segment units in this case inventory unit is represent with more than one pixel. With increased data availability the options for improving stand delineation increases.

A commonly used method to create a treatment unit is spatial optimization. The greatest challenge for the spatial optimization is to define a way in which adjacent raster cells or micro stands are similar in terms of features or management requirements and summarize it. Spatial optimization is used as a treatment unit delineation method in forestry mainly for creating a larger treatment unit out of small inventory units (Lu and Eriksson 2000; Heinonen et al. 2007, Pukkala et al. 2014). Spatial optimization as a possibility is used to improve the relative locations of forest management operations or forest resources through the small inventory units (Kurttila 2001; Baskent and Keles 2005).

Dynamic treatment unit (DTU) formation is based on the spatial optimization of standing volume which agglomerates small inventory units. The idea behind forming DTU in the study by Packalen, et al. (2011) is to increase total volume and improve the efficiency of forest use. From the conclusions of Packalen, et al. (2011) using the DTU in *Eucalyptus spp.* plantations the total volume production is always increasing. Islam, et al. (2011) show that spatial optimization through the clustering, is possible to define the micro-stands where the treatment with certain criteria (DBH, age, basal area, height etc.,) is currently more important. Islam, et al. (2011) applied optimization method from Heinonen et al. (2007). This method considers for individual spatial objectives (Islam et al., 2011).

According to Pukkala et al. (2014) UPM Kymmene in Finland, has developed segmentation approach based on the concept of micro-segmentation, a forest is divided into the small homogeneous growth conditions which they call micro-stands by applying an automated segmentation algorithm to digital aerial photography. Micro-stands give an opportunity to interpreted forest variables individually for each unit. In this way, the "micro stand" serve only as inventory unit, therefore it does not full the function of treatment unit. An algorithm calculates a harvest index for each of micro-stand segment separately, which are depended on urgency or possibility of harvesting. The algorithm may use stand age, stand density, tree size, etc, (Pukkala et al., 2014).

Öhman (2001) used mixed integer programming (MIP) model for clustering the harvest activities and areas selected for nature reserves. Karin Öhman´s clustering model requirements are incorporated into a net present value (NPV) of future harvest restricted by certain harvested yield which is harvested through the first period. The results show that the model is suitable for clustering selected pixels. According to the author these results are promising because of entry costs per ha decrease when the treatment units become larger. In the study captured size of pixels by using MIP model is no larger than 8.5 ha but some designed clusters could be too small for harvesting purposes (Öhman, 2001).

One of the methods such as optical satellite imagery presented by Holmgren and Thuresson (1997) are also suited for producing pixel level estimates. The reason why this method is not commonly used in forest inventories to support management planning is due to unsatisfactory data quality. Nevertheless, the article by Holmgren and Thuresson (1997) shows how forest management planning based on satellite imagery can increase economic profit for forest owners.

1.4. The economic consequences of erroneous data

Day by day Airborne Laser Scanning (ALS) in forestry has become more commonly used for inventories. The raw ALS data is usually a set of point clouds based on irregularly distributed x, y, z coordinates. Nevertheless, on a fully automated inventory system, the features extracted from ALS point clouds can affect the quality of forest stand delineation in multiple ways. As it was mentioned before, modern forest inventory methods allow for forest data to be interpreted as raster cells or small spatial units – micro-segments as an alternative to traditional forest compartments. To improve the efficiency of the forest management operations it is important to cluster existing raster cells into larger units. However, the result of the optimization is affected by errors from the forest inventory that was collected previously (Islam et al., 2011, Wu et al., 2013).

Two modeling methods were used by Maltamo et al, (2009), first Most Similar Neighbors is a non-parametric method based on correlation analysis to create a weighting matrix used for the selection of Most Similar Neighbors from reference data. Second method is simultaneously modeled by means of Seemingly Unrelated Regression. According to Maltamo et al, (2009) inaccuracy of inventory data using remote sensing for stem volume and crown height obtained by Most Similar Neighbors and Seemingly Unrelated Regression method is in the range of 7 % and up to 24 %.

Eid (2000) show that the effect of error of the age and height on expected losses is greater in the stands which are closer to the final felling stage.

There are expected losses occurring due to in optimal choices based on inaccurate information, this can be estimated thru cost-plus-loss analysis where also the costs of forest inventory are taken in to consideration. Traditional mean square errors cannot achieve this, it is used to estimate how implementable information is for the decision making in forest management (Hamilton 1978, Burkhart et al. 1978, Ståhl 1994; Eid 2000, Holmström et al. 2003, Eid et al. 2004, Juntunen 2006, Holopainen and Talvitie 2006, Barth et al. 2006, Duvemo et al. 2007). Based on the presented data by Kangas, (2009), different variables have different values in forest management table 1.

Table 1. The expected losses (NOK/ha) in final felling decisions due to random errors in different forest variables (Eid., 2000)

	Expected losses in NOK ha^{-1} in final felling			
RMSE, %	Basal area	Mean height	Site quality	Age
10	0	28	131	105
15	1	63	210	240
20	3	147	277	497

Studies by Juntunen (2006), Holopainen and Talvitie (2006) show higher expected losses than other authors Eid (2000), Holmström et al. (2003) and Eid et al. 2004. In the study by Holopainen and Talvitie (2006) mean losses varied from lowest 375 to highest 1 014 Euro/ha with 3 % interest rate. Other study done by Juntunen (2006) expected losses ranges from 64 to 130 Euro/ha with 4 % interest rate, generally the losses in other studies varied from 7 to 51 Euro/ha. For the calculations of expected losses in the Holopainen and Talvitie (2006) study RMSE varied from 15 % to 23 %.

2. Material and methods

The aims of this work is to investigate the effects of uncertainty in the pixel level estimates concerning the potential benefits of the dynamic, pixel-based treatment units compared to the traditional stand-based treatment allocation. An assumption is that the original airborne laser scanning, ALS, gives standing volume data that represents the "Ground truth" standing volume.

Work sequence:

1. Define the study area,
2. Introduce random errors to the "Ground truth" data of standing volume, creating 10 replicas (variants),
3. Form DTU's and allocate clearcutting treatments based on the original data and on the simulated data. Allocate clearcutting treatments using the existing stand borders,
4. Compare the outcomes.

The study area is part of the Östad foundation property located in Southern Sweden. Forest is managed in the traditional Scandinavian clearcutting regimes. The analysis area comprised of 1 848 ha. Airborne laser scanning (ALS) of the territory was carried out in year 2012.

The main tree species group in the estate is conifers with a share of 86 % (Norway spruce 58 % and Scots pine 28 %). Forest land in Östad is fertile and the majority of the land have site index ranging from 24 to 32. The age class distribution is not evenly distributed in the area and the majority of the forest is relatively young.

The data for thesis were extracted from the open data source provided by the Swedish National Forest Agency *"Skogliga Grunddata"*. The pixel size is 12.5 m by 12.5 m which is smaller than an average pixel size used in traditional forest planning.
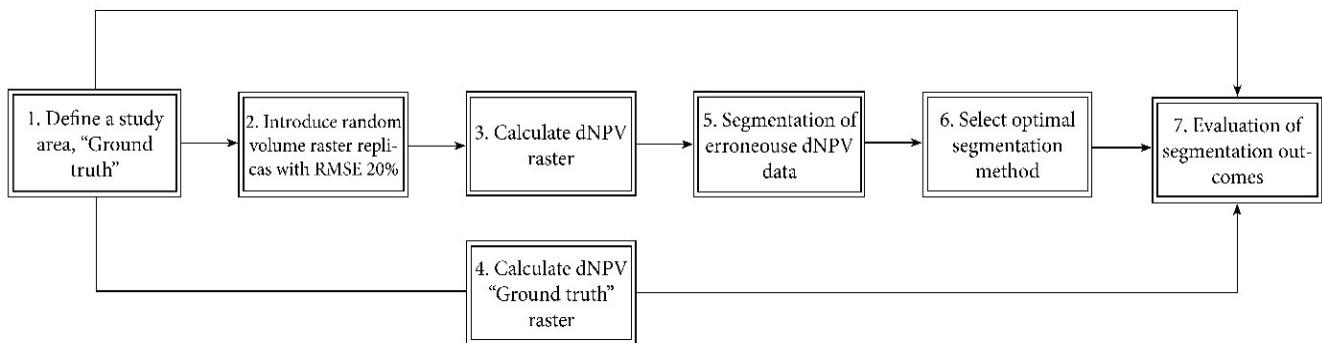

Figure 2. Flowchart

2.1. Simulation of standing volume variants

Standing wood volume data from the national ALS was assumed to represent the "Ground truth". Ten datasets with simulated errors were created using a model built in ArcGIS Model Builder. The errors were simulated according to the expression:

$$V^* = V(1 + e),$$

where V^* is the simulated volume value including error, V is the "Ground truth" volume for the given pixel, e is a random normally distributed number with mean $\mu = 0$ and variance σ^2.

Variance was set to 0.20 corresponding to a Root Mean Squared Error (RMSE) of 20%. This level of RMSE for total volume is slightly below the 24 % reported by Maltamo et al. (2009) for the plot (pixel) level. In the study by Holmgren (2004) is concluded that RSME may fluctuate depending on the stand density. Based on Holmgren (2004) results RMSE 11% for 31 m^3 ha^{-1} in average per stem volume is presented, for 55 m^3 ha^{-1} inaccuracy is presented as 20% in average per stem volume.

Restriction for raster variant simulation were set according to Eid (2000), RMSE affects the plots differently depending on volume, where the younger stands will show a higher value compare to the "Ground truth" while older stands will suffer a decrease in volume. The simulated raster values were therefore restricted to the minimum and maxim values from the "Ground truth" dataset. Which means that the imposed restriction keeps the simulated values from exceeding the range of existing values in "Ground truth". This model for random raster creation model was used ten times.

2.2. Segmentation based on economic aspects

This phase focused on DTU's specifically for final felling. DTU's were formed and evaluated using economic criteria. A planning period of 5 years was considered. The economic criteria were the projected change of NPV (dNPV) of the cut and of the un-cut pixels and the entry costs connected to starting harvest operations at a new location. NPV express net incomes that would be obtained if pixels is harvested now (NPV$_1$) or in five year period (NPV$_2$). dNPV was calculated on pixel level as the arithmetic difference between NPV$_1$ at the start of the planning period and NPV$_2$ at the end of the period. NPV$_2$ and NPV$_1$ were calculated using regression functions and coefficients from Trubins (2018). Eleven raster layers of dNPV were created: one from the "Ground truth" volume and ten from the volume datasets with simulated errors.

NPV$_2$ and NPV$_1$ were calculated using regression functions and coefficients from Trubins (2018):

$$NPV = exp(K_1 + K_2 * H + K_3 * SI + K_4 * V_{tot} - K_5 * H^2 - K_6 * V_{tot}^2 + K_7 * V_{tot}^3 - K_8 * pC - K_9 * pS - K_{10} * pOBA - K_{11} * pBr - K_{12} * pBe) - 20\,000,$$

where H is mean height, SI is site index, V_{tot} is total standing volume per ha, pC is proportion of conifers in volume, pS is proportion of spruce in volume, $pOBA$ is proportion of other broadleaves and aspen in volume, pBr is proportion of birch in volume and pBe is proportion of beech in volume. The coefficients for NPV$_1$ and NPV$_2$ functions are shown in table 2. For H and V_{tot} ("Ground truth") data from national ALS was used (Trubins, 2018).

Table 2. Coefficients of the regression functions for NPV_1 and NPV_2 (Trubins, 2018).

	variable	NPV_1	NPV_2
K_1	Mean height	8.66	8.97
K_2	Mean height	0.146	0.121
K_3	Site index	0.0191	0.0225
K_4	Volume ha^{-1}	0.00496	0.00538
K_5	Mean height^2	-0.00242	-0.00210
K_6	(Volume ha^{-1})^2	-5.89 E-06	-7.66 E-6
K_7	(Volume ha^{-1})^3	2.98E-09	4.62 E-9
K_8	Proportion of conifers, volume	-0.692	-0.754
K_9	Proportion of spruce, volume	-0.0850	-0.0321
K_{10}	Proportion of other broadleaves, volume	-1.05	-1.12
K_{11}	Proportion of birch in volume	-0.896	-0.989
K_{12}	Proportion of beech in volume	-1.07	-1.11

Entry costs were calculated using the function from Thuresson and Holmgren (1997) with a modified coefficient to account for inflation since the publication of the article.

$$EC = \frac{2000}{(A + 0.2)}$$

where A is the area of the treatment unit in ha. A was limited to the interval (0:2].

For the segmentation operation the standard Mean Shift segmentation algorithm in ArcMap was used. The three main parameters for the algorithm are spatial detail (SPD), spectral detail (SCD) and minimum segment size (MINS). Multiple segmentation variants were created in order to find the best-performing combinations of segmentation parameters. These initial segmentations were carried out on the dNPV raster based on "Ground truth" volume. Based on a pre-study, which was done before segmentation based on dNPV, it was expected that better segmentation variants would be those with SPD and SCD above 10. Therefore, and in order to minimize the computation load, combinations of SPD and SCD from 10 to 20 with the step of 1, were used for the 32, 68, 128 and 192 MINS. In total this gave 400 segmentation variants. Different harvest target volumes (80 000, 60 000, 40 000, 20 000 m^3) were used to evaluate combinations of SPD, SCD and MINS for each target harvest volume separately. Target harvest volume is important because it determines how large proportion of the total forest area (share of pixels) to be harvested. This, in turn, will affects which segmentation variant is to be preferred. For example, if forest owner has a plan to harvest 100 % of the forest then no selection for areas to harvest and consequently no segmentation is needed.

Segmentation results were evaluated based on dNPV and entry costs. The economically correct choice is harvesting stands with the lowest possible sum of dNPV and entry costs, in order to maximize the dNPV (i.e. value growth) of all the remaining pixels. Harvesting a pixel with positive dNPV, means potential value growth is lost. Harvesting a pixel with negative dNPV, means potential value loss is avoided. For convenience, we denote this sum as Avoided Value Change plus Costs (AVCC). In mathematical terms:

$$AVCC = min \sum_{i=1}^{m} (dNPV_i + EC_i),$$

where $i \dots m$ are the segments selected for harvesting.

The selection was done by ranking the segments according to the sums of dNPV and EC per ha in ascending order. Cumulative sums of standing volume were calculated for the thus ordered records. The m-th segment was defined as the last one before the cumulative volume sum exceeded the harvest target.

In an additional step the same economic evaluation was done for existing stand borders and each harvest target volume.

Table 3 shows combinations of the data and segmentation variants that were compared for each harvest volume. Cases 2.1 to 2.10 and 3.1 to 3.10 represent the real world alternatives: using data with errors with the optimized segmentation (DTU) or with existing stand borders (Original borders). Case 1 served as the ultimate reference as it combines the optimal segmentation (DTU) and the correct ranking of segments for harvest allocation. In Case 3 the existing stand borders were used with the error free - "Ground truth" data. This case represents what can be achieved using existing stand borders. All cases were evaluated Avoided Value Change plus Costs (AVCC calculation) using the "Ground truth" based dNPV data.

Table 3. Combinations of the data and segmentation variants.

Case	Border basis	Basis for segment ranking and selection for harvest	Basis for AVCC calculation
1.	Dynamic treatment units	"Ground truth"	"Ground truth"
2.1 – 2.10	Dynamic treatment units	data with errors (respective 10 variants)	"Ground truth"
3	Existing stand borders	"Ground truth"	"Ground truth"
3.1 – 3.10	Existing stand borders	data with errors (10 variants)	"Ground truth"

For comparisons of the cases following formulas were used:

Difference in Avoided Value Change plus Costs, SEK:

$$AVCC_{ci} - AVCC_{cj},$$

where C_i is case i and C_j is case j .

Difference in Avoided Value Change plus Costs per m³ of harvest, SEK/m³:

$$\frac{AVCC_{ci} - AVCC_{cj}}{V_{ht}},$$

where V_{ht} is the harvest target.

3. Results

3.1. Segmentation based on economic aspects

Raster randomization provides a chance to simulate similar data to ALS data from *"Skogliga Grunddata"* database. Figure 3 present standing volume according to "Ground truth" and "Simulated raster variant No 4" containing random errors as previously shown in table 3. "Simulate raster variant No 4" is one out of ten real world alternatives with errors which was produce by using ArcGIS Model Builder. The average standing volume per ha over the whole study area in the created rasters differs only by 0.1 m^3 to 0.5 m^3. Visually it is possible to see a difference in raster cells (figure 3) because of the effects on individual cells are greater than in average per raster. Impact on the individual cells can be noticed in the dNVP rasters (figure 4) with some adjustments of the color scales on the maps.

The differences are possible to see, most likely because of the restrictions that make younger forest pixels more influenced by errors compared to the older ones. The error distribution differs depending on volume. In figure 3 it is possible to see slim differences of volumes in the "Ground truth" and the simulated dataset. Average, maximal and minimal volume per cell is similar in all created rasters (163, 906 and 0 m^3/ha). At the same time, the simulated rasters have more even volume distribution than "Ground truth" raster with fewer extreme values.

dNPV for the following five years planning period was introduced in new rasters. Figure 4 show the "Ground truth" and one of the simulated datasets. dNPV was calculated only for the areas where the stand mean age, according to the stand register data is above 30 years. dNPV in the "Ground truth" raster varies from -35 648 to 39 781 SEK/ha and for large share of cells dNPV is in the range of -8 492 to 5 086 SEK/ha. As shown in the example, raster "Variant No 4" dNPV value range is from -32 496 to 42 320 SEK/ha and large share of cells are in the range of -12 318 to 7 860 SEK/ha.

Table 4. Summary of optimal segmentation by target harvest volume

Minimum segment size in pixels	Entry Cost	dNPV	Harvest Volume	Area (ha)	Entry Cost per ha	dNPV per ha	AVCC	AVCC per ha
32	72557	-417895	19671	45	1618	-9319	-345338	-7701
32	161538	-674922	39895	104	1558	-6510	-513384	-4952
32	263135	-812220	59922	167	1578	-4871	-549084	-3293
32	360087	-829212	79504	242	1485	-3420	-469125	-1935

In Table 4 optimal segmentations for AVCC per ha are summarized for each harvest target. Actual harvest volumes can be slightly under the target. The results are sorted by AVCC per ha in ascending order. Table 4 shows that the minimum segment size of 32 pixels (0.5 ha)

performed best for all target harvest volumes. This means that the cost for small segment size by higher entry cost does not outweigh the gain in dNPV through smaller and more uniform segments. At least not in the tested range of Minimum segment size, MINS. Target harvest volume of 20 000 m^3 is associated with the lowest AVCC per ha in all cases of tested MINS.
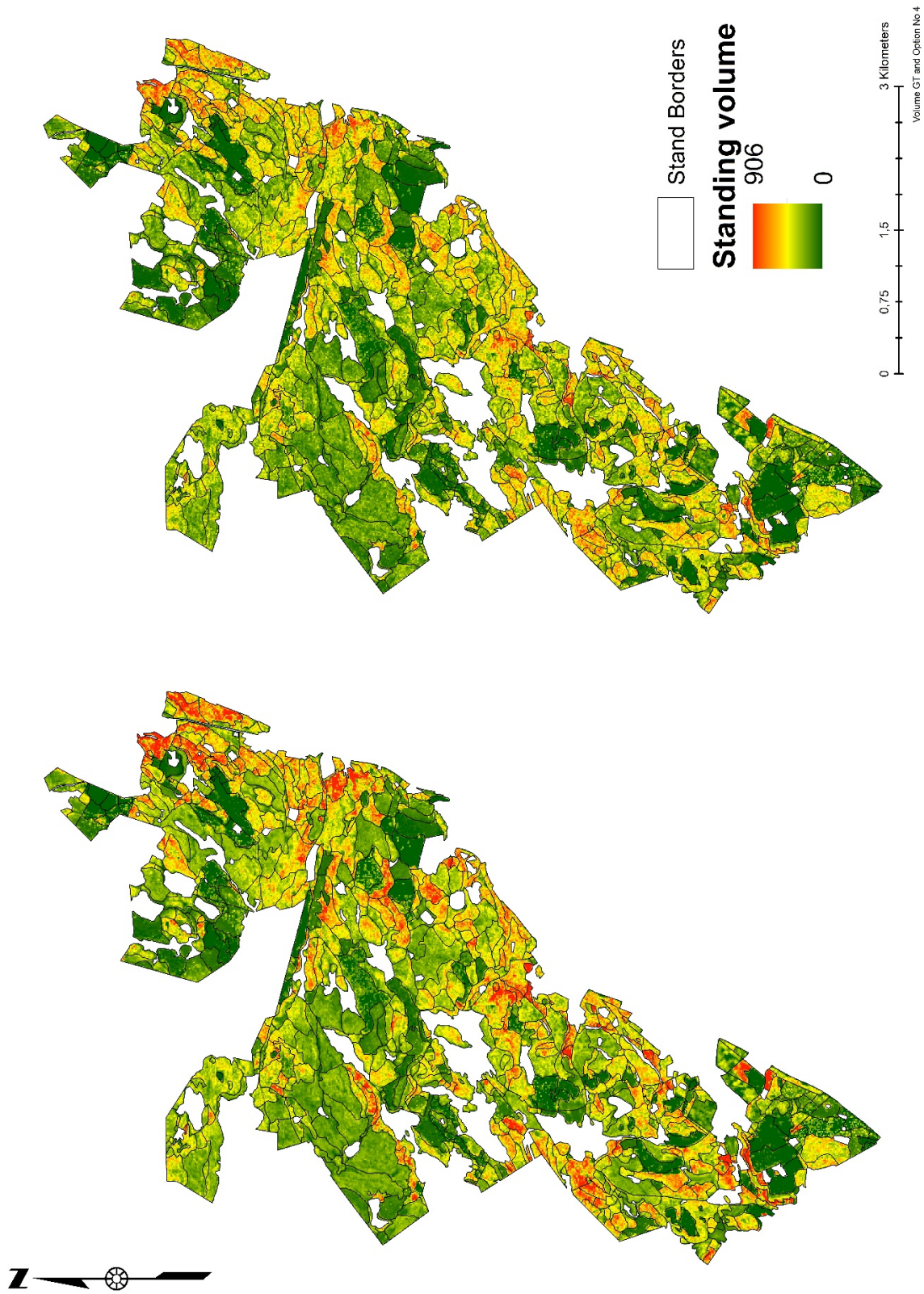
Figure 3. Standing volume according to "Ground truth" on the left side and "Created raster No 4" on the right side.
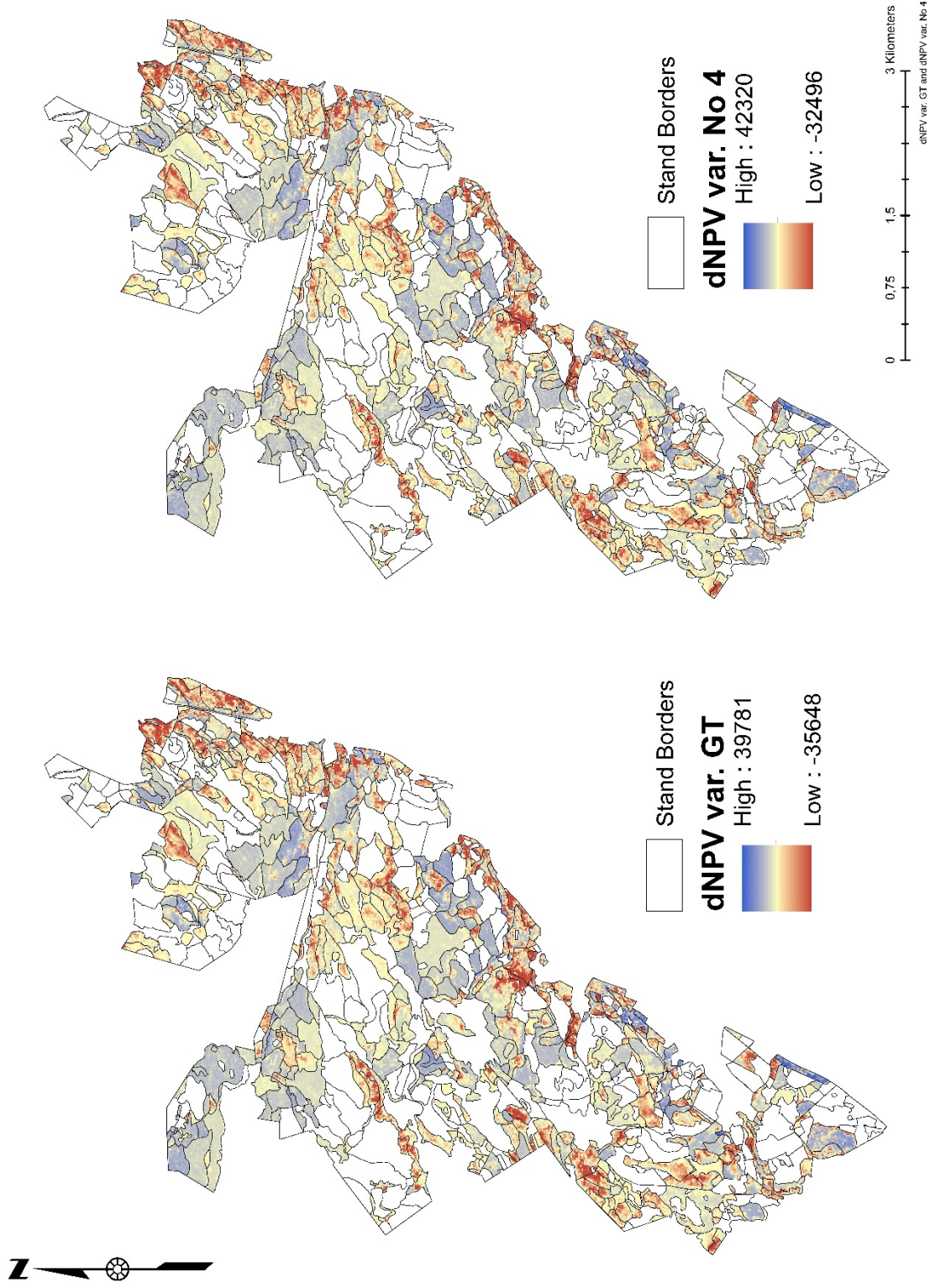
Figure 4. dNPV for the first five-year planning period according to "Ground truth" on the left side and on the right side "Simulated variant No. 4". dNPV is shown only for stands with age over 30 years.

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3.2 Evaluation of the errors effect

Since previous studies such as Packalen, et al. (2011), Holmgren and Thuresson (1997) showed that dynamic treatment units have benefits over the traditional stand delineation, the ultimate reference for comparisons, in other words "zero point" was the dynamic treatment units based on ground truth data. All other values (Cases) are compared to this reference. Figure 5 illustrates differences between the tested cases. Figure 5 is based on Table 5, which compares, firstly, created DTU variants (Case 2.1 – 2.10) and "Original border" variants (Case 3.1 – 3.10) to the "Ground truth" (GT) based segmentation variant (Case 1), secondly, the DTU variants (Case 2.1 – 2.10) and "Original border" variants based stand selection (Case 3.1 -3.10) and thirdly DTU "Ground truth" variant (Case 1) and "Original border" "Ground truth" variant (Case 3) to each other. All results in Table 5 and figure 5 are presented in average except the comparison between Case 1 and Case 3.
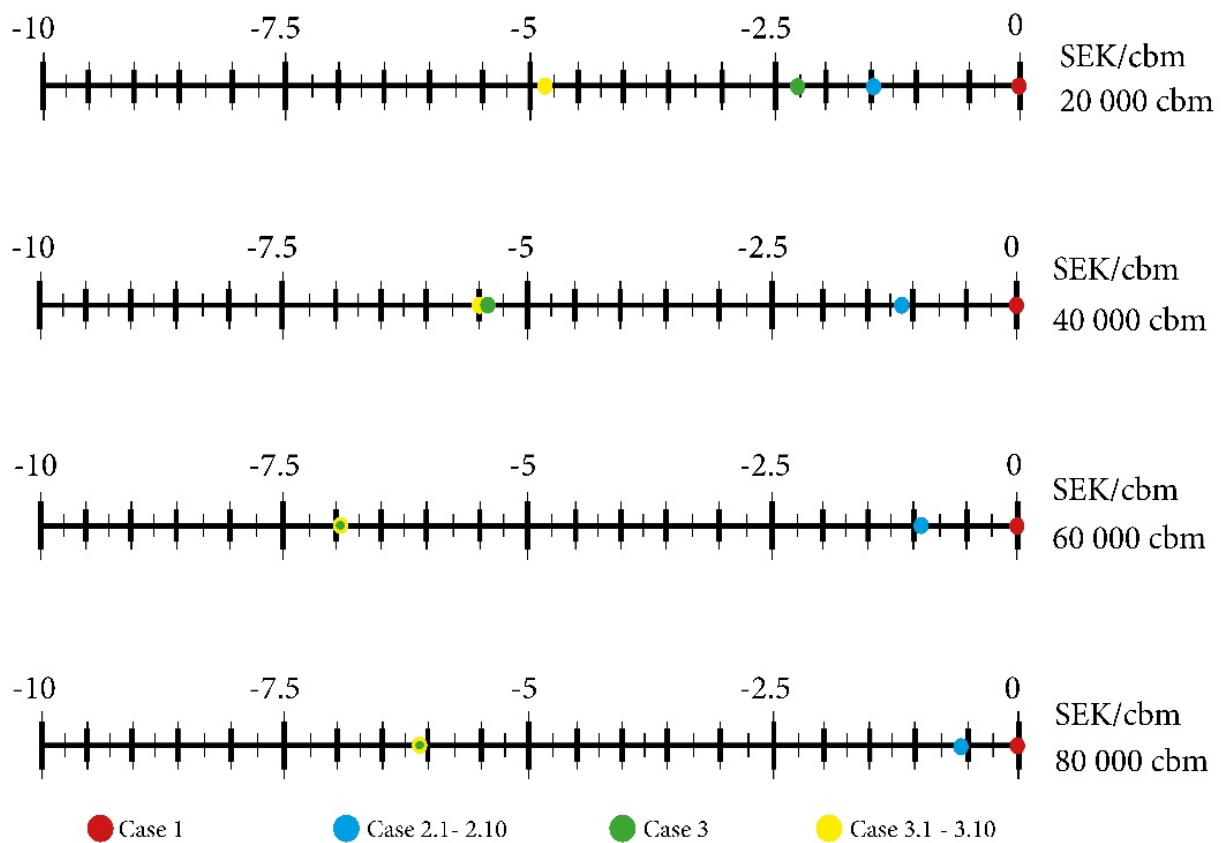

Figure 5. Comparisons of harvest allocation variants

Table 5. Comparisons of harvest allocation variants: Based on "Ground truth" (GT) dNPV (Case 1 and Case 3), DTU variants based on simulated dNPV (Case 2.1 – 2.10), original stand borders with simulated dNPV (Case 3.1 – 3.10).

Minimum segment size in ha	Target harvest volume	Average difference in AVCC per m^3 between DTU GT (Case 1) and DTU (Case 2.1 – 2.10), SEK/m^3	Average difference in AVCC per m^3 between DTU GT (Case 1) and Original borders (Case 3.1. – 3.10), SEK/m^3	Difference between DTU GT (Case 1) and Original borders GT (Case 3) in AVCC per m^3, SEK/m^3	Average difference between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1. – 3.10) in AVCC per m3, SEK/m3
0.5	20 000	-1.4	-4.7	-2.3	-3.2
0.5	40 000	-1.1	-5.5	-5.4	-4.4
0.5	60 000	-0.9	-6.9	-6.9	-5.9
0.5	80 000	-0.6	-6.1	-6.1	-5.5

As is shown in Table 5 the errors in dNPV influence the potential incomes in all cases, especially in cases where traditional stand delineation was used. The difference in Avoided Value Change plus Costs (AVCC) per m^3 between the DTU "Ground truth" and "Original border" GT is - 2.3 SEK/m^3 for harvest volume 20 000 m^3 target. Average difference in AVCC per m^3 between the DTU "Ground truth" and "Original border" for target volume 20 000 m^3 as simulated variants is -4.7 SEK/m^3 in other harvest volume which were tested in thesis uncertainty effect on potential losses is not that significant. So, when the target for harvested volume increases the average difference in AVCC per m^3 is decreasing as seen in table below for the cases previously mentioned.

The highest difference in AVCC per m^3 of all was in the case of target harvesting volume 60 000 m^3 between the DTU "Ground truth" (Case 1) which was put in to relation with "Original border" variants (Case 3.1 – 3.10) as well as "Original borders" GT (Case 3) and they bot resulted in a difference of -6.9 SEK/m^3.

According to the calculations the highest average difference in absolute AVCC between Case 2.1 – 2.10 and Case 3.1 – 3.10 is -464 601 SEK m^3 with the conditions of segment size minimum 64 pixels (1 ha) and target harvest volume 80 000 m^3 presented in expanded table in appendix. The table below shows a more detailed explanation of the effect harvest volume has on the different errors within the cases in the form of AVCC. The peak for financial losses is reached at the target harvest volume 60 000 m^3, thereafter it starts to decrease.

3.3. The errors effects on the individual raster

To explain better effect of uncertainty on the individual raster variants and potential incomes tables 12 to 15 are presented - maximal and minimal economical differences between DTU based on "Ground truth" variant (Case 1), DTU variants based on simulated dNPV data (Case 2.1 – 2.10) and "Original stand" border variants with simulated dNPV data (Case 3.1 – 3.10). Variants of raster with larger fluctuation between values for each target harvest volume variant were selected from Table 4.

Tables 12 and 13 shows relation between DTU segmentation based on GT (Case 1) and DTU variants based on simulated dNPV (Case 2.1 – 2.10) to each other. -2 SEK/m³ is the highest difference between the "Variant No 2" and "Variant GT" with target harvest volume 20 000 m³ and the smallest difference -0.4 SEK/m³ is measured by compering "Variant No 4" to "Variant GT" for 80 000 m³ target harvest volume in tables 12 and 13.

Table 6. Maximal difference between DTU based on "Ground truth" dNPV (Case 1) and DTU variants based on simulated dNPV (Case 2.1 – 2.10)

Target harvest volume	Name of variant	Max. difference in AVCC between DTU GT (Case 1) and Variants (Case 2.1 – 2.10), SEK	Max. difference in AVCC per m³ between GT (Case 1) and Variant (Case 2.1 – 2.10), SEK/m³
20 000	Variant No2	-40 165	-2.0
40 000	Variant No5	-51 322	-1.3
60 000	Variant No10	-66 871	-1.1
80 000	Variant No2	-65 772	-0.8

Table 7 Minimal difference between DTU based on "Ground truth" dNPV (Case 1) and DTU variants based on simulated dNPV (Case 2.1 – 2.10)

Target harvest volume	Name of variant	Min. difference in AVCC between DTU GT (Case 1) and Variants (Case 2.1 – 2.10), SEK	Min. difference in AVCC per m3 between GT (Case 1) and Variant (Case 2.1 – 2.10), SEK/m3
20 000	Variant No7	-19 344	-1.0
40 000	Variant No4	-28 497	-0.7
60 000	Variant No7	-39 802	-0.7
80 000	Variant No4	-31 370	-0.4

Table 8. Maximal difference between DTU based on "Ground truth" dNPV (Case 1) and original stand borders with simulated dNPV (Case 3.1 – 3.10).

Target harvest volume	Name of variant	Max. difference in AVCC between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1 – 3.10), SEK	Max. difference between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1. – 3.10) in AVCC per m³, SEK/m³
20 000	Variant No4	-151 276	-7.6
40 000	Variant No4	-193 014	-4.8
60 000	Variant No7	-376 505	-6.3
80 000	Variant No10	-466 553	-5.8

Greater max. difference between the Case 1 and Case 3.1 – 3.10 is represented by the raster "Variant No 4" with target harvest volume 20 000 m^3 potential loses in this case reached -7.6 SEK/m^3 presented in table 8. Smallest min. difference -1.7 SEK/m^3 between the Case 1 and the Case 3.1 – 3.10 is represented by the raster "Variant No 3" with target harvest volume 20 000 m^3 in table 9.

Table 9 Minimal difference between DTU based on "Ground truth" dNPV (Case 1) and original stand borders with simulated dNPV (Case 3.1 – 3.10).

Target harvest volume	Name of variant	Min. difference in AVCC between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1 – 3.10), SEK	Min. difference between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1. – 3.10) in AVCC per m^3, SEK/m^3
20 000	Variant No3	-33 982	-1.7
40 000	Variant No5	-165 429	-4.1
60 000	Variant No2	-356 241	-5.9
80 000	Variant No3	-416 398	-5.2

In the following maps, outcomes of the comparison between the cases with the greatest negative results are selected from tables 12 and 15. Generated differences of dynamic treatment units illustrate slim differences on the locations changes over the lowest dNPV pixel values, the differences are presented by figures 5 - 13. The figures show stand delineation of Case 1, Case 2.1 – 2.10 and Case 3.1 – 3.10. To highlight visual changes of stand delineation under the stand boundaries layer, dNPV raster based on "Ground truth" data is presented in illustrations as well as with the red line some changes are marked.
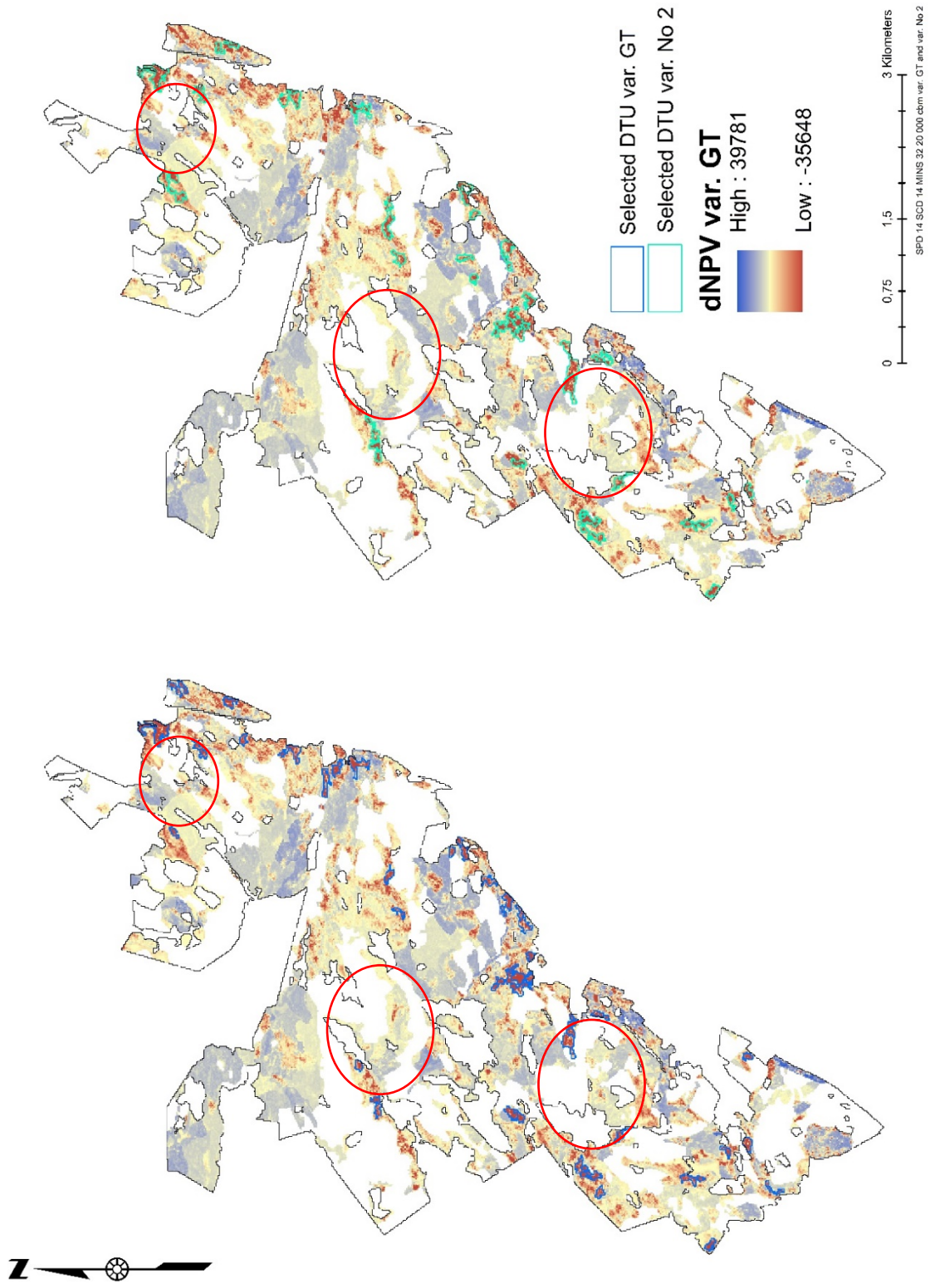
Figure 6. Selected DTU for 20 000 m³ of total harvest volume according to "Ground truth" on the left side and raster "Variant No 2" on the right side.
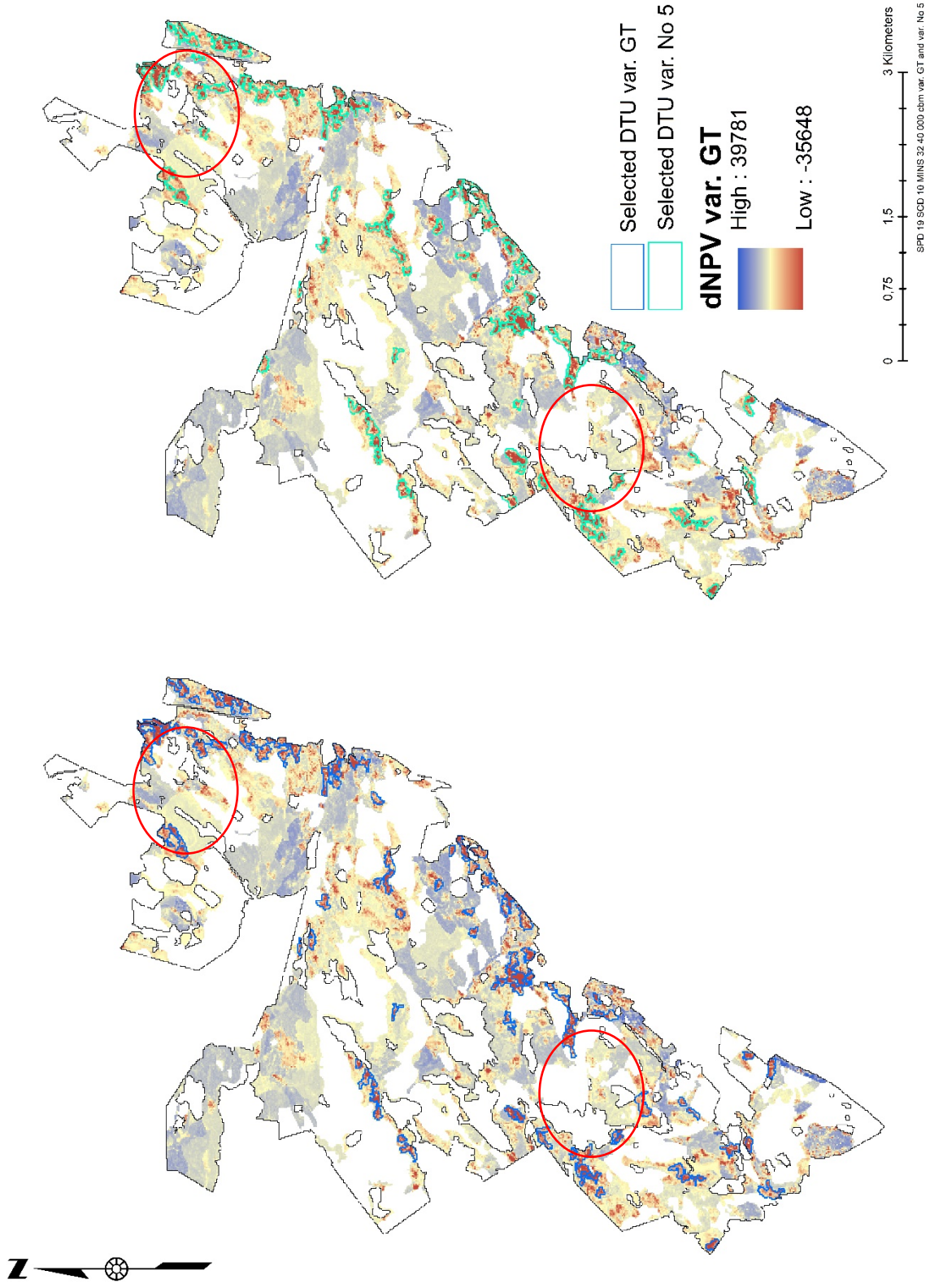
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Figure 7. Selected DTU for 40 000 m³ of total harvest volume according to "Ground truth" on the left side and raster "Variant No 5" on the right side.

Selected DTU var. GT
Selected DTU var. No 5

dNPV var. GT
High : 39781

Low : -35648

SPD 19 SGD 10 MINS 32 40 000 cbm var. GT and var. No 5
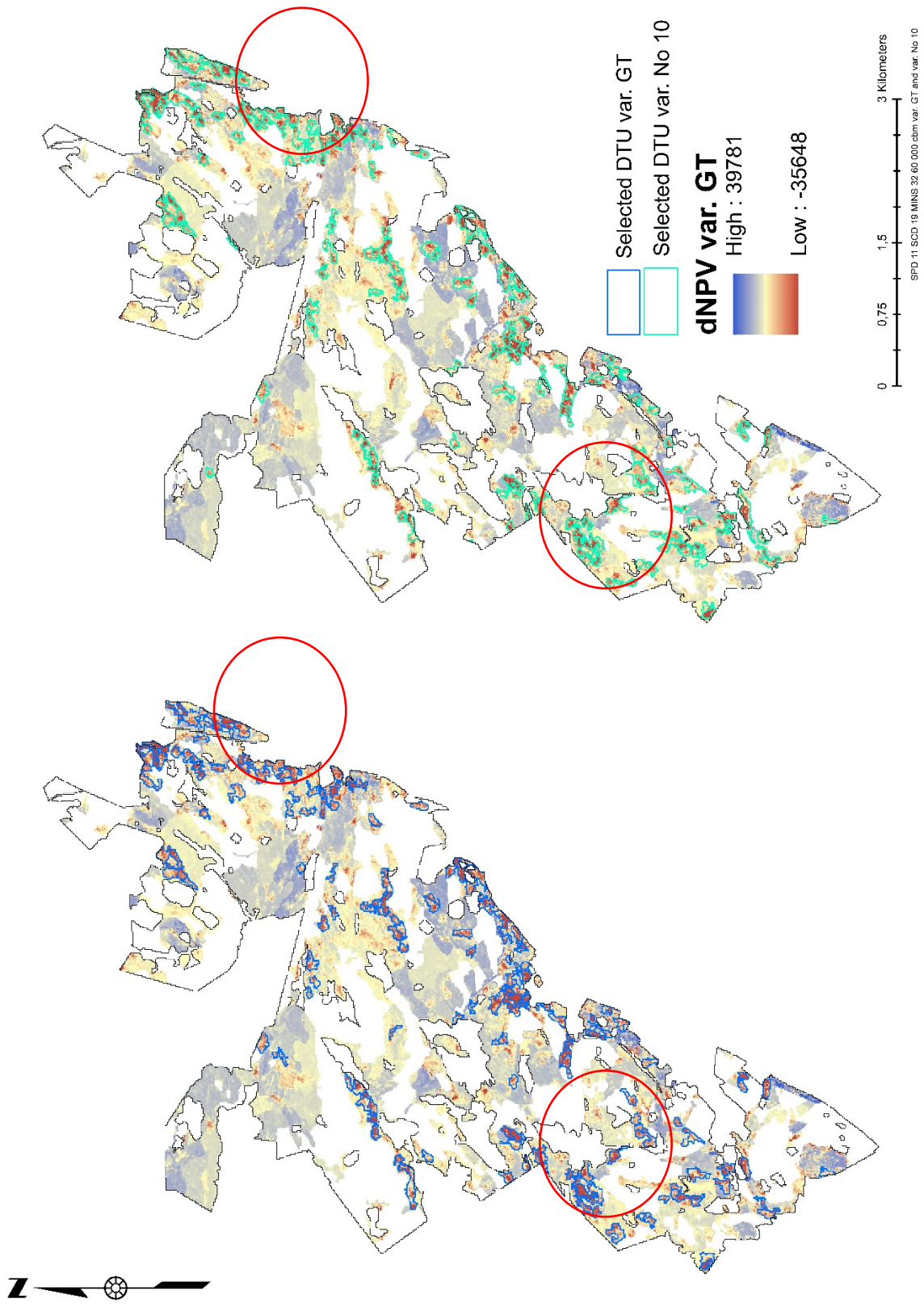
0   0.75   1.5   3 Kilometers

27

Figure 8. Selected DTU for 60 000 m³ of total harvest volume according to "Ground truth" on the left side and raster "Variant No 10" on the right side.
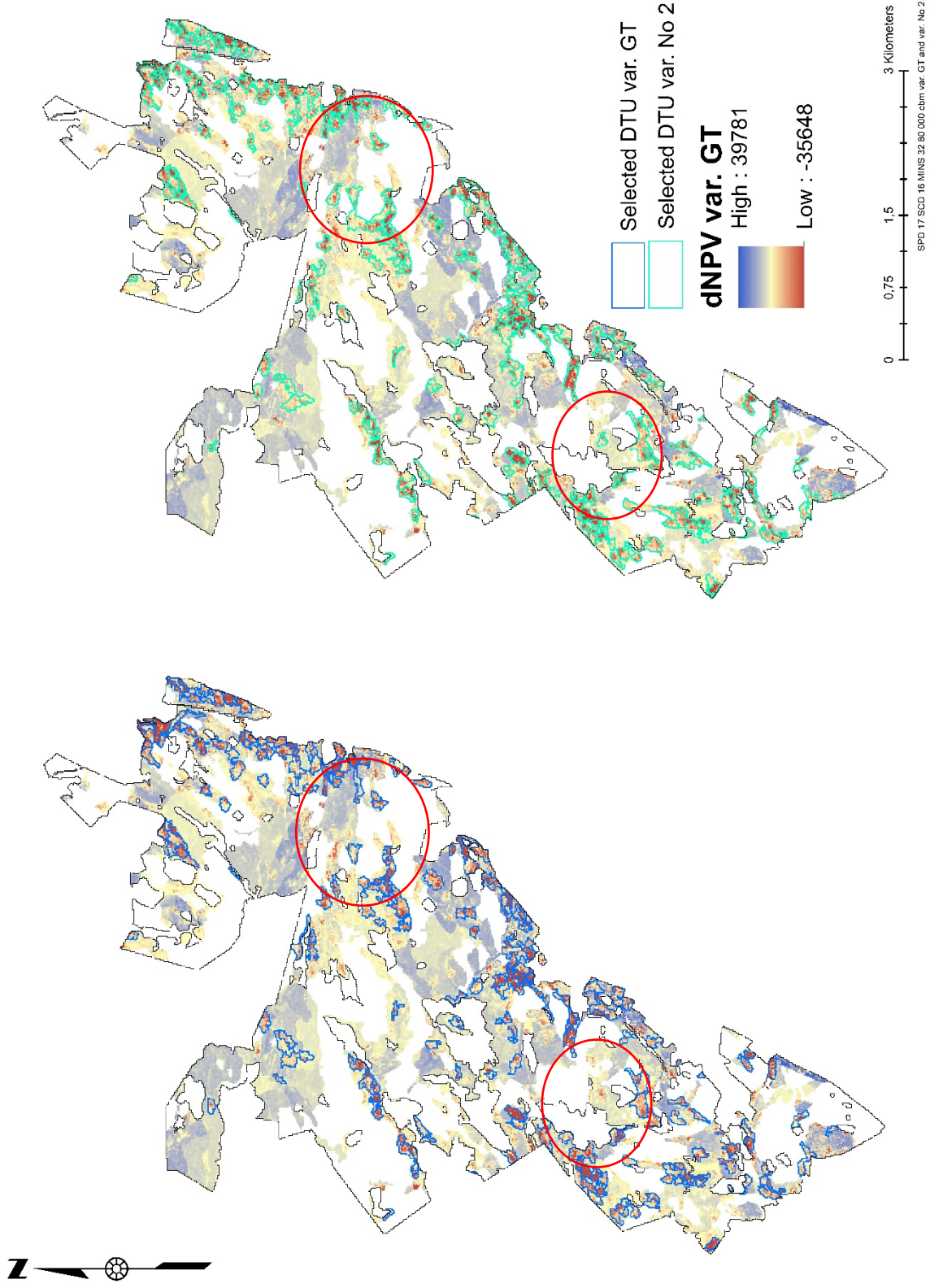
Figure 9. Selected DTU for 80 000 m³ of total harvest volume according to "Ground truth" on the left side and raster "Variant No 2" on the right side.

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Figure 10. Selected final felling stands for 20 000 m³ of total harvest volume according to Case 3.4 "Variant No 4" on the left side and Case 2.4 "Variant No 4" on the right side.

Selected orig. stands var. No 4

Selected DTU var. No 4

dNPV var. GT
High : 39781

Low : -35648

SPD 14 SCD 14 MINS 32 20 000 cbm Orig. stands var. No 4 and DTU var. No 4
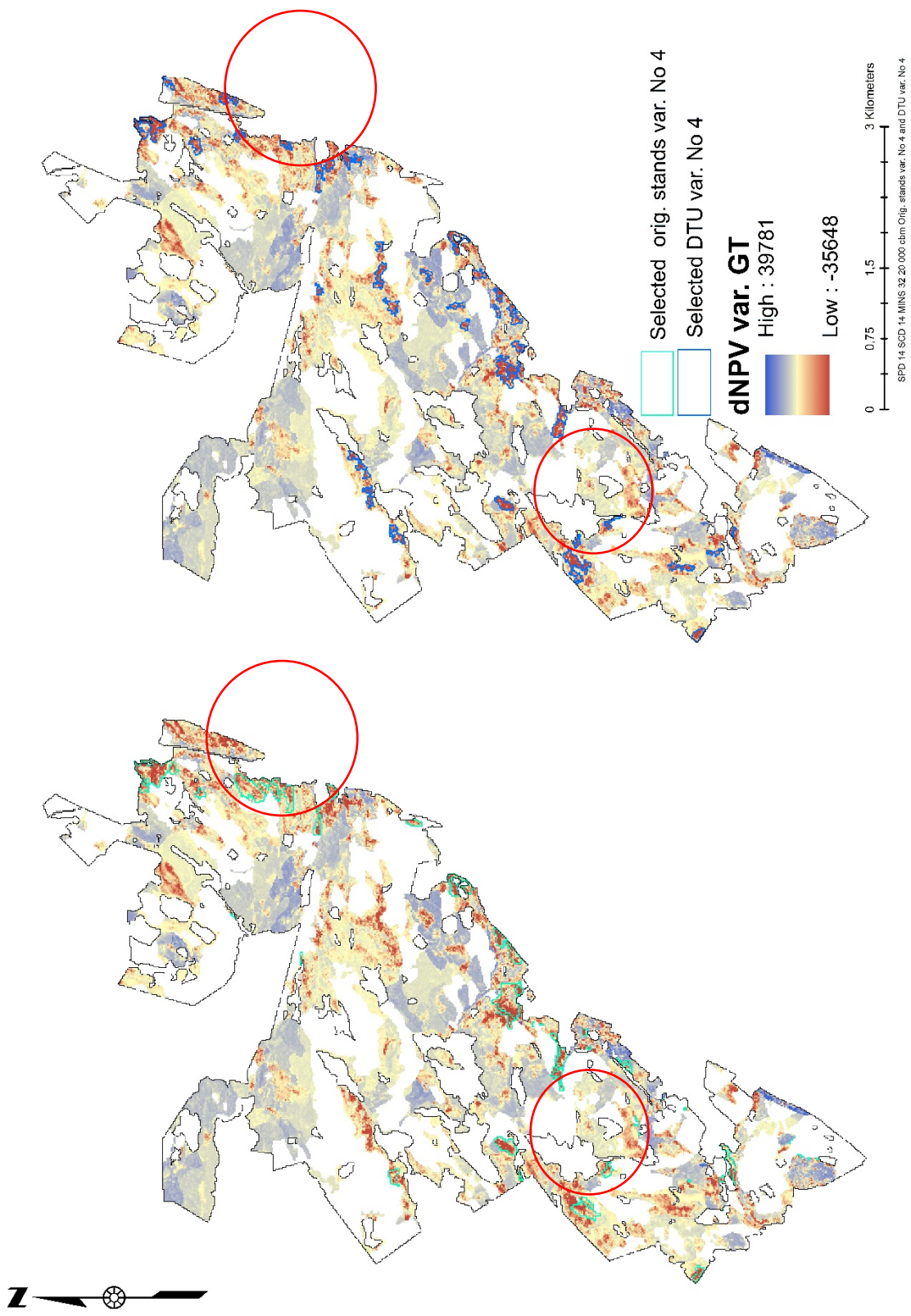
0   0,75   1,5   3 Kilometers

Figure 11. Selected final felling stands for 40 000 m³ of total harvest volume according to Case 3.4 "Variant No 4" on the left side and Case 2.4 "Variant No 4" on the right side.
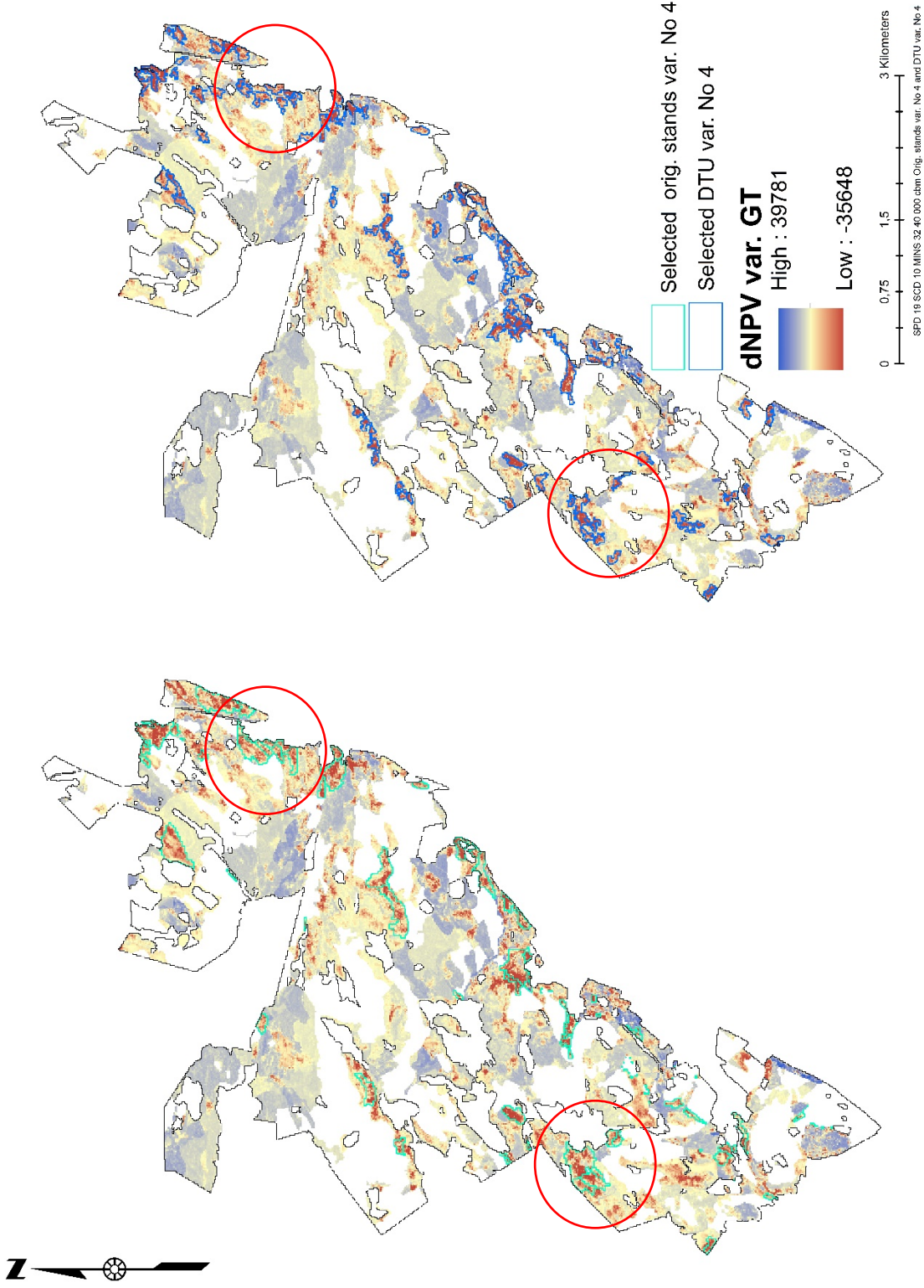
31
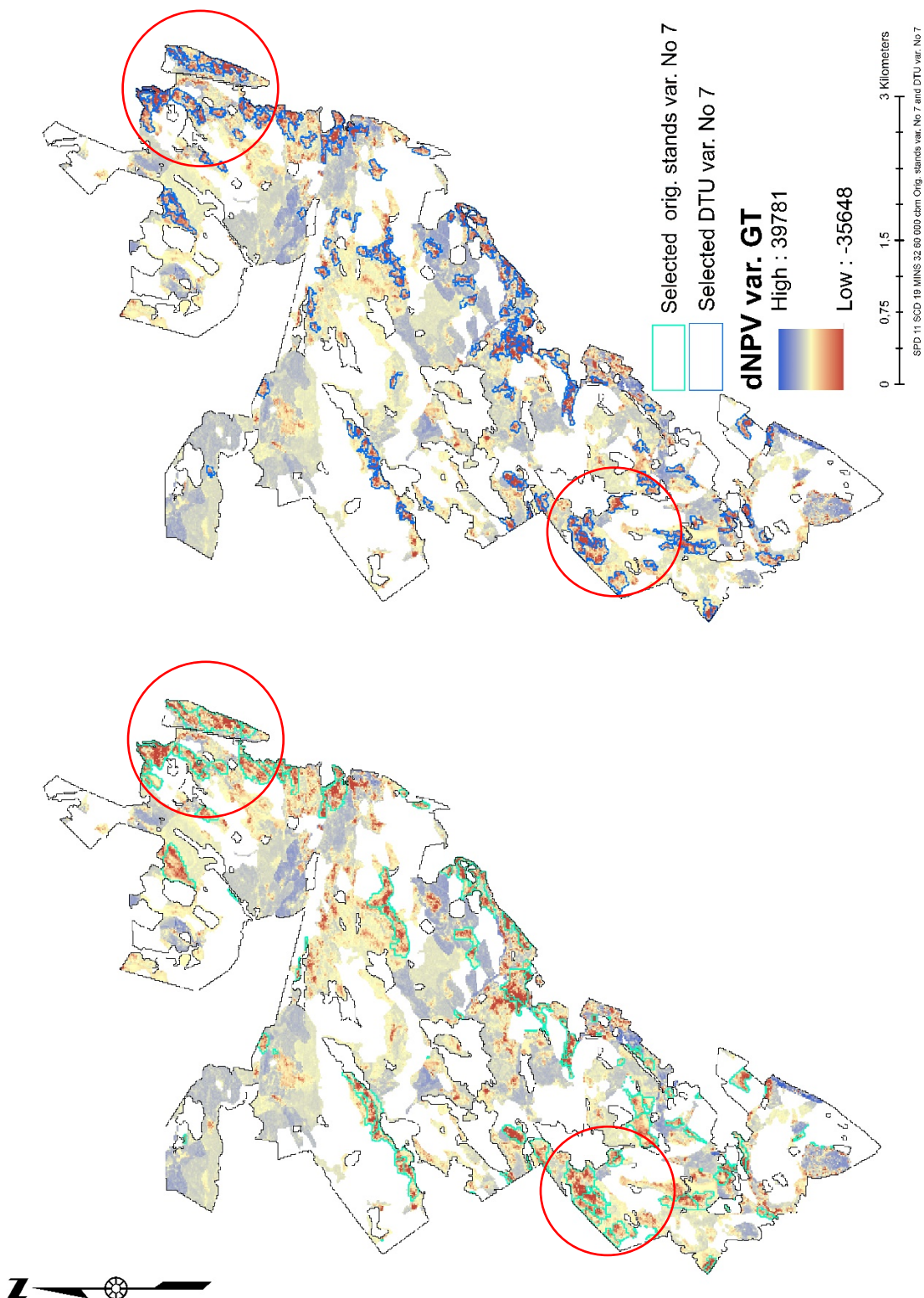
Figure 12. Selected final felling stands for 60 000 m³ of total harvest volume according to Case 3.7 "Variant No 7" on the left side and Case 2.7 "Variant No 7" on the right side.

Selected orig. stands var. No 7

Selected DTU var. No 7

dNPV var. GT
High : 39781

Low : -35648

0   0,75   1,5   3 Kilometers

SPD 11 SGD 19 MINS 32 60 000 cbm Orig. stands var. No 7 and DTU var. No 7
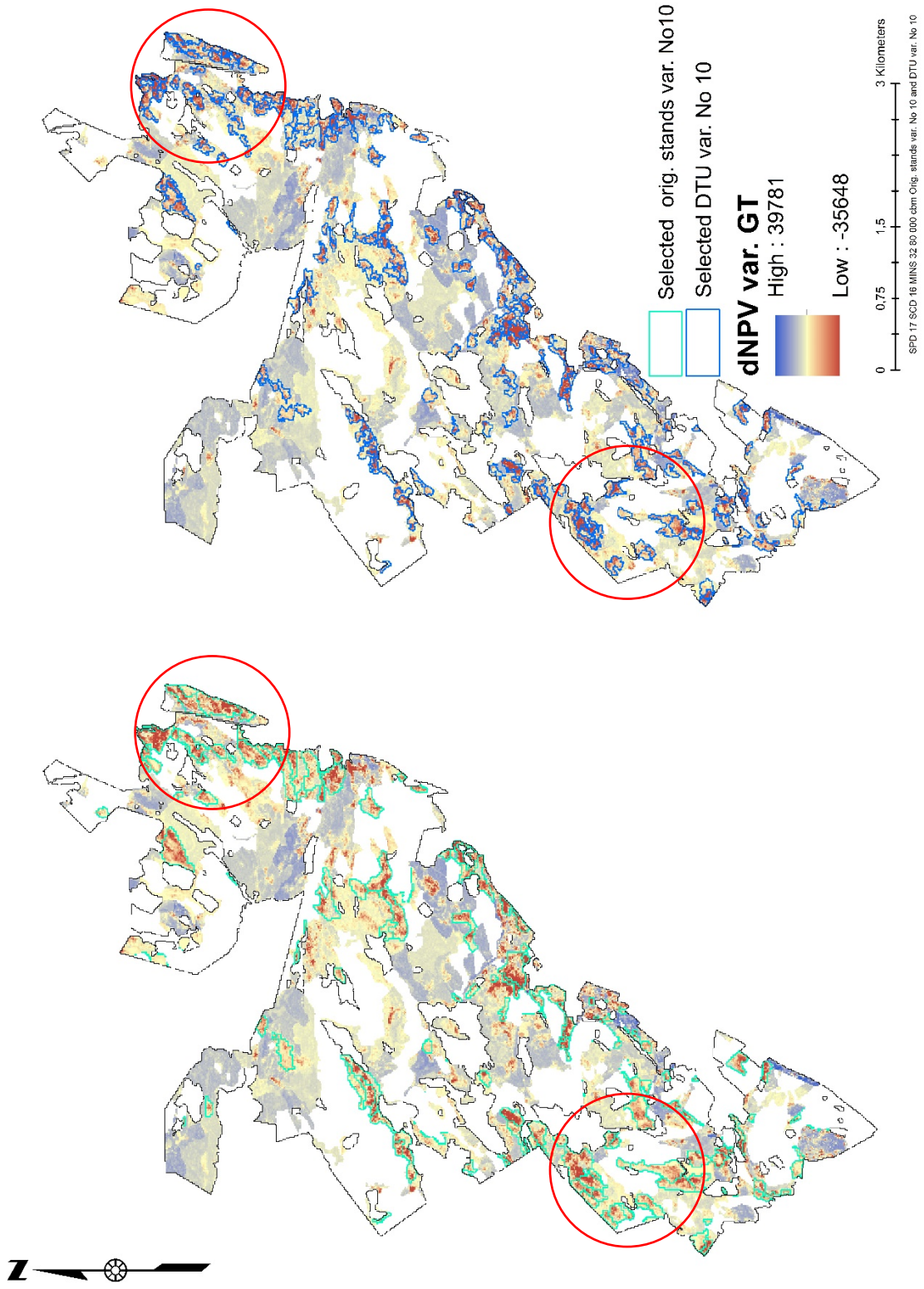
32

Figure 13. Selected final felling stands for 80 000 m³ of total harvest volume according to Case 3.10 "Variant No 10" on the left side and Case 2.10 "Variant No 10" on the right side.

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4. Discussion

One of the limitations for this thesis is the basis used for creating errors. To create the errors data non-forest lands was extracted. There was restriction set for threshold values for a single pixel to not pass 906 m^3 ha^{-1}. This restriction derives from Eid (2000) who proclaims that errors has larger effect on the stands which are closer to the final felling stage. However, there are a variety of error sources concerning the ALS data such as global navigation satellite system, internal navigation system, object characteristics, scanning angle, footprint size, flight altitude and processing, human errors, stand density etc., (Sterenczak et al., 2013, Holmgren, 2004). This is something that may have a noticeable influence on the data which is not at all taken in to consideration in the thesis. In thesis inaccuracy of 20 % was used statically over all raster.

The results show that tactical planning based on ALS data with 20 % inaccuracy in average has the economic impact which is presented in Table 5. With the included conditions simulations show some potential losses per m^3 compared to the "Ground truth" data. In some cases, the impact is insignificant. Difference per m^3 in average between Case 1 and Case 2.1 – 2.10 with the target harvest volume of 20 000 m^3 losses reach -1.4 SEK/m^3. Target harvest volume in study has an impact on the potential losses. When the target volume goes from 60 000 m^3 to 80 000 m^3 the trend of financials is changing and the potential losses per m^3 is minor decrease. Based on this outcome it could be assumed that it might be related to the total number of pixels which can be extracted. Since 80 000 m^3 covers majority of the standing volume pixels which is considered at stage of final felling. Due to this phenomenon the biggest potential loss in SEK per m^3 is reached at the target volume of 60 000 m^3.

The results concerning the average difference between dynamic treatment units, DTU, and "Original borders" in all cases favor the DTU. The largest difference between Case 2.1 - 2.10 and Case 3.1 - 3.10 is -5.9 SEK/m^3. This result is achieved at 60 000m^3 target harvest volume. At the same time the difference between Case 1 and Case 3 is -6.9 SEK/m^3, also at 60 000 m^3. In all tested variants the difference between Case 1 and Case 3 was by approximately 1 SEK/m^3 larger the difference between the averages of Cases 2.1 – 2.10 and Cases 3.1 – 3.10.

Minimum segment size has an effect the potential losses as well, for example 3 ha large minimum segment has smaller difference per SEK/m^3 than any other size-based segmentation variant when comparing specific target volume among themselves. In authors opinion those differences are related to the homogeneity, because more homogeneous stand delineation gives less opportunity for variations within the stand locations and takes away the opportunity to select the less profitable cells in the raster for cutting. Smaller segments also open an opportunity to combine the units afterwards which give more flexibility for the forest manager to make more self-depended choices than by using already set restrictions in ArcMap software. The question is how small the minimum segment size could be and still be efficient, in this work the smallest tested minimum segment size was 0.5 ha.

In practice, tactical planning can be improved by applying the dynamic treatment units as a method to improve the economic output for the forest management and it can also improve the land use by extracting the microsegments with the lowest value growth and replacing them with new segments with positive value growth. In addition, it can give the opportunity for forest

managers to, instead of planning for final felling in the whole stand with negative dNPV, have the choice to extract the part which starts to produce economic losses.

The finding in this work is similar to studies such as presented by Packalen, et al. (2011), Holmgren and Thuresson (1997) where the authors presents that dynamic treatment units such as an alternative to traditional stand delineation with higher efficiency. In other articles the authors did not consider the potential errors in the data therefore the main difference is that in this thesis uncertainty is taken into a count. Potential errors according to the results from thesis tactical planning based on dynamic treatment units have economic advantage over the planning based on "Original stand" borders.

The results indicate that applying dynamic treatment units to the tactical planning based on ALS data with 20 % inaccuracy will increase the land use even with a smaller final harvest volume.

For the future study one possibility could be to try to determine ALS data accuracy of an economic break-even point with the traditional forest inventory when ALS is used in a DTU framework.

5. Conclusions

Dynamic treatment units are more efficient than original stand borders. Even if the effect of volume data errors is considered dynamic treatment units have economic advantage over the original stand borders.

1. The efficiency gain of dynamic treatment units is affected by the share of harvested pixels;
2. Average difference between dynamic treatment unit variants and original stand border variants in all cases favor the dynamic treatment unit variants with economical aspect:

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Appendix

Expanded Table 5. Comparisons of harvest allocation variants: DTU based on GT dNPV (Case 1), DTU variants based on simulated dNPV (Case 2.1 – 2.10), original stand borders with simulated dNPV (Case 3.1 – 3.10).

Minimum segment size in pixels	Target harvest volume	Average difference in AVCC per m^3 between DTU GT (Case 1) and DTU variants (Case 2.1 – 2.10), SEK/m^3	Average difference in AVCC per m^3 between DTU GT (Case 1) and Original border variants (Case 3.1. – 3.10), SEK/m^3	Average difference in AVCC between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1 – 3.10), SEK	Average difference between DTU (Case 2.1 – 2.10) and Original borders (Case 3.1. – 3.10) in AVCC per m^3, SEK/m^3	Difference in AVCC between DTU GT (Case 1) and Original borders GT (Case 3), SEK	Difference in AVCC per m3 between DTU GT (Case 1) and Original borders GT (Case 3), SEK/m^3
32	20000	-1.4	-4.7	-66261	-3.2	-46245	-2.3
64	20000	-2.0	-4.8	-55582	-2.8	-48670	-2.4
128	20000	-2.1	-2.8	-14155	-0.7	-8894	-0.4
194	20000	-2.1	-1.6	10556	0.5	15844	0.8
32	40000	-1.1	-5.5	-175041	-4.4	-215139	-5.4
64	40000	-1.2	-5.4	-167276	-4.2	-211860	-5.3
128	40000	-1.2	-3.3	-85245	-2.1	-127471	-3.2
194	40000	-0.9	-2.2	-51056	-1.3	-84975	-2.1
32	60000	-0.9	-6.9	-359124	-6.0	-411066	-6.9
64	60000	-0.8	-6.8	-364995	-6.1	-410349	-6.8
128	60000	-1.0	-5.2	-250181	-4.2	-312741	-5.2
194	60000	-1.0	-4.3	-200277	-3.3	-260497	-4.3
32	80000	-0.6	-6.1	-443432	-5.5	-485402	-6.1
64	80000	-0.5	-6.3	-464601	-5.8	-495088	-6.2
128	80000	-0.6	-5.1	-360288	-4.5	-400226	-5.0
194	80000	-0.9	-4.2	-266956	-3.3	-333223	-4.2

Expanded Table 4. Summary of optimal segmentation parameters.

Segment size in pixels	Para-meters	Entry Cost	dNPV	Harvest Volume m³	Area (ha)	Entry Cost per ha	dNPV per ha	AVCC	AVCC per ha
32	SPD14 SCD14	72557	-417895	19671	45	1618	-9319	-345338	-7701
64	SPD19 SCD12	54273	-402037	19857	49	1104	-8176	-347763	-7072
128	SPD11 SCD11	52279	-360267	19755	50	1044	-7194	-307988	-6150
192	SPD20 SCD12	50991	-334240	19502	52	976	-6397	-283249	-5421
32	SPD19 SCD10	161538	-674922	39895	104	1558	-6510	-513384	-4952
64	SPD11 SCD19	112154	-622258	39819	106	1057	-5866	-510104	-4809
128	SPD15 SCD13	104951	-530666	40000	112	935	-4727	-425715	-3792
192	SPD12 SCD18	109979	-493199	38790	114	963	-4317	-383220	-3354
32	SPD11 SCD19	263135	-812220	59922	167	1578	-4871	-549084	-3293
64	SPD12 SCD18	189967	-738333	59947	174	1094	-4251	-548366	-3157
128	SPD17 SCD17	169427	-620187	59039	178	951	-3481	-450759	-2530
192	SPD12 SCD18	178595	-577110	59091	186	960	-3101	-398515	-2141
32	SPD17 SCD16	360087	-829212	79504	242	1485	-3420	-469125	-1935
64	SPD10 SCD19	265235	-744046	79895	249	1066	-2991	-478811	-1925
128	SPD14 SCD20	248962	-632911	79571	262	950	-2415	-383948	-1465
192	SPD12 SCD18	257115	-574061	77983	266	965	-2154	-316946	-1189