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1       **What makes segmentation good? A case study in boreal**  
2                               **forest habitat mapping**

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8



54 been Fractal Net Evolution Approach (FNEA) developed by Baatz and Schäpe (2000),  
55 and implemented in eCognition software. FNEA has been used as a benchmark  
56 segmentation, against which other methods have been compared. Although some  
57 authors have claimed to have developed better methods (Derivaux et al. 2010; H. Li et  
58 al. 2010; N. Li, Huo, and Fang 2010; Z. Wang, Sousa, and Gong 2010), FNEA has been  
59 a good performer in method comparisons (Neubert and Meinel 2003; Meinel and  
60 Neubert 2004; Carleer, Debeir, and Wolff 2005; Neubert, Herold, and Meinel 2008;  
61 Marpu et al. 2010) and seems to still be the standard method (e.g. Bar Massada et al.  
62 2012; Duro, Franklin, and Dubé 2012). Also many other standard remote sensing  
63 analysis products such as ENVI, ERDAS Imagine and IDRISI Selva have included  
64 segmentation methods in their newer versions. Yet, there are also numerous other  
65 methods, algorithms and software applications for segmenting remotely sensed data. To  
66 analyse the goodness of these methods, segmentation evaluation has been performed  
67 (Zhang 1996; Clinton et al. 2010; Marpu et al. 2010).

68 Segmentation evaluation can be divided into two major categories: subjective  
69 (visual) and objective evaluation. Objective evaluation can be further divided into  
70 system-level, which evaluates the overall system in which segmentation is performed,  
71 and direct evaluation (Zhang, Fritts, and Goldman 2008). As an example, final  
72 classification output can be regarded as a system when assessing segmentation quality  
73 (sensu H. Li et al. 2010; Smith 2010; Z. Wang, Sousa, and Gong 2010; Gao et al. 2011).  
74 Direct evaluation can be either analytical or empirical, of which the former evaluates  
75 the method itself and the latter its results. Empirical methods consist of supervised and  
76 unsupervised methods, i.e. if ground truth is used as a reference or not (Zhang, Fritts,  
77 and Goldman 2008).

78 In remote sensing, analytical methods (Hay et al. 2003) and unsupervised  
79 methods (Espindola et al. 2006; Corcoran, Winstanley, and Mooney 2010; Drăguț,  
80 Tiede, and Levick 2010; Yue et al. 2012; Hou et al. 2013) have been used in  
81 segmentation evaluation. For instance, Corcoran, Winstanley, and Mooney (2010)  
82 evaluate segmentation goodness by measuring contrast between segments that share a  
83 boundary. However, evaluation has largely been performed using supervised methods,  
84 more specifically either area based or location based measures. From these two, area  
85 based measures evaluate either if segmentation is too coarse (undersegmentation) or too  
86 fine (oversegmentation). Over- and undersegmentation measures can also be combined.  
87 Location based measures, on the other hand, are based on distances between segment  
88 centroids and reference polygon centroids or distances between boundary pixels. For a  
89 good review of these measures and an evaluation of different measures, see Clinton et  
90 al. (2010). These goodness measures are applicable especially in mapping clearly  
91 bordered urban features (Tian and Chen 2007; Zhan et al. 2005; Weidner 2008; Clinton  
92 et al. 2010), agricultural areas (Lucieer and Stein 2002; Möller, Lymburner, and Volk  
93 2007; Z. Wang, Sousa, and Gong 2010) or larger land use / land cover types (Weidner  
94 2008). Yet, goodness measures have also been used in natural area segmentations  
95 (Carleer, Debeir, and Wolff 2005; Ke, Quackenbush, and Im 2010; Bar Massada et al.  
96 2012). Some of the supervised segmentation evaluation methods use a larger set of  
97 reference polygons inside a larger area (e.g. Clinton et al. 2010) whereas some of the  
98 methods use only a couple of distinct reference polygons and semi-automated  
99 approaches (e.g. Marpu et al. 2010).

100 Segmentation evaluation can be used to compare different types of segmentation  
101 methods, i.e. boundary against region-based (Carleer, Debeir, and Wolff 2005). As well,

102 evaluation can be made between different segmentation methods or software, or inside a  
103 segmentation method as parameter optimization (Marpu et al. 2010). Although similar  
104 methods can be used in all these problems, also task-specific methodology for the  
105 problems has been developed, especially to parameter optimization. For instance,  
106 genetic algorithms have been used in optimizing segmentation to match reference  
107 delineation (Feitosa et al. 2006; Chabrier et al. 2008). Optimization has also been made  
108 without supervised goodness measures based on unsupervised evaluation. For instance,  
109 Drăguț, Tiede, and Levick (2010) developed a scale parameter optimization tool which  
110 measures rate of change of local variance inside a scene. Optimal scale parameters are  
111 those which have local maximum of the rate of change. In a bit similar vein, Espindola  
112 et al. (2006), Gao et al. (2011), and Yue et al. (2012) tried to combine low intrasegment  
113 variance and low intersegment autocorrelation. On the other hand, Kim, Madden, and  
114 Warner (2008, 2009) hypothesized that optimal scales should only have low spatial  
115 autocorrelation between segments; whereas L. Wang, Sousa, and Gong (2004)  
116 maximized Battacharya distance between candidate segments. Finally, Smith (2010)  
117 optimized segmentation scale by minimizing classification error in a random forest  
118 classifier.

119 Forest inventory or forest habitat mapping is only one instance of where  
120 segmentation is often used. Yet, forest inventories are more and more dependent on  
121 automatic segmentations (Pekkarinen 2002; Hay et al. 2005; Castilla, Hay, and Ruiz-  
122 Gallardo 2008; Mustonen, Packalén, and Kangas 2008; Wulder et al. 2008; Falkowski  
123 et al. 2009; Kim, Madden, and Warner 2009; Ke, Quackenbush, and Im 2010; Hou et al.  
124 2013). Segmentations used in forest inventory are usually made with feature values  
125 calculated from aerial or satellite images; however, the usage of light detection and  
126 ranging (LiDAR) data has recently become popular (Mustonen, Packalén, and Kangas  
127 2008; Ke, Quackenbush, and Im 2010; Breidenbach et al. 2011; Eysn et al. 2012; Hou et  
128 al. 2013). It has been noted that synergy of imagery and LiDAR provide promising  
129 segmentation results and the selection of input data has an effect on segmentation  
130 quality (Geerling et al. 2007, 2009; Mustonen, Packalén, and Kangas 2008; Ke,  
131 Quackenbush, and Im 2010; Hou et al. 2013). Despite of this, studies incorporating  
132 different datasets remain scarce; both in forest inventory and in other applications.

133 In forest inventory or habitat mapping, segmentation goodness evaluations have  
134 been performed both qualitatively (Leckie et al. 2003; Wulder et al. 2008) and  
135 quantitatively using unsupervised (Kim, Madden, and Warner 2008, 2009; Hou et al.  
136 2013) or supervised methods (Radoux and Defourny 2007; Ke, Quackenbush, and Im  
137 2010). Some evaluations have been based on thematic quality of segments against  
138 reference polygons (Pekkarinen 2002; Mustonen, Packalén, and Kangas 2008). Wulder  
139 et al. (2008) criticize quantitative evaluation because used ground truth is a subjective  
140 delineation of forest patches; hence, real truth does not exist. Therefore, objects in  
141 forests are not as clearly separable as e.g. urban features. Furthermore, also in urban  
142 features, supervised evaluation has been criticized due to inaccurate ground truth  
143 (Corcoran, Winstanley, and Mooney 2010). In this work, we wanted to test if supervised  
144 segmentation evaluation methods are applicable to forested areas on a larger set of  
145 reference polygons.

146 It has been stated and tested that segmentation goodness affects directly  
147 classification accuracy in OBIA classification (Kim, Madden, and Warner 2009;  
148 Clinton et al. 2010; Ke, Quackenbush, and Im 2010; Gao et al. 2011). Although there  
149 are many different approaches and measures for segmentation goodness evaluation, the

150 evaluation of goodness measures has not been thorough. In this paper, we will test if  
151 widely used supervised segmentation goodness measures are applicable in boreal forest  
152 habitat type mapping and if best segmentation leads to best classification accuracy. We  
153 test supervised methods instead of unsupervised methods, because our goal is to find a  
154 segmentation which matches with habitat type patches that are delineated using field  
155 work. Furthermore, we try to find a segmentation method, parameter value and  
156 image/data layer combination which suits our purposes. To do this, we test two different  
157 methods (FNEA region based segmentation and IDRISI watershed segmentation),  
158 several parameter combinations and different layers derived from WorldView-2  
159 imagery and LiDAR data. We also test if different methods are habitat type, reference  
160 polygon, or area sensitive.

## 161 2 Methods

### 162 2.1 Study area and reference polygons

163 We studied a 7 km<sup>2</sup> rural-forested area southwest of the city of Jyväskylä located in  
164 Southern Finland. The area belongs to southern boreal vegetation zone (Ahti, Hämet-  
165 Ahti, and Jalas 1968). The geographic coordinates (WGS84) of the site are 62° 10'30''–  
166 62° 13'30'' N and 25° 29'0''–25° 38'0'' E. The study area mainly consists of both  
167 coniferous and deciduous forest habitats, mires and agricultural area. The main tree  
168 species of the study area are the Scots Pine (*Pinus sylvestris*), Norwegian Spruce (*Picea*  
169 *abies*) and Birches (*Betula pubescens* and *B. verrucosa*). The study area was divided  
170 into three sub-areas with slightly varying land cover. The sub-areas were classified into  
171 25 different habitat types (Table 1), which were mapped by field work during June-  
172 August 2011. Habitat patches were used as reference polygons in segmentation  
173 goodness measures.

174 (Table 1 should be inserted here)

175 Most of the studied forest area is under heavy forestry and clear-cuts which  
176 create a human induced dynamic. Yet, two of the three delineated sub-areas included  
177 also one protected area which covered 100 ha and 25 ha of these sub-areas. Protected  
178 areas were dominated by semi-natural, over 100-year-old, forest. The larger protected  
179 area is part of a NATURA 2000 area. Inside the NATURA area and our study area,  
180 several different NATURA 2000 habitats are found. NATURA 2000 habitats were not  
181 mapped per se, but they were included in some of our mapped habitat types.

182 The three studied sub-areas were selected from different parts of a larger area  
183 southwest of Jyväskylä so that they included many different habitat types and different  
184 landscape configurations. Each sub-area was delineated into habitat patches whom there  
185 were 628 in total. Sub-area 1 (Sallaajärvi) included small to medium sized patches of  
186 different age, mostly mesic forest, some spruce mires, small streams, meadows, lakes  
187 and yards. In the area, there are also some old fields, which have been afforested.  
188 Moreover, in the middle of the area, there is a 250 ha conservation area with semi-  
189 natural forest. Sub-area 2 (Kuusimäki) included large areas of protected old mesic forest  
190 with spruce mire patches. As well, this sub-area had some open and pine mires, small  
191 lakes and fields, yards, and different aged forest around the old forest. Sub-area 3  
192 (Lapinmäki) included areas of bare rock surrounded by mesic forest, and with yards,  
193 fields and lakes on the fringes.

194 During field work, patches were drawn into paper printouts of orthophotos,  
195 which included 5 meter contour lines derived from a topographic map. Additionally,  
196 Trimble GeoXT and Juno SB GPS devices with differential location correction were  
197 used for checking accurate location and in delineating patches, which were difficult to  
198 distinguish from aerial images. ArcGIS 9.3.1 editor was used when patches were  
199 manually drawn into digital format. Patches were initially mapped as they were in the  
200 terrain. Afterwards, some recent clear-cuts were modified to be of the same age and  
201 forest type as neighbouring forest patches to match the state of the forest in the used  
202 satellite image and LiDAR data.

203 As alternative reference polygons, we used a forestry planning dataset created  
204 for the City of Jyväskylä and a biotope classification dataset created by Finnish Forest  
205 and Park Service (FFPS) (Vesterbacka 2010). In forestry planning dataset, polygons are  
206 drawn first from aerial imagery and after initial drawings; polygons are double checked  
207 using field work. This data was from sub-area 1 only. . FFPS biotope data is also  
208 generated using field work and aerial imagery and was from sub-area 2 only.

## 209 **2.2 Remotely sensed data**

210 Our primary data consisted of 8-band multispectral 2-meter resolution WorldView-2  
211 (WV-2) satellite image taken in July 14<sup>th</sup> 2010 and LiDAR data with a minimum of 0.5  
212 points per 1 m<sup>2</sup> from May 2010. Additionally, we used 20 cm resolution aerial images  
213 (orthophotos) taken in 2007 in assisting the drawing of reference polygons.

214 WV-2 image, taken by Digital Globe Inc., consists of 8 bands: coastal blue  
215 (band 1, 400–450 nm), blue (2, 450–510 nm), green (3, 510–580 nm), yellow (4, 585–  
216 625 nm), red (5, 630–690 nm), red-edge (6, 705–745 nm), NIR1 (7, 770–895 nm), NIR2  
217 (8, 860–1040 nm) in 2 meter resolution and a panchromatic band (450–800 nm) in 50  
218 cm resolution. Image was delivered radiometrically and sensor corrected, projected to a  
219 plane with average terrain elevation. In our preprocessing phase, the image was first  
220 orthorectified using 5-meter resolution digital elevation model derived from LiDAR  
221 data. In georeferencing, 13 ground control points from block features (buildings etc.)  
222 which were scattered all over study area were taken from orthophotos and nearest  
223 neighbour sampling was used. In visual interpretation, the differences between  
224 orthophotos, LiDAR data and orthorectified WV-2 were at maximum a couple of  
225 meters. From WV-2, we used all multispectral bands in 2 m resolution.

226 LiDAR data was created by National Land Survey of Finland. Flying altitude is  
227 on average 2000 meters. Used scan angle was  $\pm 20^\circ$  and laser pulse footprint on the  
228 ground approximately 50 cm. Mean error in elevation information is at maximum 15  
229 centimetres and in planar information at maximum 60 cm. Data was delivered  
230 automatically classified to ground hits, low vegetation hits, low error hits and  
231 unclassified hits.

232 LiDAR point clouds were first triangulated and after that rasterized using  
233 LASTOOLS (Isenburg 2011). We first derived two layers in 2 m resolution from  
234 LiDAR: digital terrain model (DTM) and digital surface model (DSM). In DTM, only  
235 ground hits were used whereas in DSM, point cloud was first thinned to one meter  
236 resolution to include highest hits. Then we subtracted DTM from DSM to create canopy  
237 height model (CHM). CHM was further manipulated to include values only between 0  
238 and 40 meters to filter out unrealistic values. The CHM still had some wrong values  
239 below 40 meters but these could not be corrected easily.

240 From DTM, we calculated also Saga Wetness Index (SWI) in 2 m resolution  
 241 using SAGA-GIS to model soil moisture; and thus, potential places for mires. SWI is a  
 242 modification of topographic wetness index (TWI). It has been noted that in wetland  
 243 mapping standard TWI performed worse than some other models; however, mainly  
 244 because in these studies TWI underestimated extent and contiguity of wetlands (Grabs  
 245 et al. 2009, Murphy, Ogilvie, and Arp 2009). This might be due to that the standard  
 246 TWI concentrates large values to stream networks where water flow is concentrated.  
 247 This underestimation problem is overcome in SWI, which assumes homogenous  
 248 hydrologic conditions in flat areas and predicts larger moisture values for cells with  
 249 small vertical distance to streams (Böhner and Selige 2006, Equations 1 and 2).

$$250 \quad \alpha_M = \alpha_{max} t^{-\beta \exp(t^\beta)} \quad \text{for} \quad \alpha < \alpha_{max} t^{-\beta \exp(t^\beta)} \quad (1)$$

251 Specific catchment area ( $\alpha$ ) used in TWI is defined as the pixels upslope contributing  
 252 area per contour width whereas  $\alpha_M$  is modified catchment area used in SWI. In  
 253 calculating  $\alpha$ , slope angle  $\beta$  (in radians) and neighbouring cell maximum  $\alpha_{max}$  are taken  
 254 into account unless results remain unchanged. Parameter  $t$  is a value for suction, so that  
 255 lower values, e.g. under 10, lead to stronger suction and stronger spreading of large  $\alpha$   
 256 values, and higher values lead to weaker suction. After counting  $\alpha_M$ , SWI is calculated  
 257 with the standard equation given in Equation (2).

$$258 \quad \text{SWI} = \ln \left( \frac{\alpha_M}{\tan \beta} \right) \quad (2)$$

259 Before calculations, DTM was filled to remove uncertainties, missing values and false  
 260 values from the data. Before the filling, values in DTM in known and evident places of  
 261 bridges and culverts were manipulated to let imagined water to flow through road banks  
 262 in those locations. To angle  $\beta$ , 0.0174532 rad was added so that division by 0 was  
 263 avoided. In flow direction calculations, we used multiple flow direction method by  
 264 Freeman (1991). In this method, the slope value is raised to the power of 1.1. Thus,  
 265 steeper slopes are weighted only a bit. It has been noted that in relatively flat areas  
 266 multiple flow direction methods, in which slope value is raised by a low exponent (e.g.  
 267 0.5 to 2), give good results in TWI calculation (Güntner, Seibert, and Uhlenbrook 2004;  
 268 Sørensen, Zinko, and Seibert 2006; Kopecký and Čížková 2010). Furthermore,  
 269 parameter  $t$  in Equation 1 was decided to be default 10 after visual interpretation of SWI  
 270 with different  $t$  values.

271 Before segmentation, SWI was quantized to 32 classes using equal intervals and  
 272 CHM was quantized to 40 classes (nearest integer). WV-2 layers were first filtered  
 273 using a 3×3 window and a median filter. After filtering, layers were quantized to 256  
 274 classes.

### 275 **2.3 Segmentation methods**

276 Data was segmented using different datasets, methods and parameters. To compare  
 277 different types of segmentation methods, two segmentation methods were used: one  
 278 watershed segmentation and one region based segmentation method. Next, brief  
 279 introductions of the used segmentation methods and their parameters are given.

280 Watershed segmentation was implemented in IDRISI Taiga software. In IDRISI  
 281 segmentation, a variance image is derived from each layer by moving window analysis.



282 A weighted average of variance images is the final surface image for watershed  
283 delineation. Both the size of the moving window as well as the weights of averaging can  
284 be adjusted by the user. The values of this surface image are treated as elevation values  
285 like in a DEM, and pixels are grouped into watersheds. After watershed delineation,  
286 watersheds are merged iteratively. Pairs of segments are merged if they are most similar  
287 segments to each other in the neighbourhood and if their difference is smaller than a  
288 similarity tolerance adjusted by the user. Difference is evaluated by two aspects: the  
289 mean value and the standard deviation. The weights for the mean and for the standard  
290 deviation are set by the user.

291 Our region based segmentation was the widely used segmentation method of  
292 eCognition software, Fractal Net Evolution Approach (FNEA) (Baatz and Schäpe 2001;  
293 Benz et al. 2004). FNEA segmentation was carried out using TerraLib 4.2.0 C++-GIS-  
294 library (Câmara et al. 2008). In FNEA, regions are formed by merging pixels; i.e. in the  
295 beginning, each pixel is treated as a region. In segmentation, three user parameters can  
296 be adjusted: scale parameter and weights between colour and shape ( $w_{color} + w_{shape} =$   
297  $1$ ) as well as smoothness and compactness ( $w_{smooth} + w_{compt} = w_{shape}$ ). Scale  
298 parameter controls the average object size. The more weight is given to colour (or  
299 spectral) homogeneity, the less weight is given to a specific shape i.e. spatial  
300 homogeneity. Smoothness and compactness define the shape as follows. Smoothness is  
301 the ratio of the border length of the segment and border length of the bounding box of  
302 the segment. Compactness, on the other hand, is the ratio of the border length of the  
303 segment and the square root of the number of pixels in the segment. Hence, they are not  
304 antagonistic but the weight is defined between them. Finally, the weights for the  
305 different layers are set by the user.

#### 306 **2.4 Initial work for segmentation goodness evaluation**

307 In segmentation, several issues affect the final segmentation goodness: segmentation  
308 method, parameterization including weights for the layers (e.g. Marpu et al. 2010), used  
309 layers (e.g. Ke, Quackenbush, and Im 2010), (re)classification of the layers,  
310 transformations made for the layers and filtering of the layers (e.g. Carleer, Debeir, and  
311 Wolff 2005). Easily thousands of different combinations can be tested. Therefore, we  
312 first did initial trial-and-error testing and visual interpretation for different types of  
313 segmentation. We segmented single layers, reclassified and filtered the layers and tried  
314 different parameter combinations and segmentation methods. In our initial analysis, the  
315 goal was to find good segmentation methods that could be further evaluated using the  
316 evaluation measures. As well, we wanted to scale our layers so that they could be used  
317 in same segmentations; in other words, the segments that are produced in single layer  
318 segmentations should be approximately of same size. Needless to say, our initial  
319 evaluation was not thorough but it was good enough to find good segmentation  
320 methods. All possible combinations could not be tested but we found a set of  
321 segmentations that were probably among the best that are available.

#### 322 **2.5 Used parameter and layer combinations**

323 Four different layer combinations were tested: (a) WV-2 layers only, (b) LiDAR layers  
324 only, (c) WV-2 bands 2, 3, 5, 7 (blue, green, red, NIR1) and LiDAR layers, and (d) all  
325 layers. IDRISI segmentation was performed using a window size of 5. Similarity

326 tolerance was varied between 20 and 70 with intervals of 5. Three different  
327 combinations of mean and variance weights were used: mean 0.5, variance 0.5; mean  
328 0.9, variance 0.1; and mean 0.1, variance 0.9. Hence, overall 33 IDRISI segmentations  
329 were performed for all layer combinations. FNEA segmentation was performed by  
330 varying the scale parameter between 5 and 50 with intervals of 5, and using colour  
331 parameter values of 0.25, 0.5 and 0.75. Therefore, 30 different FNEA segmentations  
332 were done for all layer combinations. In all segmentations, all layers were given equal  
333 weight.

## 334 **2.6 Different reference polygons**

335 We tested different segmentation methods using eight different reference polygon sets.  
336 First, all reference polygons from the whole study area were used. Second, three sets  
337 included all reference polygons from three different sub-areas separately. Third, two  
338 sets included reference polygons of only one habitat type: one set included all mires and  
339 one set water. Finally, we tested segmentation quality against two other reference  
340 polygon sets (FFPS biotope and forestry planning data) (Figure 1).

341 (Figure 1 should be inserted here)

## 342 **2.7 Goodness evaluation measures**

343 Segmentation goodness was evaluated using several different supervised measures  
344 (Table 2) reviewed by Clinton et al. (2010) with a Java tool that they developed. For  
345 more clarification and equations, please refer to Clinton et al. (2010) and original  
346 publications listed in Table 2. All measures were calculated as a mean of all reference  
347 polygons inside a reference polygon set. The value for a specific reference polygon was  
348 calculated as a mean (or standard deviation) of the values of those segments that met at  
349 least one out of four criteria. Criteria were: (1) the centroid of the segment is inside the  
350 reference polygon, (2) the centroid of the reference polygon is inside the segment, (3)  
351 the shared area of the segment and the reference polygon is over 0.5 of the segment  
352 area, and (4) the shared area of the segment and the reference polygon is over 0.5 of the  
353 reference polygon area (Clinton et al. 2010). Some of the measures were weighted by  
354 the reference objects (Table 2). Furthermore, we calculated combined measures which  
355 were proposed by Clinton et al. (2010) and which all included measures from single  
356 authors only (Table 3). Some of the combined measures were calculated as root mean  
357 square (RMS) individual criterion values whereas some of them were simple sum  
358 calculations. In RMS calculations, all measures were adjusted so that ideal segmentation  
359 was set to 0. Finally, a combined measure COMBINED was calculated which was a  
360 RMS of all basic area and location-based measures as suggested by Clinton et al.  
361 (2010). However, QLoc was not included since it was the same measure as RPsub.  
362 Before RMS calculation in COMBINED, all measures were scaled to [0,1] by dividing  
363 each value with the maximum and setting ideal segmentation to 0.

364 (Tables 2 and 3 should be inserted here)

365 Furthermore, we measured segmentation goodness using visual interpretation. In  
366 visual interpretation, we paid detail especially to if the segmentation methods find the  
367 boundaries of some reference polygons and habitat types. Hence, we were more worried  
368 about undersegmentation than oversegmentation. Additionally, we checked if different  
369 kinds of habitat types are segmented and if the segmentation produces objects that are

370 meaningful entities and can be easily used in classification and planning (Hay et al.  
371 2005). Therefore, segments should not be too complex (Mustonen, Packalén, and  
372 Kangas 2008). Due to the large number of different segmentations, our visual  
373 interpretation was not thorough; instead, we tried to find some general trends from  
374 different segmentation methods as well as layer and parameter combinations.

## 375 **2.8 Classifications**

376 After segmentation evaluation, we selected 12 segmentations for classification.  
377 Segmentations were selected using subjective evaluation; so that meaningful evaluation  
378 of segmentation performance versus classification accuracy could be made and some of  
379 the segmentations could be compared to each other. Both good and not as good  
380 segmentations, based on evaluation measures and visual interpretation, were selected. In  
381 classification, we calculated mean values of each layer per segment. In all  
382 classifications, all layers were always used regardless of which layer combination a-d  
383 was used in the segmentation phase.

384 Supervised classification was performed using the random forest classifier  
385 (Breiman 2001) with R package randomForest (Liaw and Wiener 2004) in R version  
386 2.15.2 (R Development Core Team 2012). Random forest classification has been used  
387 in remote sensing and OBIA with good experience (Lawrence, Wood, and Sheley 2006;  
388 Rodriguez-Galiano et al. 2012). Random forest is an ensemble classifier, which  
389 combines several bootstrapped classification trees. In the final classification majority  
390 vote over all trees is made. Trees are randomized at each node by selecting only a subset  
391 of variables of which the best split is chosen. When a tree is built, approximately 2/3 of  
392 the data is selected for training the classifier and the rest is called out of bag (OOB) test  
393 data. OOB data is used for error rate estimation, which is averaged over all trees to get  
394 an error rate for the whole classification. Because of the OOB, independent test data or  
395 cross-validation is not needed when random forest is used (Breiman 2001; Breiman and  
396 Cutler 2007) which has been confirmed in remote sensing studies (Lawrence, Wood,  
397 and Sheley 2006; Rodriguez-Galiano et al. 2012).

398 When random forest was performed, 500 trees were built and the number of  
399 features at each split was given the default value of square root of all features. We used  
400 our own reference polygons over all three sub-areas as training data, not the FP nor the  
401 FFPS data. Training set in random forest run was all those segments that had a  
402 minimum of 60 % coverage of one reference habitat type. Classification accuracies  
403 were calculated using all reference polygons with simple cross-tabulation matrices.

## 404 **3 Results**

### 405 **3.1 Segmentation goodness based on evaluation measures**

406 Based on all area and COMBINED measure, best segmentation was FNEA with layer  
407 set b, scale parameter 25 and colour parameter 0.5 (Table 4, Table 5). However,  
408 choosing this segmentation as the best was contradictory, since no other segmentation  
409 evaluation measure ranked it as the best method. As well, its rank was between 4 and 94  
410 when COMBINED measure and other reference polygons than all area were used.  
411 Hence, different segmentations were chosen as the best or being among the best, when  
412 different goodness measures or reference polygons were used (Table 4). Some of the

413 measures (UnderMerging, OverMerging, CountOver, SimSize sd, RAsuper, RAsub,  
414 OverSegmentation, UnderSegmentation), nonetheless, gave rather consistent results,  
415 i.e., the same segmentation was the best or one of the best using different reference  
416 polygon sets. Other measures, on the other hand, had larger variation in their results.  
417 Consistency in results can be seen as a downside, since reference sets were different as  
418 illustrated in Figure 1. For instance, individual measures may prefer segmentation  
419 result, which is as fine or as coarse as possible. On the other hand, consistency can also  
420 be seen as an asset if some of the segmentations truly are better despite of the reference  
421 set used, i.e. those segmentations contain almost all meaningful patch boundaries.

422 (Tables 4 and 5 should be inserted here)

423 Some overall evaluations can be made from segmentations ranked as the best  
424 (Table 6). First, FNEA segmentation outperformed IDRISI segmentation, since FNEA  
425 was ranked best 140 times against 44 times of IDRISI. Second, layer set b outperformed  
426 other layer sets. Therefore, it could be thought that FNEA with layer set b provides the  
427 best results. If undersegmentation is wanted to be avoided, low scale parameter brings  
428 good results. Vice versa, high scale parameter should be selected when  
429 oversegmentation is not desired. Segmentations with intermediate scale or similarity  
430 parameter value were not ranked as best as often as segmentations with high or low  
431 parameter value. Yet, different combined measures as well as AFI, RP measures,  
432 SimSize mean, QLoc mean, QLoc sd and QR usually preferred intermediate scale  
433 parameter values. For instance, when all area reference polygons were used, the  
434 COMBINED measure favoured intermediate scale parameter values; whereas it ranked  
435 those segmentations with low scale parameter value as the worst (Table 5). In FNEA  
436 segmentations, high value for colour parameter gave more often best segmentations  
437 than low or intermediate value for colour. In IDRISI segmentations, on the other hand,  
438 high mean, low variance combination gave the largest number of best segmentations.

439 (Table 6 should be inserted here)

440 When correlations between different goodness measure results were evaluated  
441 (Table 7), it was found out that correlations range from large negative correlations to  
442 high positive correlations. Hence, measures did give different results and preferred  
443 different issues in segmentation. It can also be seen that measures that measure  
444 oversegmentation had positive correlations with the COMBINED measure whereas  
445 undersegmentation measures had negative correlations (for over- and  
446 undersegmentation measures, see Table 2). Some measures (RPsuper, MergeSum, M,  
447 ZH1) had even both positive and negative correlations. Correlations were dependent on  
448 reference polygons used; but correlations between the COMBINED measure based on  
449 different reference polygons were rather high and positive (Table 8). Only water has  
450 correlations below 0.75.

451 (Tables 7 and 8 should be inserted here)

### 452 **3.2 Segmentation goodness based on visual interpretation**

453 In visual interpretation, it was found out that segmentations based on layer set b  
454 (LiDAR data only) were especially successful in delineating mires and small streams.  
455 Also the problem of shadow effect in WV-2 imagery was overcome when LiDAR data  
456 was used. On the other hand, the shorelines of water bodies were insufficiently  
457 delineated with LiDAR data only. As well, boundaries between deciduous and  
458 coniferous forests were better delineated using WV-2 imagery. However, more gradual

459 boundaries, for instance between mesic and xeric forests, could not be easily segmented  
460 using any method or layer combination. In visual interpretation, we could not make a  
461 preference between layer sets c and d. Although segmentation outputs were slightly  
462 different, differences were minor. Same kinds of observations were made, when  
463 different IDRISI mean/variance weight alternatives were compared. Furthermore, to  
464 delineate some small objects, small values of scale or similarity parameters were  
465 needed. In finding meaningful and simple entities, it was found out that FNEA  
466 segmentation with low (0.25) or intermediate (0.5) weight for colour brought superior  
467 results over other segmentation methods. Putting little weight to colour had its  
468 downside, on the other hand. In other words, segment boundaries did not necessarily  
469 follow natural or data boundaries but segments were equally sized objects with often  
470 arbitrary boundaries. Nevertheless, FNEA segmentations with large weight for colour  
471 and IDRISI segmentations were unnecessarily complex. Additionally in IDRISI  
472 segmentations, boundaries were often crisscrossing reference polygon boundaries.  
473 Using visual interpretation, we chose FNEA segmentation with layer combination c,  
474 scale parameter 10 and colour parameter 0.5, as the best one (Figure 2c). This selection  
475 was, yet, more or less arbitrary, since many different segmentation options gave quite  
476 similar results. Furthermore, since there were so many different segmentation options,  
477 visual interpretation was not thoroughly reliable in finding the best parameter values.  
478 Hence, choosing the best segmentation using visual interpretation was tricky.

### 479 **3.3 Classification results**

480 Classification accuracies between classifications derived from different segmentations  
481 varied a bit (Table 9, some of the segmentations in Figure 2). Best accuracy (0.72) was  
482 achieved using best segmentation in visual interpretation (Figure 2c) whereas worst  
483 accuracy (0.60) was got using segmentation that was ranked high using some of the  
484 measures (Figure 2h). Many of the different segmentations got reasonably good results  
485 compared to the best classification. Some of these segmentations were selected based on  
486 measures, some by using visual interpretation. On the other hand, best segmentation  
487 based on COMBINED measure and all area (Figure 2e), was not among the best  
488 segmentations in classification accuracy analysis. It can be seen that fine or moderately  
489 fine segmentations led to better classification accuracies. Vice versa, coarse  
490 segmentation led to poorer accuracies. On the other hand, too fine segmentation can  
491 lead to salt-and-pepper effect (Figure 2b) and thus possibly also make classification  
492 accuracy worse. Also in visual interpretation it became evident that classifications  
493 performed with FNEA segmentations and scale parameter value 5 suffered from this  
494 effect more than classifications performed with segmentations with scale value 10. Best  
495 classification accuracies were achieved using segmentations with both LiDAR and WV-  
496 2 layers. This might be due to the fact that boundaries were best detected using both  
497 data types in segmentation. Yet, classification accuracies using only segmentations  
498 performed with LiDAR or WV-2 data were nevertheless little worse. In all,  
499 classification accuracy evaluation was not thorough; in other words, good classification  
500 accuracies can be got using segmentations, which were not among the 12 segmentations  
501 tested here. Moreover, some measures may be good in selecting segmentations that  
502 maximize classification accuracy.

503 (Table 9 and Figure 2 should be inserted here)

## 504 4 Discussion

### 505 4.1 Segmentation goodness compared to classification accuracy

506 One of our study objectives was to test if better segmentation leads to better  
507 classification accuracy as it has been argued by others (Kim, Madden, and Warner  
508 2009; Clinton et al. 2010; Ke, Quackenbush, and Im 2010; Gao et al. 2011). After our  
509 analysis, it is obvious that there is no straightforward answer to this question. Although  
510 it is self-evident that good segmentation is needed for good classification, there is no  
511 adequate definition of what makes a good segmentation. After classification analysis  
512 one can easily state that the best segmentation was the segmentation with the best  
513 classification accuracy. There is no method, however, to test before classification,  
514 which segmentation will give the best classification accuracy. This is illustrated also by  
515 the studies of Kim, Madden, and Warner (2009) and Gao et al. (2011). While they both  
516 claim that optimal segmentation produced best classification output, their definitions of  
517 optimal segmentation were contradictory. Kim, Madden, and Warner (2009) minimized  
518 spatial autocorrelation between different segments, whereas Gao et al. (2011) sought for  
519 segmentations that combined low intersegment autocorrelation and intrasegment  
520 variance. Furthermore, Gao et al. (2011) had the lowest intersegment autocorrelation at  
521 the coarsest scale which did not produce best classification accuracy. On the other hand,  
522 the tasks in these studies were different, since Kim, Madden, and Warner (2009) used 4-  
523 m resolution IKONOS data in forest type mapping, while Gao et al. (2011) used 25-m  
524 Landsat ETM+ data in mixed mountainous shrub-forest-grassland landscape.

525 Based on ambivalence of what segmentation is good, we propose that the  
526 goodness of segmentation should be defined in each case. In other words, one should  
527 know and clarify what he/she wants from segmentation; and critically evaluate if the  
528 best segmentation can be selected based on evaluation criteria. In our case, good  
529 segmentation was segmentation with (1) meaningful and not too complex segments, (2)  
530 boundaries parallel to reference polygon boundaries even for the smallest reference  
531 polygons but (3) as coarse as possible. Taking the best segmentation based on some  
532 measure does not automatically lead to the best classification accuracy, as it has been  
533 already noted by Verbeeck, Hermy, and van Orshoven (2012). Nevertheless, the  
534 classification accuracies between different classifications were rather small in our case  
535 study. This might point out to the robustness of OBIA methodology: good classification  
536 accuracy can be obtained even if the segmentation is not the best possible. On the other  
537 hand, the classification outputs that had better classification accuracies were visually  
538 more appealing. Boundaries were more often in right place, different habitat types could  
539 be mapped and patches were not too small.

540 Many authors have argued that oversegmentation is a smaller problem than  
541 undersegmentation in post-segmentation classification (e.g. Weidner 2008; Marpu et al.  
542 2010). However, in the analysis by Verbeeck, Hermy, and van Orshoven (2012), it was  
543 found out that more under-segmented output gave better classification accuracy than  
544 more over-segmented output. Our results suggest that both arguments are partly correct.  
545 In other words, both oversegmentation and undersegmentation are problematic in  
546 classification as it was found out also by Kim, Madden, and Warner (2009) and Gao et  
547 al. (2011). First, segmentation cannot be very coarse, since smaller objects are thus  
548 easily under-segmented. Second, if segmentation is too fine, salt-and-pepper effect is  
549 obtained. Salt-and-pepper effect can lead to worse classification accuracy as it has been

550 found out in OBIA vs. pixel-based classification studies (e.g. Bock et al. 2005;  
551 Whiteside, Boggs, and Maier 2011). Also, objects are more meaningful when they are  
552 not too small (Blaschke 2010). Yet, the better classification accuracy of OBIA is not  
553 automatic and some smaller, but rare, objects may be easily missed in OBIA  
554 classification (Dingle Robertson and King 2011). Overall, it has been noted that in  
555 single-scale segmentation optimal segmentation is class-dependent, i.e., some classes  
556 can be poorly segmented even if overall segmentation is optimal. Hence, multi-scale  
557 segmentation has been offered as a solution to this problem (Hay et al. 2003; Kim et al.  
558 2011; dos Santos et al. 2012).

#### 559 *4.2 Object and patch delineation*

560 We found out that some habitat patches were not segmented properly using any of the  
561 methods, layers or parameter combinations. For instance stream-sided habitats or mires  
562 were often poorly delineated. Therefore, some extra analysis is needed, such as stream  
563 network mapping (Räsänen et al., in prep), other ancillary information or expert  
564 knowledge (Mustonen, Packalén, and Kangas 2008) or segmentation post-modification  
565 to delineate some of the patches correctly. It can even be asked, can the segmentation  
566 goodness over difficult patch delineation even be calculated. For instance, Radoux and  
567 Defourny (2007) delineated only those patches that could be seen from imagery.  
568 Therefore, it is not realistic to expect that segmentation delineates those objects that  
569 cannot be easily seen from the data that is segmented. LiDAR data, however, helped in  
570 finding some of the tricky features, such as mires. On the other hand, segmentations  
571 with LiDAR data and four WV-2 layers were not significantly different compared to  
572 segmentations with LiDAR data and eight WV-2 layers. As well, our study reasserted  
573 earlier studies that the problematic shadow effect of aerial or satellite imagery can be  
574 mitigated using LiDAR data (Geerling et al. 2007; Mustonen, Packalén, and Kangas  
575 2008; Ke, Quackenbush, and Im 2010). Segmentations based on imagery only;  
576 nonetheless, produced classifications with almost as high classification accuracies as  
577 segmentations based on both imagery and LiDAR data. There can be at least two  
578 possible reasons for this small difference. First, segmentation based only on imagery  
579 may have other benefits compared to segmentation using both data types. Second, the  
580 proportion of shadow areas over all area can be rather small, especially with data  
581 resolution not higher than 2 m.

582 One major question in segmentation evaluation is whether it is better to  
583 delineate meaningful objects with meaningful thematic quality and maximum  
584 homogeneity (e.g. Mustonen, Packalén, and Kangas 2008) or to find segmentation that  
585 mimics field observations. Some authors (Wulder et al. 2008; Corcoran, Winstanley,  
586 and Mooney 2010) have questioned the rationality of supervised segmentation  
587 evaluation, especially in natural environments. It is true that nature is not easy to  
588 interpret. Different mappers classify habitat patches differently and also delineate patch  
589 boundaries differently. Yet, according to Cherrill and McClean (1995, 1999) the former  
590 type of error was more common in habitat mapping in the UK. Nevertheless, boundaries  
591 are not easy to draw and their location depends on the study scale (Lang et al. 2010). In  
592 our analysis, there were differences between boundary locations when our field data  
593 was compared to either FP or FFPS data. There were some differences between optimal  
594 segmentations based on different reference polygons. These differences were mostly  
595 minor, and approximately same kinds of segmentations were preferred irrespective of

596 the reference data. As well, correlations between COMBINED measures based on  
597 different reference data were rather high (SA1 to FP 0.79 and SA2 to FFPS 0.89).  
598 Furthermore, segmentation evaluation based on thematic quality is not unproblematic  
599 either. Although the segmentation has good thematic quality, the segmentation  
600 boundaries do not necessarily match with habitat type boundaries that exist in nature.  
601 This can lead to difficulties in habitat classification, if it is performed, and eventually to  
602 differences in planning decisions.

603 In a more general level, one can question if automated segmentation is worse  
604 than manual delineation when it cannot find the boundaries that are manually  
605 delineated. Delineations are different; that is true, but it is not straightforward to judge  
606 either one of them better. For instance, automated delineation often produces more  
607 complex objects. Complexity of the objects, however, can be both good and bad.  
608 Although complexities hinder the usage in operational context, complexity can be  
609 reduced using GIS techniques. Furthermore, complex boundaries can be even truer,  
610 since natural boundaries are not always straight (Wulder et al. 2008). Therefore,  
611 automated and manual delineations are two different interpretations and both of them  
612 can be either good or bad depending on the segmentation method, mapper skills or the  
613 operational context. In other words, question is not necessarily if one of them is correct  
614 or incorrect but whether it is appropriate or inappropriate (Lang et al. 2010).

### 615 **4.3 How to evaluate and measure segmentation goodness?**

616 According to our analysis, the FNEA was better segmentation method than the  
617 watershed segmentation in IDRISI Taiga. Still, also IDRISI's segmentation method  
618 provided good results. As already noted earlier, FNEA has been a good performer in  
619 segmentation evaluations and is a standard method in OBIA studies. However, we  
620 cannot give any percentage or any other quantitative evaluation which indicates how  
621 much better FNEA is compared to IDRISI contrary to values given e.g. by N. Li, Huo,  
622 and Fang (2010). N. Li, Huo, and Fang (2010) classified different types of objects to  
623 correctly delineated, acceptably delineated and wrongly delineated. From these  
624 classifications, they calculated performances of different segmentations and also the  
625 percentage difference of performance. In our framework, such quantitative difference  
626 evaluation would be more or less artificial, since in our study different measures of  
627 segmentation goodness gave different results. This inconsistency has also been noted by  
628 Clinton et al. (2010). Partly this inconsistency can be explained in terms of over- and  
629 undersegmentation; i.e., deliberately avoiding one of them results often in getting the  
630 other. However, also evaluation measures that should quantify the same phenomenon  
631 can give different results. One explanation to this is that we tested several different  
632 segmentations of which some were rather similar to each other. Furthermore, measures  
633 are a bit dependent on the training data set used. One should, thus, be careful in the  
634 selection of the reference data. On the other hand, some of the measures were robust,  
635 i.e. produced similar results irrespective of the reference data. Additionally, general  
636 picture was more or less similar with different reference polygons.

637 According to classification accuracies derived in our study, the best  
638 segmentation was found using visual interpretation. Therefore, it could be argued that  
639 supervised segmentation goodness evaluation measures evaluated by Clinton et al.  
640 (2010) are not good. On the other hand, we knew what we wanted from visual  
641 interpretation and fixed our objectives based on these needs. Automated supervised



642 segmentation goodness evaluation measures, on the contrary, were just selected based  
643 on what has been done before. Therefore, we knew better what we want from  
644 segmentation when we evaluated them visually: meaningful objects and boundaries.  
645 Yet, we would have included our own automated and supervised evaluation method in  
646 our analysis, if we had found a successful way to do automated evaluation. One reason  
647 that supervised segmentation goodness evaluation measures partly failed in our analysis  
648 could be that we used continuous reference polygon data and objects that were difficult  
649 to delineate. On the other hand, segmentation goodness measures did not work that well  
650 on water bodies either although water bodies are usually easy to delineate and are not  
651 bordered by each other. Based on measures, best segmentations for water bodies were  
652 usually segmentations using LiDAR data or segmentations as fine as possible. In our  
653 visual interpretation, it was, nonetheless, found out that water bodies cannot be  
654 delineated using LiDAR data alone. Only evaluation measure M ranked best a  
655 segmentation that could be good in water body delineation. Nevertheless, we cannot say  
656 that supervised evaluation measures are completely useless. On the contrary, one should  
657 know what evaluation measures favour and what she/he wants from segmentation  
658 before using evaluation measures. As well, visual interpretation is subjective, tedious  
659 and time-consuming (Zhang, Fritts, and Goldman 2008). It can be even practically  
660 impossible if several different segmentations over large areas should be evaluated.

661 Automated segmentation goodness evaluation could be done using landscape or  
662 shape metrics and thus unsupervised evaluation (Neubert and Meinel 2003, Meinel and  
663 Neubert 2004, Neubert, Herold, and Meinel 2008, H. Li et al. 2010, Ji et al. 2012). This  
664 is problematic, though, since for instance FNEA method uses shape metrics as  
665 parameters which the user can modify. Hence, using shape metrics also in evaluation  
666 could lead to circular reasoning. Another possible solution in finding good segmentation  
667 evaluation measures could be focusing on boundaries. In other words, it could be  
668 examined if boundaries drawn in the reference map are found in segmentation. For  
669 instance, Neubert and Herold (2008) measured what proportion of segment's perimeter  
670 is inside specific reference polygon's buffer zone. In similar vein, Lucieer and Stein  
671 (2002) have proposed boundary based measure and Clinton et al. (2010) included a  
672 modification of this measure in their analysis. Whereas Lucieer and Stein (2002)  
673 calculated shortest distances from reference polygons to any boundary pixel in  
674 segmentation, Clinton et al. (2010) averaged all distances to all segments inside  
675 reference polygon. Of these measures, original measure by Lucieer and Stein (2002) is  
676 more tempting, since boundaries inside reference polygon can disappear in  
677 classification but boundaries near reference polygon boundaries cannot be moved.  
678 However, Lucieer and Stein (2002) noted that finest segmentations ranked best using  
679 this evaluation. Taking this into account, they modified the original measure to take the  
680 length of boundary into account. These kinds of modifications, on the other hand, are  
681 difficult to design, because they easily favour either undersegmentation or  
682 oversegmentation. Furthermore, boundaries of natural objects are not exact. Hence, it is  
683 not always meaningful to find the "real" boundaries but boundaries that are visible in  
684 data.

685 Finally, unsupervised segmentation evaluation methods that often measure  
686 intersegment and intrasegment homogeneity or heterogeneity have been found useful in  
687 segmentation evaluation (Kim, Madden, and Warner 2009; Gao et al. 2011; Yue et al.  
688 2012; Hou et al. 2013). While in our case the goal was to find segmentation that mimics

689 reference polygons, it could be interesting to test if unsupervised methods work well in  
690 this kind of task.

## 691 **5 Conclusion**

692 We tested different supervised segmentation goodness evaluation measures and visual  
693 interpretation to find a good segmentation for boreal forest habitat mapping. While  
694 different supervised segmentation goodness measures were fast to calculate from  
695 several segmentations, they provided inconsistent results. In other words, different  
696 segmentations stood out as being best when different measures were used. Visual  
697 interpretation, on the other hand, was tedious and segmentations could not be evaluated  
698 thoroughly in reasonable time. Although we selected only one segmentation as being  
699 the best based on visual interpretation, also other segmentations were visually good. In  
700 classification analysis, the visually selected segmentation gave the best classification  
701 accuracy but differences between different segmentations were rather small. Better  
702 segmentation may lead to better classification but there are several different definitions  
703 for good segmentation. Therefore, the relationship between segmentation and  
704 classification is not straightforward. We propose that the goodness of segmentation  
705 should be defined in each case separately and evaluation measures should be selected  
706 based on that definition. In our case, good segmentation was segmentation with (1)  
707 meaningful and not too complex segments, (2) boundaries parallel to reference polygon  
708 boundaries even for the smallest reference polygons but (3) as coarse as possible. There  
709 were, however, no evaluation measures to find these kinds of segmentations  
710 automatically. Overall, the best segmentations were FNEA segmentations with both  
711 imagery and LiDAR data. We conclude that different segmentation evaluation methods  
712 should be used with care especially in natural environment mappings. When  
713 segmentation evaluation is rigorously used; though, it can assist in finding a more  
714 optimal segmentation. Quantitative segmentation evaluation might provide better results  
715 in urban environments but more thorough testing is needed to support this claim.

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993 Table 1. Different habitat types that were mapped during field work when the reference  
 994 polygons were drawn and that were used in the classification part of the research.

Habitat type	Number of age groups/management possibilities
xeric (pine dominated) forests	4: clear-cut, sapling stand, young, mature
mesic (spruce dominated) forests	5: clear-cut, sapling stand, young, mature, natural
herb-rich (mixed/deciduous) forests	4: sapling stand, young, mature, natural
bare rock	1
pine mires	1
spruce mires	2: not drained, drained
open mires	1
water (lakes and streams)	1
small creeks	1
springs	1
grasslands	1
fields	1
roads	1
yards	1
sand pits	1

995

996 Table 2. Simple segmentation goodness evaluation measures that were used in  
 997 segmentation evaluation. Column MEASURES refers to what the method should  
 998 measure. Column SOURCE refers to the article where the measure was first used.  
 999 Column WEIGHTED refers to if the measure is weighted by a reference object.

METHOD	MEASURES	SOURCE	WEIGHTED	NOTE
UnderMerging	undersegmentation	Yang et al. (1995)		
OverMerging	oversegmentation	Yang et al. (1995)		
AFI	area match	Lucieer & Stein (2002)		
CountOver	oversegmentation	Lucieer & Stein (2002)		based on AFI
CountUnder	undersegmentation	Lucieer & Stein (2002)		based on AFI
SimSize mean	area match	Zhan et al. (2005)	X	
SimSize sd	area match	Zhan et al. (2005)	X	
RAsuper	undersegmentation	Möller, Lymburner, and Volk (2007)	X	
RAsub	oversegmentation	Möller, Lymburner, and Volk (2007)	X	
QR	area match	Weidner (2008)	X	
OverSegmentation	oversegmentation	Clinton et al. (2010)	X	
UnderSegmentation	undersegmentation	Clinton et al. (2010)	X	
RPsuper	distance to centroid	Möller et al. (2007)	X	
RPsub	distance to centroid	Möller et al. (2007)	X	
QLoc mean	distance to centroid	Zhan et al. (2005)	X	=RPsub
QLoc sd	distance to centroid	Zhan et al. (2005)	X	

1000

1001

1002 Table 3. Combined segmentation goodness evaluation measures that were used in  
 1003 segmentation evaluation. Column INCLUDES refers to the simple measures that are  
 1004 included in the respective combined measure. Column CALCULATION refers to how  
 1005 the combined measure was calculated.

METHOD	INCLUDES	CALCULATION
M	RAsuper, RAsub, RPsuper, RPsub	RMS
ZH1	SimSize mean, SimSize std, QLoc mean, QLoc std	RMS
ZH2	SimSize mean, QLoc mean	RMS
D	OverSegmentation, UnderSegmentation	RMS
OverUnder	CountOver, CountUnder	SUM
MergeSum	OverMerging, UnderMerging	SUM
COMBINED	all other simple measures than QLoc mean	RMS, normalized

1006

1007 Table 4. Best segmentations according to different measures and reference polygons. Segmentation methods are marked as follows. Text  
 1008 refers to method, letter after the text to layer combination a-d (see text), s to scale (FNEA) or similarity parameter (IDRISI), c to colour  
 1009 parameter, m to weight given to mean and v to weight given to variance.

MEASURE	All area	SA1	SA2	SA3	water	mires	FP	FFPS
UnderMerging	FNEA_d_s5_c.75	FNEA_d_s5_c.75	FNEA_a_s5_c.75	FNEA_a_s5_c.75	FNEA_a_s5_c.5	FNEA_d_s5_c.75	FNEA_c_s5_c.75	FNEA_a_s5_c.5
OverMerging	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_b_s50_c.5	FNEA_b_s50_c.5	IDRISI_b_s70_m1_v9	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_c_s50_c.75
AFI	IDRISI_a_s25_m9_v1	IDRISI_a_s25_m1_v9	IDRISI_d_s20_m9_v1	IDRISI_c_s35_m1_v9	IDRISI_d_s70_m5_v5	FNEA_b_s5_c.25	IDRISI_a_s45_m5_v5	IDRISI_b_s35_m9_v1
CountOver	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_c_s50_c.25*	FNEA_b_s50_c.5	FNEA_d_s45_c.25*	FNEA_b_s50_c.5*	FNEA_b_s50_c.75*
CountUnder	IDRISI_a_s20_m1_v9*	IDRISI_a_s25_m1_v9*	IDRISI_a_s20_m9_v1*	IDRISI_b_s50_m9_v1	FNEA_b_s25_c.25*	IDRISI_a_s40_m1_v9*	IDRISI_a_s70_m1_v9*	IDRISI_a_s70_m1_v9*
SimSize mean	FNEA_b_s30_c.75	FNEA_b_s30_c.75	FNEA_d_s30_c.75	IDRISI_c_s65_m9_v1	FNEA_b_s45_c.75	IDRISI_c_s55_m9_v1	FNEA_c_s30_c.25	FNEA_d_s40_c.25
SimSize sd	FNEA_a_s5_c.75	FNEA_b_s5_c.75	FNEA_a_s5_c.75	FNEA_a_s5_c.75	FNEA_a_s5_c.5	FNEA_b_s50_c.25	FNEA_a_s5_c.75	FNEA_d_s5_c.75
RASuper	FNEA_b_s5_c.75	FNEA_b_s5_c.75	FNEA_b_s5_c.75	FNEA_a_s5_c.75	FNEA_c_s5_c.5	FNEA_d_s5_c.75	FNEA_b_s5_c.75	FNEA_b_s5_c.75
RASub	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_b_s50_c.5	FNEA_b_s50_c.25	FNEA_b_s50_c.5	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_b_s50_c.25
QR	FNEA_b_s35_c.75	FNEA_b_s30_c.75	FNEA_c_s30_c.75	FNEA_a_s45_c.75	IDRISI_b_s65_m9_v1	IDRISI_a_s45_m1_v9	FNEA_c_s45_c.75	FNEA_d_s40_c.75
OverSegmentation	FNEA_b_s50_c.5	FNEA_b_s50_c.25	FNEA_b_s50_c.5	FNEA_b_s50_c.5	IDRISI_b_s70_m1_v9	FNEA_b_s50_c.25	FNEA_b_s50_c.25	FNEA_c_s50_c.75
UnderSegmentation	FNEA_b_s5_c.75	FNEA_b_s5_c.75	FNEA_b_s5_c.75	FNEA_b_s5_c.75	IDRISI_a_s20_m5_v5	FNEA_b_s5_c.75	FNEA_b_s5_c.75	FNEA_b_s5_c.75
RPsuper	IDRISI_d_s55_m9_v1	FNEA_b_s20_c.5	FNEA_d_s20_c.5	FNEA_b_s15_c.5	IDRISI_b_s65_m9_v1	FNEA_d_s10_c.25	FNEA_d_s30_c.75	IDRISI_d_s60_m9_v1
RPsub	FNEA_b_s35_c.75	IDRISI_b_s55_m5_v5	FNEA_a_s40_c.75	FNEA_c_s40_c.75	IDRISI_b_s65_m9_v1	FNEA_b_s15_c.25	FNEA_c_s30_c.75	FNEA_d_s40_c.75
QLoc mean	FNEA_b_s35_c.75	IDRISI_b_s55_m5_v5	FNEA_a_s40_c.75	FNEA_c_s40_c.75	IDRISI_b_s65_m9_v1	FNEA_b_s15_c.25	FNEA_c_s30_c.75	FNEA_d_s40_c.75
QLoc sd	FNEA_a_s45_c.25	IDRISI_b_s65_m9_v1	FNEA_c_s45_c.75	FNEA_c_s40_c.75	IDRISI_b_s65_m1_v9	FNEA_b_s20_c.25	FNEA_c_s30_c.75	FNEA_c_s50_c.25
M	FNEA_c_s25_c.75	IDRISI_b_s45_m9_v1	FNEA_a_s5_c.5	FNEA_b_s20_c.75	FNEA_c_s45_c.75	FNEA_d_s5_c.75	FNEA_b_s5_c.75	FNEA_a_s25_c.5
ZH1	FNEA_d_s50_c.25	FNEA_d_s50_c.25	FNEA_c_s5_c.25	FNEA_b_s45_c.5	IDRISI_b_s40_m5_v5	FNEA_b_s50_c.25	FNEA_a_s5_c.25	FNEA_a_s45_c.25
ZH2	FNEA_b_s35_c.75	IDRISI_b_s60_m9_v1	FNEA_d_s30_c.75	FNEA_c_s40_c.75	FNEA_b_s45_c.75	IDRISI_c_s55_m9_v1	FNEA_c_s30_c.25	FNEA_d_s45_c.25
D	FNEA_d_s35_c.5	FNEA_d_s35_c.5	FNEA_d_s35_c.5	FNEA_b_s35_c.75	IDRISI_b_s70_m1_v9	FNEA_b_s20_c.75	FNEA_c_s35_c.75	FNEA_d_s40_c.5
OverUnder	IDRISI_b_s70_m9_v1	IDRISI_b_s65_m1_v9	IDRISI_a_s70_m5_v5	IDRISI_b_s70_m9_v1	FNEA_b_s50_c.5	IDRISI_a_s70_m9_v1	FNEA_c_s50_c.75	IDRISI_a_s70_m1_v9
MergeSum	FNEA_b_s15_c.5	FNEA_b_s15_c.5	FNEA_a_s15_c.75	FNEA_b_s20_c.75	IDRISI_b_s65_m9_v1	FNEA_b_s10_c.25	FNEA_c_s25_c.5	FNEA_d_s25_c.25
COMBINED	FNEA_b_s25_c.5	IDRISI_b_s50_m5_v5	FNEA_b_s45_c.75	FNEA_b_s30_c.75	IDRISI_b_s70_m1_v9	FNEA_a_s40_c.5	FNEA_b_s45_c.5	FNEA_a_s35_c.25

\*=tie with other segmentations which are not indicated here. Segmentation that is shown ranked best using OverUnder evaluation method

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1013 Table 5. 20 best and 10 worst segmentations based on all area reference polygons and  
1014 COMBINED measure. Segmentation methods are named as in Table 4.

	<u>SEGMENTATION</u>	<u>COMBINED</u>
1	FNEA_b_s25_c.5	0.646
2	FNEA_b_s25_c.75	0.649
3	FNEA_b_s30_c.75	0.650
4	FNEA_c_s25_c.75	0.650
5	FNEA_d_s25_c.75	0.651
6	IDRISI_b_s55_m9_v1	0.652
7	FNEA_a_s30_c.75	0.652
8	IDRISI_b_s65_m9_v1	0.652
9	IDRISI_d_s65_m9_v1	0.652
10	FNEA_d_s30_c.75	0.652
11	IDRISI_b_s50_m5_v5	0.653
12	FNEA_b_s20_c.5	0.653
13	IDRISI_b_s55_m5_v5	0.653
14	IDRISI_b_s60_m9_v1	0.653
15	IDRISI_b_s50_m9_v1	0.653
16	IDRISI_c_s60_m5_v5	0.653
17	IDRISI_a_s60_m1_v9	0.653
18	IDRISI_a_s70_m9_v1	0.653
19	IDRISI_d_s65_m5_v5	0.654
20	IDRISI_a_s60_m5_v5	0.654
...		
243	IDRISI_c_s20_m9_v1	0.770
244	FNEA_a_s5_c.25	0.771
245	FNEA_c_s5_c.5	0.782
246	FNEA_d_s5_c.5	0.789
247	FNEA_a_s5_c.5	0.796
248	FNEA_b_s5_c.5	0.797
249	FNEA_c_s5_c.75	0.801
250	FNEA_d_s5_c.75	0.805
251	FNEA_a_s5_c.75	0.811
252	FNEA_b_s5_c.75	0.813

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1017 Table 6. Best segmentations based on different measures sorted by segmentation  
 1018 method, layer combinations, and different parameter options. Numbers refer to the  
 1019 number of segmentations that were regarded as best.

all segmentations			FNEA segmentations			IDRISI segmentations		
method	value	count		value	count		value	count
	FNEA	140	scale	5	36	similarity	20	4
	IDRISI	44		10	2		25	3
				15	6		30	0
layers	a	35		20	6		35	2
	b	93		25	6		40	2
	c	28		30	13		45	3
	d	28		35	10		50	2
				40	12		55	5
				45	13		60	2
				50	36		65	9
							70	12
			colour	0.25	40			
				0.5	30	mean/var	0.1/0.9	15
				0.75	70		0.5/0.5	8
							0.9/0.1	21

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1021 Table 7. Correlations between the COMBINED goodness measure and individual  
 1022 goodness measures based on different reference polygons. SA refers to sub-area, FP to  
 1023 forestry planning data and FFPS for FFPS data.

MEASURE	ALL	SA1	SA2	SA3	water	mires	FP	FFPS
UnderMerging	-0.24	-0.39	-0.63	-0.13	-0.63	-0.61	-0.69	-0.33
OverMerging	0.89	0.90	0.95	0.90	0.88	0.97	0.91	0.90
AFI	-0.22	-0.36	-0.63	-0.10	-0.40	-0.61	-0.54	-0.24
CountOver	0.69	0.78	0.91	0.73	0.87	0.91	0.88	0.71
CountUnder	-0.25	-0.31	-0.73	-0.31	-0.53	-0.62	-0.53	-0.10
SimSize mean	0.89	0.91	0.91	0.89	0.85	0.29	0.92	0.82
SimSize sd	-0.91	-0.93	-0.93	-0.91	-0.94	-0.34	-0.93	-0.85
RAsuper	-0.79	-0.86	-0.94	-0.83	-0.95	-0.93	-0.96	-0.86
RAsub	0.43	0.54	0.80	0.53	0.86	0.75	0.85	0.52
QR	0.91	0.94	0.93	0.92	0.95	0.35	0.95	0.90
OverSegmentation	0.48	0.60	0.79	0.56	0.81	0.84	0.84	0.50
UnderSegmentation	-0.52	-0.65	-0.82	-0.58	-0.79	-0.86	-0.87	-0.63
RPsuper	0.85	0.67	0.52	0.78	0.88	-0.55	0.74	0.96
RPsub	0.86	0.94	0.88	0.94	0.95	0.01	0.92	0.87
QLoc mean	0.86	0.94	0.88	0.94	0.95	0.01	0.92	0.87
QLoc sd	0.63	0.68	0.80	0.79	0.80	0.30	0.80	0.72
M	0.98	0.98	-0.88	0.97	-0.50	-0.72	-0.90	0.97
ZH1	0.66	0.60	-0.83	0.84	0.76	-0.29	-0.87	0.83
ZH2	0.89	0.96	0.92	0.94	0.94	0.29	0.92	0.89
D	0.77	0.82	0.88	0.81	0.83	0.36	0.90	0.65
OverUnder	0.76	0.84	0.90	0.78	0.91	0.86	0.89	0.75
MergeSum	0.41	0.50	-0.34	0.69	0.86	-0.52	0.85	0.90

1024

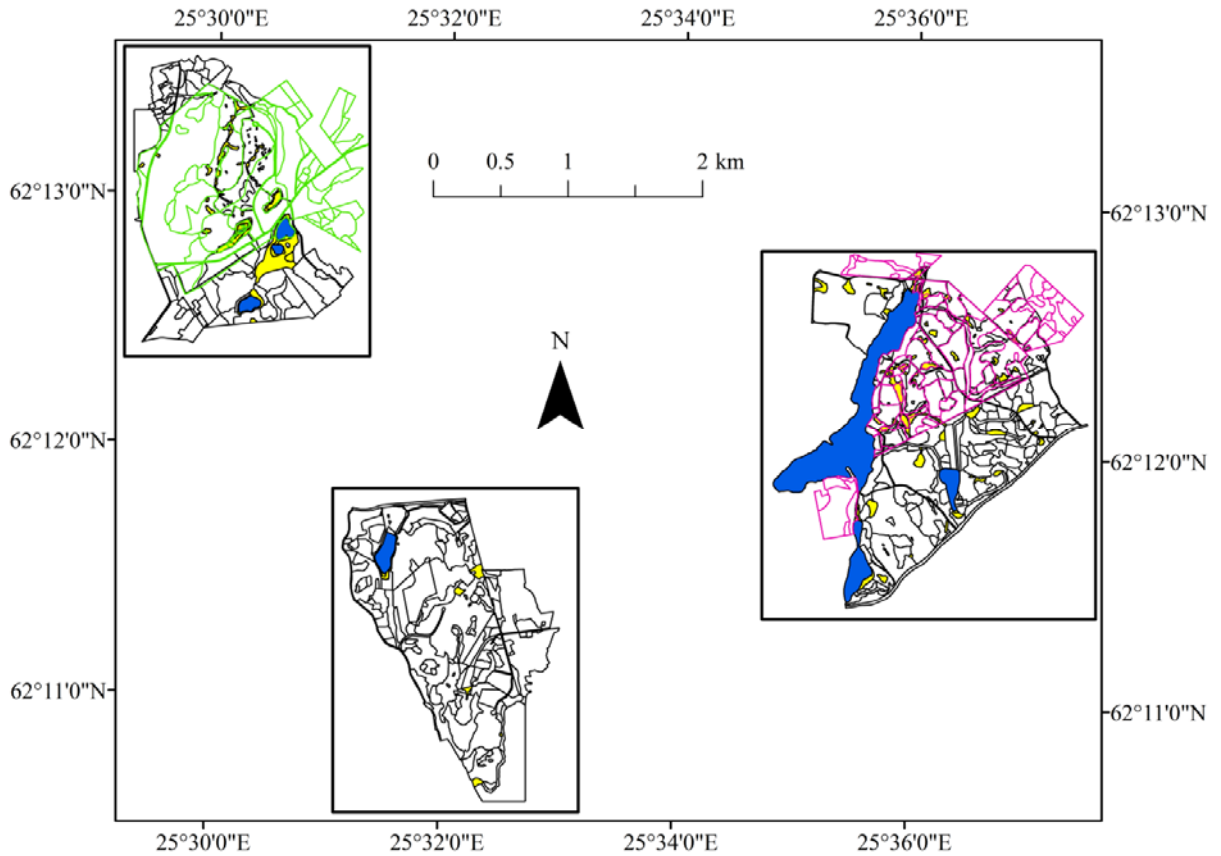
1025 Table 8. Correlations between the COMBINED measure values based on different  
 1026 reference polygons.

	ALL	SA1	SA2	SA3	water	mires	FP	FFPS
ALL	1.00	0.89	0.85	0.94	0.64	0.84	0.78	0.94
SA1	0.89	1.00	0.83	0.84	0.59	0.83	0.79	0.88
SA2	0.85	0.83	1.00	0.87	0.82	0.97	0.97	0.89
SA3	0.94	0.84	0.87	1.00	0.73	0.87	0.83	0.88
water	0.64	0.59	0.82	0.73	1.00	0.80	0.80	0.63
mires	0.84	0.83	0.97	0.87	0.80	1.00	0.95	0.85
FP	0.78	0.79	0.97	0.83	0.80	0.95	1.00	0.84
FFPS	0.94	0.88	0.89	0.88	0.63	0.85	0.84	1.00

1027 Table 9. Classification accuracies derived from classifications based on different  
 1028 segmentations. Segmentations are marked as in Table 2. Also, criteria why each  
 1029 segmentation was chosen to the classification analyses are given.

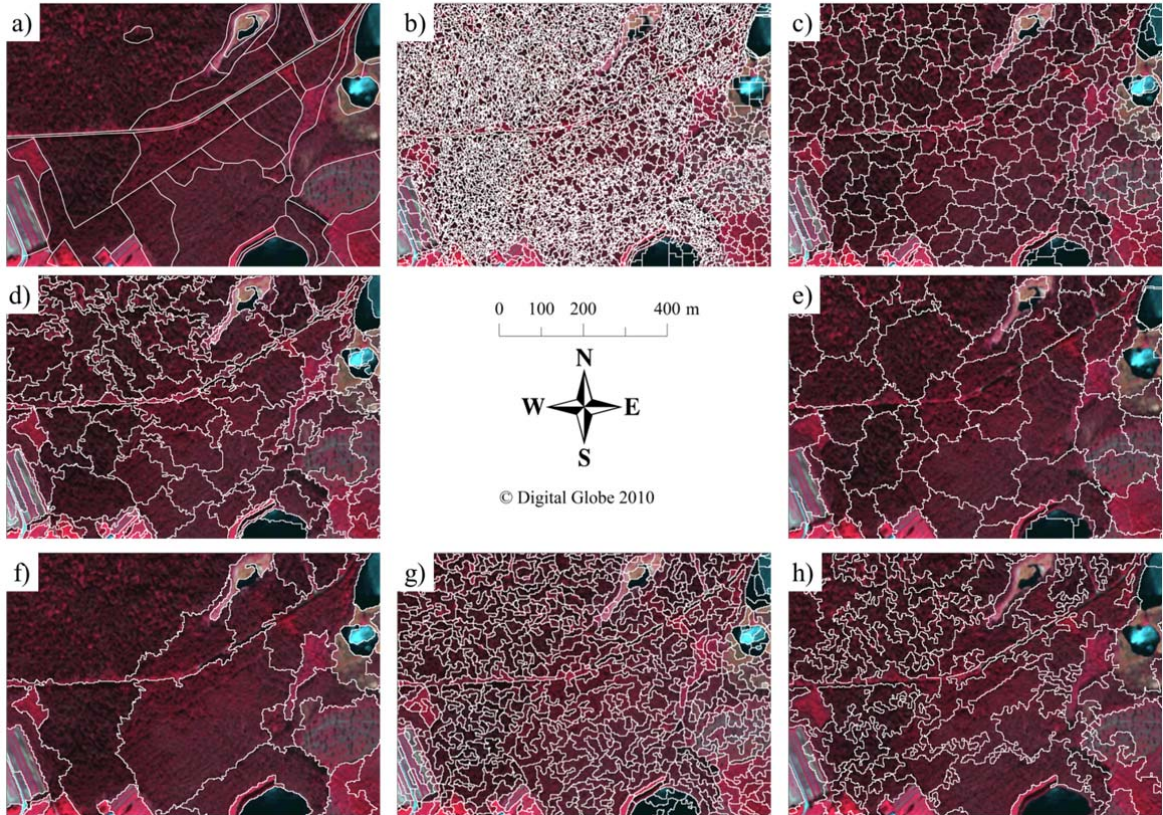
SEGMENTATION	ACC	Why segmentation was selected to classification
FNEA_b_s5_c.75	0.69	BEST in avoiding undersegmentation, WORST based on COMBINATION and ALL AREA
FNEA_c_s5_c.75	0.69	Comparison against FNEA_b_s5_c.75
FNEA_a_s10_c.5	0.71	WV-2 layers only, comparison against FNEA_c_s10_c.5
FNEA_c_s10_c.5	0.72	BEST segmentation based on visual interpretation
FNEA_d_s15_c.25	0.71	GOOD in visual interpretation
FNEA_a_s20_c.75	0.69	Segmentation based on WV-2 data only, OK visually
FNEA_b_s25_c.5	0.66	BEST segmentation based on COMBINATION and ALL AREA, OK visually
FNEA_d_s35_c.5	0.66	BEST based on D and ALL AREA
FNEA_c_s50_c.75	0.65	GOOD in avoiding oversegmentation, GOOD in visual boundary evaluation
IDRISI_d_s30_m9v1	0.70	OK in visual interpretation, small segments
IDRISI_c_s40_m5v5	0.69	OK in visual interpretation, quite small segments
IDRISI_b_s70_m9v1	0.60	BEST based on OverUnder and ALL AREA, BAD in visual interpretation

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1032 Figure 1. Different reference polygons used. Reference polygons drawn in our field  
 1033 work are marked with black borders. Sub-area 1 is located in the eastern, sub-area 2 in  
 1034 the north-western and sub-area 3 in the southern part of the whole area. Water bodies  
 1035 are drawn with blue colour and mires with yellow colour. Forestry planning polygons  
 1036 are marked with magenta outlines and FFPS polygons with green outlines. FNEA  
 1037 segmentations were performed inside the black rectangles whereas IDRISI  
 1038 segmentations were performed also in the areas between the black rectangles.



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1040 Figure 2. Reference polygons and a visually chosen set of different segmentations  
 1041 drawn on a WV-2 false colour image (red: band 7/NIR1, green: band 5/red, blue: band  
 1042 3/green) in background. a) reference polygons, b) FNEA\_b\_s5\_c.75, c)  
 1043 FNEA\_c\_s10\_c.5, d) FNEA\_a\_s20\_c.75, e) FNEA\_b\_s25\_c.5, f) FNEA\_c\_s50\_c.75,  
 1044 g) IDRISI\_d\_s30\_m9v1, and h) IDRISI\_b\_s70\_m9v1. Images are from the southern  
 1045 part of the sub-area 2.