

**This is an electronic reprint of the original article.
This reprint *may differ* from the original in pagination and typographic detail.**

Author(s): Räsänen, Aleks; Rusanen, Antti; Kuitunen, Markku; Lensu, Anssi

Title: What makes segmentation good? A case study in boreal forest habitat mapping

Year: 2013

Version:

Please cite the original version:

Räsänen, A., Rusanen, A., Kuitunen, M., & Lensu, A. (2013). What makes segmentation good? A case study in boreal forest habitat mapping. *International Journal of Remote Sensing*, 34(23), 8603-8627.
<https://doi.org/10.1080/01431161.2013.845318>

All material supplied via JYX is protected by copyright and other intellectual property rights, and duplication or sale of all or part of any of the repository collections is not permitted, except that material may be duplicated by you for your research use or educational purposes in electronic or print form. You must obtain permission for any other use. Electronic or print copies may not be offered, whether for sale or otherwise to anyone who is not an authorised user.

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

3 Aleksi Räsänen*, Antti Rusanen, Markku Kuitunen and Anssi Lensu

4 *Department of Biological and Environmental Science, University of Jyväskylä,*
5 *Jyväskylä, Finland*

6 *Corresponding author. Department of Biological and Environmental Science, P.O. Box
7 35, FI-40014 University of Jyväskylä, Email: t.aleksi.rasanen@jyu.fi

8

9 **What makes segmentation good? A case study in boreal** 10 **forest habitat mapping**

11 Segmentation goodness evaluation is a set of approaches meant for deciding
12 which segmentation is good. In this study, we tested different supervised
13 segmentation evaluation measures reviewed by Clinton et al. (2010) and visual
14 interpretation in the case of boreal forest habitat mapping in Southern Finland.
15 Used data were WorldView-2 satellite imagery and LiDAR digital elevation
16 model (DEM) and canopy height model (CHM) in 2-m resolution. Tested
17 segmentation methods were Fractal Net Evolution Approach (FNEA) and IDRISI
18 watershed segmentation. Overall, 252 different segmentation method, layer and
19 parameter combinations were tested. We also used eight different habitat
20 delineations as reference polygons against which 252 different segmentations
21 were tested. The ranking order of segmentations depended on the chosen
22 supervised evaluation measure; hence, no single segmentation could be ranked as
23 the best. In visual interpretation, we found out that several different
24 segmentations were rather good and selected one of them as the best. In
25 literature, it has been noted that better segmentation leads to higher classification
26 accuracy. We tested this argument by classifying 12 of our segmentations with
27 the random forest classifier. It was found out that there is no straightforward
28 answer to the argument, since the definition of good segmentation is inconsistent.
29 Highest classification accuracy (0.72) was obtained with segmentation which was
30 regarded as one of the best in visual interpretation. However, almost as high
31 classification accuracies were obtained with other segmentations. We conclude
32 that one has to decide what she/he wants from segmentation and use
33 segmentation evaluation measures with care.

34 **1 Introduction**

35 Since the early 2000s, with the rise of object-based image analysis (OBIA)
36 methodology (Blaschke 2010), segmentation goodness evaluation has been an emerging
37 topic within the remote sensing literature (Clinton et al. 2010; Marpu et al. 2010).
38 Evaluation has been concentrated on segmentation method development and
39 comparison as well as parameter optimization.

40 Generally in segmentation, the goal is to partition imagery into regions that are
41 meaningful; and thus, either mimic real world objects (Zhang, Fritts, and Goldman
42 2008; Clinton et al. 2010) or minimize intrasegment and maximize intersegment
43 heterogeneity (Zhang, Fritts, and Goldman 2008; Hou et al. 2013). Remote sensing
44 segmentation methods are a special case of more general image segmentation methods,
45 which can be divided into two complementary groups: similarity or region based
46 segmentation and discontinuity based segmentation. In region based segmentation, a
47 similarity measure is used to find suitable regions. In discontinuity based segmentation,
48 discontinuities of the images, usually boundaries, are detected (Zhang 1997; Gonzales
49 and Woods 2002). Some of the methods combine concepts from both groups. For
50 instance, in watershed segmentation, dividing lines between basin areas are sought by
51 flooding the image (Gonzales and Woods 2002).

52 Within remote sensing, many of the segmentation implementations have been
53 region based. Arguably, the most widely used remote sensing segmentation method has

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; Wolfer 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; Wolfer 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). Wolfer
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 km² 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 14th 2010 and LiDAR data with a minimum of 0.5
212 points per 1 m² 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 (α) used in TWI is defined as the pixels upslope contributing
 252 area per contour width whereas α_M is modified catchment area used in SWI. In
 253 calculating α , slope angle β (in radians) and neighbouring cell maximum α_{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 α
 256 values, and higher values lead to weaker suction. After counting α_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 β , 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) (Batz 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.

716 **6 Acknowledgements**

717 This research was funded by Maj and Tor Nessling foundation. We are grateful to City of
718 Jyväskylä for providing us the reference polygon dataset and the aerial imagery as well as to
719 Finnish Forest and Park Service for the reference polygon dataset. MK received from Jenny and
720 Antti Wihuri foundation a sabbatical scholarship for the year 2013 that was partly funded also
721 by the EU IMPERIA-project (LIFE11 ENV/FI/905) and the University of Jyväskylä.

722 **7 References**

- 723 Ahti, Teuvo, Leena Hämet-Ahti, and Jaakko Jalas. 1968. "Vegetation Zones and Their
724 Sections in Northwestern Europe." *Annales Botanici Fennici* 5: 169–211.
- 725 Baatz, Martin and Arno Schäpe. 2000. "Multiresolution Segmentation – An
726 Optimization Approach for High Quality Multi-Scale Image Segmentation." In
727 *Angewandte Geographische Informationsverarbeitung XII*, edited by J. Strobl
728 and G. Griesebner, 12–23. Heidelberg: Wichmann.
- 729 Bar Massada, Avi, Rafi Kent, Lior Blank, Avi Perevolotsky, Liat Hadar, and Yohay
730 Carmel. 2012. "Automated Segmentation of Vegetation Units in a

- 731 Mediterranean Landscape.” *International Journal of Remote Sensing* 33 (2):
732 346–364.
- 733 Benz, Ursula C., Peter Hofmann, Gregor Willhauck, Iris Lingenfelder, and Markus
734 Heynen. 2004. Multi-Resolution, Object-Oriented Fuzzy Analysis of Remote
735 Sensing Data for GIS-Ready Information. *ISPRS Journal of Photogrammetry
736 and Remote Sensing* 58: 239–258.
- 737 Blaschke, Thomas. 2010. “Object Based Image Analysis for Remote Sensing.” *ISPRS
738 Journal of Photogrammetry and Remote Sensing* 65: 2–16.
- 739 Bock, Michael, Panteleimon Xofis, Jonathan Mitchley, Godela Rossner, and Michael
740 Wissen. 2005. “Object-Oriented Methods for Habitat Mapping at Multiple
741 Scales – Case Studies from Northern Germany and Wye Downs, UK.” *Journal
742 of Nature Conservation* 13: 75–89.
- 743 Böhner, Jürgen, and Thomas Selige. 2006. “Spatial Prediction of Soil Attributes using
744 Terrain Analysis and Climate Regionalisation.” In *SAGA – Analysis and
745 Modelling Applications*, edited by Jürgen Böhner, K. R. McCloy, and J. Strobl,
746 13–28. Göttinger Geographische Abhandlungen, Vol.115.
- 747 Breidenbach, Johannes, Erik Næsset, Vegard Lien, Terje Gobakken, and Svein Solberg.
748 2010. “Prediction of Species Specific Forest Inventory Attributes using a
749 Nonparametric Semi-Individual Tree Crown Approach Based on Fused
750 Airborne Laser Scanning and Multispectral Data.” *Remote Sensing of
751 Environment* 114: 911–924.
- 752 Breiman, Leo. 2001. “Random Forests.” *Machine Learning* 45: 5–32.
- 753 Breiman, Leo, and Adele Cutler. 2007. “Random Forest: Classification Description.”
754 http://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm.
- 755 Câmara, Gilberto, Lúbia Vinhas, Karine Reis Ferreira, Gilberto Ribeiro de Queiroz,
756 Ricardo Cartaxo Modesto De Souza, Antonio Miguel Vieira Monteiro, Marcelo
757 Tílio de Carvalho, Marco Antonio Casanova, and Ubirajara Moura De Freitas.
758 2008. “TerraLib: An Open Source GIS Library for Large-Scale Environmental
759 and Socio-Economic Applications.” In *Open Source Approaches in Spatial Data
760 Handling*, edited by G. Brent Hall, and Michael G. Leahy, 247–270. Berlin:
761 Springer.
- 762 Carleer, A. P., O. Debeir, and E. Wolff. 2005. “Assessment of Very High Resolution
763 Satellite Image Segmentations.” *Photogrammetric Engineering & Remote
764 Sensing* 71 (11): 1285–1294.
- 765 Castilla, Guillermo, Geoffrey J. Hay, and Jose R. Ruiz-Gallardo. 2008. “Size-
766 Constrained Region Merging (SCRM): An Automated Delineation Tool for
767 Assisted Photointerpretation.” *Photogrammetric Engineering & Remote Sensing*
768 74 (4): 409–419.
- 769 Chabrier, S., C. Rosenberger, B. Emile, and H. Laurent, H. 2008. “Optimization-Based
770 Image Segmentation by Genetic Algorithms.” *EURASIP Journal on Image and
771 Video Processing*, Article ID 842029. doi:10.1155/2008/842029.
- 772 Cherrill, Andrew, and Colin McClean. 1995. An Investigation of Uncertainty in Field
773 Habitat Mapping and the Implications for Detecting Land Cover Change.
774 *Landscape Ecology* 10 (1): 5–21.
- 775 Cherrill, Andrew, and Colin McClean. 1999. The Reliability of ‘Phase 1’ Habitat
776 Mapping in the UK: The Extent and Types of Observer Bias. *Landscape and
777 Urban Planning* 45: 131–143.

- 778 Clinton, Nicholas, Ashley Holt, James Scarborough, Li Yan, and Peng Gong. 2010.
779 "Accuracy Assessment Measures for Object-based Image Segmentation
780 Goodness." *Photogrammetric Engineering & Remote Sensing* 76 (3): 289–299.
- 781 Corcoran, Pdraig, Adam Winstanley, and Peter Mooney. 2010. "Segmentation
782 Performance Evaluation for Object-Based Remotely Sensed Image Analysis".
783 *International Journal of Remote Sensing* 31 (3): 617–645.
- 784 Derivaux, S., G. Forestier, C. Wemmert, and S. Lefèvre. 2010. "Supervised Image
785 Segmentation using Watershed Transform, Fuzzy Classification and
786 Evolutionary Computation." *Pattern Recognition Letters* 31 (15): 2364–2374.
- 787 Dingle Robertson, Laura, and Douglas J. King. 2011. "Comparison of Pixel- and
788 Object-Based Classification in Land Cover Change Mapping." *International
789 Journal of Remote Sensing* 32 (6): 1505–1529.
- 790 dos Santos, Jefferson Alex, Philippe-Henri Gosselin, Sylvie Phillipp-Foliguet, Ricardo
791 da S. Torres, and Alexandre Xavier Falcão. 2012. "Multiscale Classification of
792 Remote Sensing Images". *IEEE Transactions on Geoscience and Remote
793 Sensing* 50 (10): 3764–3775.
- 794 Drăguț, Lucian, Dirk Tiede, and Shaun R. Levick. 2010. "ESP: A Tool to Estimate
795 Scale Parameter for Multiresolution Image Segmentation of Remotely Sensed
796 Data." *International Journal of Geographical Information Science* 24 (6): 859–
797 871.
- 798 Duro, Dennis C., Steven E. Franklin, and Monique G. Dubé. 2012. "A Comparison of
799 Pixel-Based and Object-Based Image Analysis with Selected Machine Learning
800 Algorithms for the Classification of Agricultural Landscapes using SPOT-5
801 HRG Imagery." *Remote Sensing of Environment* 118: 259–272.
- 802 Espindola, G. M., G. Camara, I. A. Reis, L. S. Bins, and A. M. Monteiro. 2006.
803 "Parameter Selection for Region-Growing Image Segmentation Algorithms
804 using Spatial Autocorrelation." *International Journal of Remote Sensing* 27
805 (14): 3035–3040.
- 806 Eysn, Lothar, Markus Hollaus, Klemens Schadauer, and Norbert Pfeifer. 2012. "Forest
807 Delineation Based on Airborne LIDAR Data." *Remote Sensing* 4: 762–783.
808 doi:10.3390/rs4030762.
- 809 Falkowski, Michael J., Michael A. Wulder, Joanne C. White, and Mark G. Gillis. 2009.
810 "Supporting Large-Area, Sample-Based Forest Inventories with Very High
811 Spatial Resolution Satellite Imagery." *Progress in Physical Geography* 33 (3):
812 403–423.
- 813 Feitosa, R. Q., G. A. O. P. Costa, T. B. Cazes, and B. Feijo. 2006. "A Genetic Approach
814 for the Automatic Adaptation of Segmentation Parameters." In *Bridging Remote
815 Sensing and GIS: 1st International Conference on Object-based Image Analysis
816 (OBIA 2006)*, edited by: Stefan Lang, Thomas Blaschke, and Elisabeth
817 Schöpfer. International Archives of the Photogrammetry, Remote Sensing and
818 Spatial Information Sciences – Volume XXXVI/4-C42.
- 819 Freeman, T. Graham. 1991. "Calculating catchment area with divergent flow based on a
820 regular grid." *Computers and Geosciences* 17: 413–422.
- 821 Gao, Yan, Jean Francois Mas, Norman Kerle, and Jose Antonio Navarrete Pacheco. 2011. "Optimal
822 Region Growing Segmentation and Its Effect on Classification Accuracy."
823 *International Journal of Remote Sensing* 32 (13): 3747–3763.
- 824 Geerling, G. W., M. Labrador-Garcia, J. P. G. W. Clevers, A. M. J. Rags, and A. J. M.
825 Smits. 2007. "Classification of Floodplain Vegetation by Data-Fusion of

826 Spectral (CASI) and LiDAR Data.” *International Journal of Remote Sensing* 28
827 (19): 4263–4284.

828 Geerling, G. W., M. J. Vreeken-Buijs, P. Jesse, A. M. J. Ragas, and A. J. M. Smits.
829 2009. “Mapping River Floodplain Ecotopes by Segmentation of Spectral (CASI)
830 and Structural (LiDAR) Remote Sensing Data.” *River Research and*
831 *Applications* 25: 795–813.

832 Gonzales, Rafael C., and Richard E. Woods. 2002. *Digital Image Processing*. 2nd ed.
833 Upper Saddle River: Prentice Hall.

834 Grabs, T., Jan Seibert, K. Bishop, and H. Laudon. 2009. “Modeling Spatial Patterns of
835 Saturated Areas: A Comparison of the Topographic Wetness Index and a
836 Dynamic Distributed Model. *Journal of Hydrology* 373: 15–23.

837 Güntner, Andreas, Jan Seibert, and Stefan Uhlenbrook. 2004. “Modeling Spatial
838 Patterns of Saturated Areas: An Evaluation of Different Terrain Indices.” *Water*
839 *Resources Research* 40, W05114. doi:10.1029/2003WR002864.

840 Hay, Geoffrey J., Thomas Blaschke, Danielle J. Marceau, and André Bouchard. 2003.
841 “A Comparison of Three Image-Object Methods for the Multiscale Analysis of
842 Landscape Structure.” *ISPRS Journal of Photogrammetry and Remote Sensing*
843 57: 327–345.

844 Hay, Geoffrey J., Guillermo Castilla, Michael A. Wulder, and Jose R. Ruiz 2005. “An
845 Automated Object-Based Approach for the Multiscale Image Segmentation of
846 Forest Scenes. *International Journal of Applied Earth Observation and*
847 *Geoinformation* 7: 339–359.

848 Hou, Zhengyang, Qing Xu, Tuula Nuutinen, and Timo Tokola. 2013. “Extraction of
849 remote sensing-based forest management units in tropical forests”. *Remote*
850 *Sensing of Environment* 130: 1–10.

851 Isenburg, Martin. 2011. *LAStools: Efficient Tools for LiDAR Processing*. Version
852 110815. <http://lastools.org>.

853 Ji, Xiaole, Yanchen Bo, Jiehai Cheng, Yaqian He, and Xiaolong Liu. 2012. “The
854 Method of Assessing Shape Similarity of Object-Based Classification Result of
855 Remote Sensing Imagery”. In *Proceedings of the Second International*
856 *Workshop on Earth Observation and Remote Sensing Applications (EORSA*
857 *2012)*, 157–160. IEEE.
858 <http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=6248407/>.

859 Ke, Yinghai, Lindi J. Quackenbush, and Jungho Im. 2010. “Synergistic Use of
860 QuickBird Multispectral Imagery and LIDAR Data for Object-Based Forest
861 Species Classification.” *Remote Sensing of Environment* 114: 1141–1154.

862 Kim, Minho, Marguerite Madden, and Timothy A. Warner. 2008. “Estimation of
863 Optimal Image Object Size for the Segmentation of Forest Stands with
864 Multispectral IKONOS Imagery.” In *Object-Based Image Analysis: Spatial*
865 *Concepts for Knowledge-Driven Remote Sensing Applications*, edited by
866 Thomas Blaschke, Stefan Lang, and Geoffrey J. Hay, 291–307. Berlin: Springer.

867 Kim, Minho, Marguerite Madden, and Timothy A. Warner. 2009. “Forest Type
868 Mapping using Object-specific Texture Measures from Multispectral Ikonos
869 Imagery: Segmentation Quality and Image Classification Issues.”
870 *Photogrammetric Engineering & Remote Sensing* 75 (7): 819–829.

871 Kim, Minho, Timothy A. Warner, Marguerite Madden, and Douglas S. Atkinson. 2011.
872 “Multi-Scale GEOBIA with Very High Spatial Resolution Digital Aerial

- 873 Imagery: Scale, Texture and Image Objects.” *International Journal of Remote*
874 *Sensing* 32 (10): 2825–2850
- 875 Kopecký, Martin and Štěpánka Čížková. 2010. “Using Topographic Wetness Index in
876 Vegetation Ecology: Does the Algorithm Matter?” *Applied Vegetation Science*
877 13: 450–459.
- 878 Lang, Stefan, F. Albrecht, S. Kienberger, and Dirk Tiede. 2010. “Object Validity for
879 Operational Tasks in a Policy Context.” *Journal of Spatial Science* 55 (1): 9–22.
- 880 Lawrence, Rick L., Shana D. Wood, and Roger L. Sheley. 2006. “Mapping Invasive
881 Plants using Hyperspectral Imagery and Breiman Cutler Classifications
882 (RandomForest).” *Remote Sensing of Environment* 100: 356–362.
- 883 Leckie, Donald G., François A. Gougeon, Nicholas Walsworth, and Dennis Paradine.
884 2003. “Stand Delineation and Composition Estimation using Semi-Automated
885 Individual Tree Crown Analysis”. *Remote Sensing of Environment* 85: 355–369.
- 886 Li, Haitao, Haiyan Gu, Yanshun Han, and Jinghui Yang. 2010. “Object-Oriented
887 Classification of High-Resolution Remote Sensing Imagery based on an
888 Improved Colour Structure Code and a Support Vector Machine.” *International*
889 *Journal of Remote Sensing* 31 (6): 1453–1470.
- 890 Li, Nan, Hong Huo, and Tao Fang. 2010. “A Novel Texture-Preceded Segmentation
891 Algorithm for High-Resolution Imagery.” *IEEE Transactions on Geoscience*
892 *and Remote Sensing* 48 (7): 2818–2828.
- 893 Liaw, Andy, and Matthew Wiener. 2002. “Classification and Regression by
894 randomForest.” *R News* 2/3: 18–22.
- 895 Lucieer, Arko, and Alfred Stein. 2002. “Existential Uncertainty of Spatial Objects
896 Segmented From Satellite Sensor Imagery.” *IEEE Transactions on Geoscience*
897 *and Remote Sensing* 40 (11): 2518–2521.
- 898 Marpu, P. R., M. Neubert, H. Herold, and I. Niemeyer. 2010. “Enhanced Evaluation of
899 Image Segmentation Results”. *Journal of Spatial Science* 55 (1): 55–68.
- 900 Meinel, G., and M. Neubert. 2004. “A Comparison of Segmentation Programs for High
901 Resolution Remote Sensing Data.” In *XX ISPRS Congress: Technical*
902 *Commission IV*, edited by Orhan Altan, 1097–1105. International Archives of
903 the Photogrammetry, Remote Sensing and Spatial Information Sciences –
904 Volume XXXV Part B4.
- 905 Möller, M., L. Lymburner, and M. Volk. 2007. “The Comparison Index: A Tool for
906 Assessing the Accuracy of Image Segmentation.” *International Journal of*
907 *Applied Earth Observation and Geoinformation* 9: 311–321.
- 908 Mustonen, Jukka, Petteri Packalén, and Annika Kangas. 2008. “Automatic
909 Segmentation of Forest Stands Using a Canopy Height Model and Aerial
910 Photography.” *Scandinavian Journal of Forest Research* 23 (6): 534–545.
- 911 Murphy, P. N. C., J. Ogilvie, and P. Arp. 2009. “Topographic Modeling of Soil
912 Moisture Conditions: a Comparison and Verification of Two Models.”
913 *European Journal of Soil Science* 60: 94–109.
- 914 Neubert, M., and H. Herold. 2008. “Assessment of Remote Sensing Image
915 Segmentation Quality.” In *GEOBIA 2008 - Pixels, Objects, Intelligence:*
916 *GEOgraphic Object Based Image Analysis for the 21st Century Proceedings*,
917 edited by Geoffrey J. Hay, Thomas Blaschke and Danielle Marceau.
918 International Archives of Photogrammetry, Remote Sensing and Spatial
919 Information Sciences XXXVIII-4/C1.

- 920 Neubert, M., and G. Meinel. 2003. "Evaluation of Segmentation Programs for High
 921 Resolution Remote Sensing Applications." In *Proceedings Joint ISPRS/EARSeL*
 922 *Workshop "High Resolution Mapping from Space 2003"*, edited by M.
 923 Schroeder, K. Jacobsen, and C. Heipke. [http://www.ipi.uni-](http://www.ipi.uni-hannover.de/fileadmin/institut/pdf/neubert.pdf)
 924 [hannover.de/fileadmin/institut/pdf/neubert.pdf](http://www.ipi.uni-hannover.de/fileadmin/institut/pdf/neubert.pdf).
- 925 Neubert, M., H. Herold, and G. Meinel. 2008. "Assessing Image Segmentation Quality
 926 – Concepts, Methods and Applications." In *Object-Based Image Analysis:*
 927 *Spatial Concepts for Knowledge-Driven Remote Sensing Applications*, edited by
 928 Thomas Blaschke, Stefan Lang, and Geoffrey J. Hay, 769–784. Berlin: Springer.
- 929 Pekkarinen, Anssi. 2002. "Image Segment-Based Spectral Features in the Estimation of
 930 Timber Volume." *Remote sensing of Environment* 82: 349–359.
- 931 R Development Core Team. 2012. *R: A Language and Environment for Statistical*
 932 *Computing*. Vienna: R Foundation for Statistical Computing. ISBN 3-900051-
 933 07-0, URL <http://www.R-project.org/>.
- 934 Radoux, J. and P. Defourny. 2007. "A Quantitative Assessment of Boundaries in
 935 Automated Forest Stand Delineation using Very High Resolution Imagery."
 936 *Remote Sensing of Environment* 110: 468–475.
- 937 Rodriguez-Galiano, V. F., B. Ghimire, J. Rogan, M. Chica-Olmo, and J. P. Rigol-
 938 Sanchez. 2012. "An Assessment of the Effectiveness of a Random Forest
 939 Classifier for Land-Cover Classification." *ISPRS Journal of Photogrammetry*
 940 *and Remote Sensing* 67: 93–104.
- 941 Smith, A. 2010. "Image Segmentation Scale Parameter Optimization and Land Cover
 942 Classification using the Random Forest Algorithm." *Journal of Spatial Science*
 943 55(1): 69–79.
- 944 Sørensen, R., U. Zinko, and Jan Seibert. 2006. "On the Calculation of the Topographic
 945 Wetness Index: an Evaluation of Different Methods based on Field
 946 Observations." *Hydrology and Earth System Sciences* 10: 101–112.
- 947 Tian, J. and D.-M. Chen. 2007. "Optimization in Multi-Scale Segmentation of High-
 948 Resolution Satellite Images for Artificial Feature Recognition." *International*
 949 *Journal of Remote Sensing* 28 (20): 4625–4644.
- 950 Verbeeck, Klaartje, Martin Hermy, and Jos van Orshoven. 2012. "External Geo-
 951 Information in the Segmentation of VHR imagery Improves the Detection of
 952 Imperviousness in Urban Neighborhoods." *International Journal of Applied*
 953 *Earth Observation and Geoinformation* 18: 428–435.
- 954 Vesterbacka, Raisa. 2010. Luontopalvelujen luontotyypin inventoinnin maastotyöohje.
 955 Vantaa: Metsähallitus.
- 956 Wang, L., W. Sousa, and Peng Gong. 2004. "Integration of Object-Based and Pixel-
 957 Based Classification for Mapping Mangroves with IKONOS Imagery."
 958 *International Journal of Remote Sensing* 25 (24): 5655–5668.
- 959 Wang, Zhongwu, John R. Jensen, and Jungho Im. 2010. "An Automatic Region-Based
 960 Image Segmentation Algorithm for Remote Sensing Applications."
 961 *Environmental Modelling and Software* 25: 1149–1165.
- 962 Weidner, Uwe 2008. "Contribution to the Assessment of Segmentation Quality for
 963 Remote Sensing Applications." In *XXIst ISPRS Congress: Technical*
 964 *Commission VII*, edited by Chen Jun, Jiang Jie, and John van Genderen, 479–
 965 484. International Archives of Photogrammetry, Remote Sensing and Spatial
 966 Information Sciences – Volume XXXVII Part B7.

- 967 Whiteside, Timothy G., Guy S. Boggs, and Stefan W. Maier. 2011. "Comparing Object-
968 Based and Pixel-Based Classifications for Mapping Savannas." *International*
969 *Journal of Applied Earth Observation and Geoinformation* 13: 884–893.
- 970 Wulder, Michael A., Joanne C. White, Geoffrey J. Hay, and Guillermo Castilla. 2008.
971 "Towards Automated Segmentation of Forest Inventory Polygons on High
972 Spatial Resolution Satellite Imagery." *The Forestry Chronicle* 84 (2): 221–230.
- 973 Yang, Luren, Fritz Albrechtsen, Tor Lønnestad, and Per Grøttum. 1995. "A Supervised
974 Approach to the Evaluation of Image Segmentation Methods." *Computer*
975 *Analysis of Images and Patterns: 6th International Conference, CAIP '95*
976 *Prague Czech Republic, September 6-8, 1995 Proceedings*, edited by Václav
977 Hlaváč, and Radim Šára, 759–765. Lecture Notes on Computer Science,
978 Volume 970. Heidelberg: Springer.
- 979 Yue, Anzhi, Jianyu Yang, Chao Zhang, Wei Su, Wenju Yun, Dehai Zhu, Shunxi Liu,
980 and Zhongwu Wang. 2012. "The Optimal Segmentation Scale Identification
981 Using Multispectral WorldView-2 Images". *Sensor Letters* 10 (1–2): 285–
982 291(7).
- 983 Zhan, Qingming, Martien Molenaar, Klaus Tempfli, and Wengzhong Shi. 2005.
984 "Quality Assessment for Geo-Spatial Objects Derived from Remotely Sensed
985 Data." *International Journal of Remote Sensing* 26 (14): 2593–2974.
- 986 Zhang, Hui, Jason E. Fritts, and Sally A. Goldman. 2008. "Image Segmentation
987 Rvaluation: A Survey of Unsupervised Methods." *Computer Vision and Image*
988 *Understanding* 110: 260–280.
- 989 Zhang, Y. J. 1996. "A Survey on Evaluation Methods for Image Segmentation." *Pattern*
990 *Recognition* 29 (8): 1335–1346.
- 991 Zhang, Y. J. 1997. "Evaluation and Comparison of Different Segmentation
992 Algorithms." *Pattern Recognition Letters* 18 (10): 963–974.

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

1010

1011

1012

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

1015

1016

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

1020

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

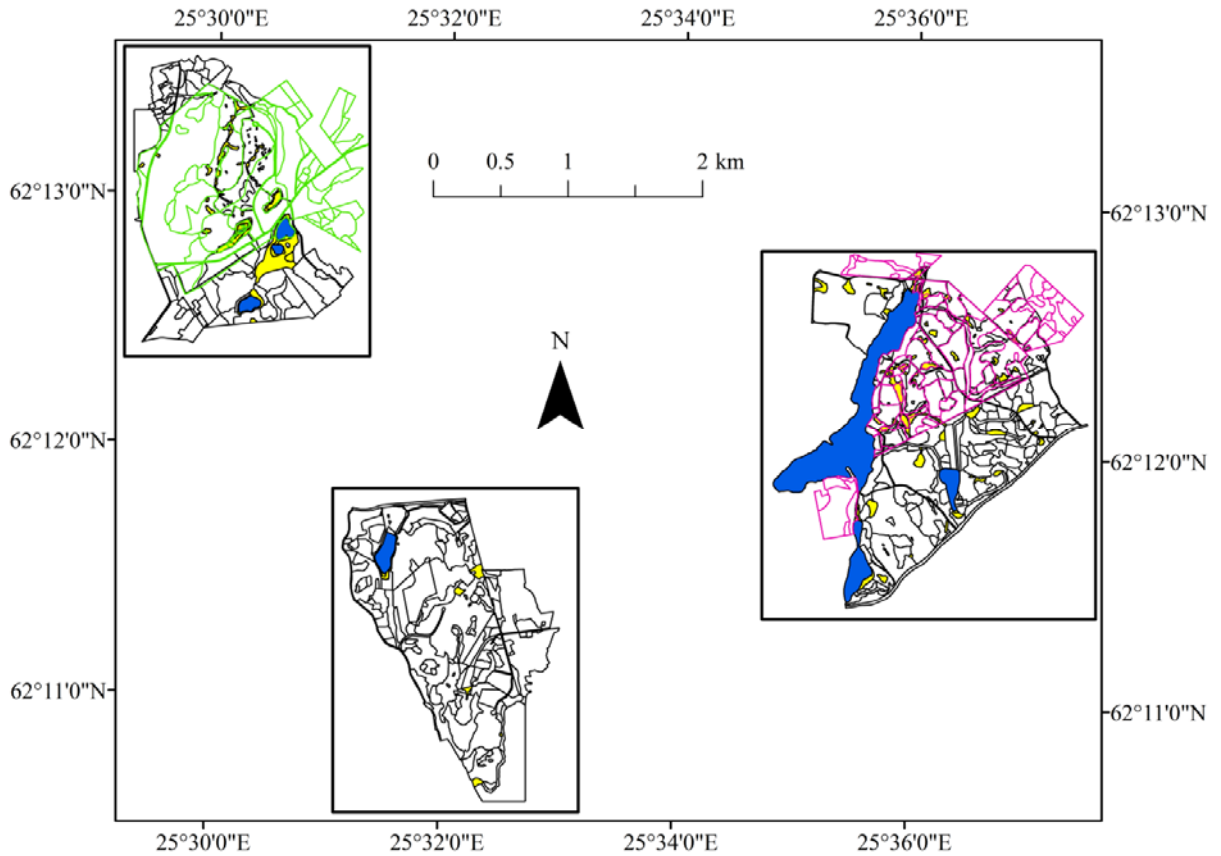
1025 Table 8. Correlations between the COMBINED measure values based on different
 1026 reference polygons.

	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.

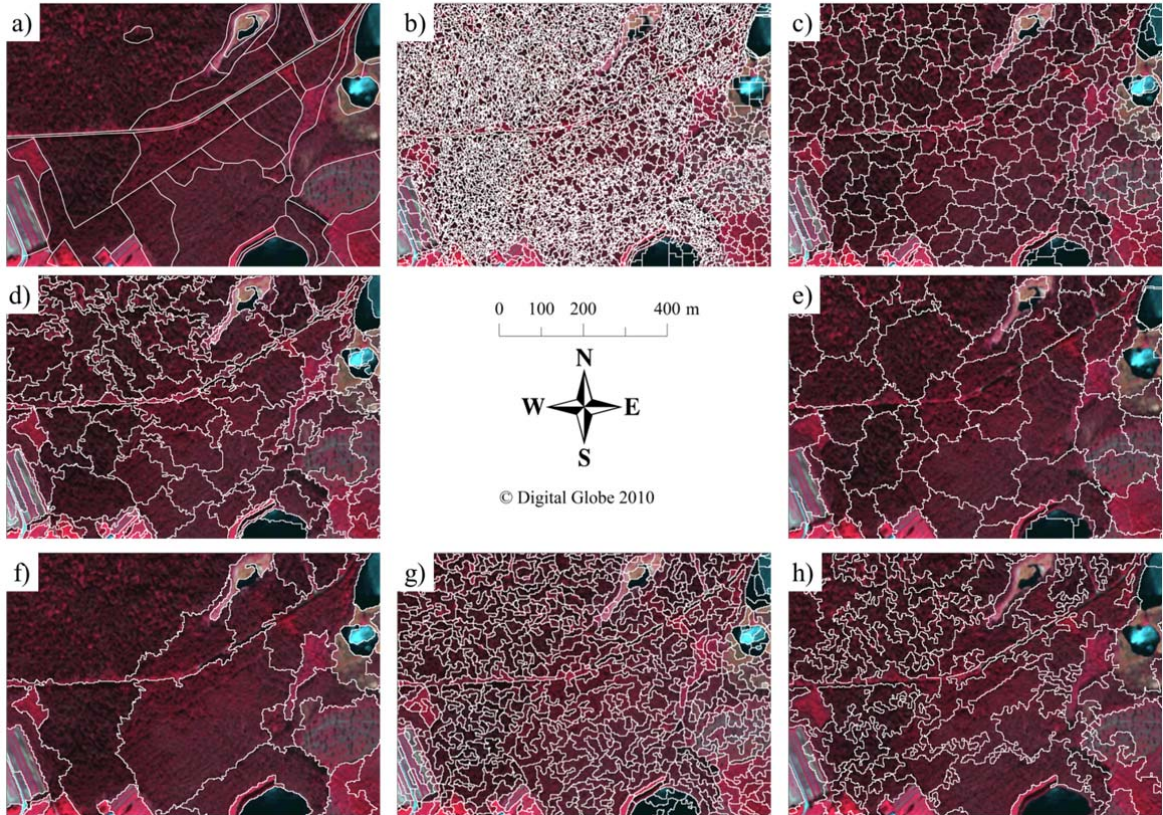
SEGMENTATION	ACC	Why segmentation was selected to classification
FNEA_b_s5_c.75	0.69	BEST in avoiding undersegmentation, WORST based on COMBINATION and ALL AREA
FNEA_c_s5_c.75	0.69	Comparison against FNEA_b_s5_c.75
FNEA_a_s10_c.5	0.71	WV-2 layers only, comparison against FNEA_c_s10_c.5
FNEA_c_s10_c.5	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

1030



1031

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.



1039

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.