

A METHOD FOR ADAPTING GLOBAL IMAGE SEGMENTATION METHODS TO IMAGES OF DIFFERENT RESOLUTIONS

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ABSTRACT

In the context of object-based image analysis (OBIA) in the most cases a so-called bottom-up-approach of analyzing images is applied. This means, beginning with an initial global segmentation, a subsequent classification of the segments is performed. Herein the image segments act as the building blocks for the following classification within the feature space spanned by the segments' properties of color, shape and texture. In many cases, after each step of classification, the initial segmentation is enhanced by merging, splitting or re-segmenting the classified segments with respect to their class assignments or other properties they have in common. This enhanced segmentation then leads to newly shaped segments with new segment-properties and consequently to new class-descriptions and a new step of classification and so on. Repeating this sequence of segmentation, classification and focused re-segmentation leads in the end to an iterative process which can also be understood as a localized (and knowledge-based) iterative segmentation. Since OBIA tends to extract information from an image about the imaged objects, the better the image segments represent the real-world-objects in the image, the better the segment-classes describe the real-world-classes in the image. Assuming the image segments do represent the real-world-objects in the image at best, the segment-classes then should be ideally identical to the real-world-classes extended by the properties determined by sensor specifications and imaging conditions. Such an ideal classification with its corresponding class-descriptions would be most transparent, since each class-description would be completely comprehensible. Additionally, the underlying rule-base with its class-descriptions would be highly transferable, since its variability is only determined by the variability of the classes' properties but not by the variability of imaging conditions. This means: the more the initial image segmentation is able to produce similar image objects, the more a rule-base is transferable. Thus, it is necessary to have methods of image segmentation, which are able to compensate the external imaging conditions as far as possible in order to produce comparable image objects. The article present will demonstrate some research results investigating the influence of different image resolutions on the properties of image segments and introduce a mechanism which is mostly able to compensate different resolutions.

1. INTRODUCTION

Performing object based image analysis (OBIA) in a common sense means to analyze the content of an image by analyzing image objects and their properties which are the result of initially applied image segmentation(s) (see Benz, U. et al., 2004; Hay, G. & Castilla, G., 2006). Therefore, the image segments act as building blocks for any further analysis. Hence, the quality of the analysis of the generated image segments, i.e. their assignment to classes which are described by rule bases which depend on the segments' properties is highly dependent on the quality of the initially generated image segments. Thereby, as a rule of thumb, the better the generated segments are capable to represent the imaged objects in the image data, the better the quality of the segmentation and consequently the classification results respectively the analysis results are. Nevertheless, it is quite clear that the ability of the segments to represent real world objects of interest in image data strongly depends among other factors on the spatial resolution (see Figure 1). A further aspect that has to be taken into account is the transferability of the analysis methods. By regarding the effort that has to be spent for the development of a rule base, this means the less a rule base needs to be manually adapted to different imaging conditions, the more transferable the rule base is. In consequence, during the development stage of a rule base

it should be avoided to formulate rules, which are too dependent on the image data. I.e. a well designed rule base depends on object properties which are in a first stage as image independent as possible and in a second stage only depends on properties, which can be easily adapted to differing imaging conditions.

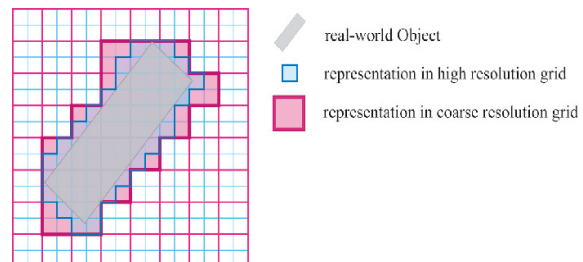


Figure 1: Representation of a real-world object in image data of different resolution.

The so-called multi resolution segmentation (MRS) as described in Baatz & Schäpe 2000 and Definiens, 20004 is a very popular segmentation method in the context of OBIA. This is amongst other reasons because it is implemented in the widely distributed Definiens™ products. Thus, we were

focusing our investigations on potentials for adapting this segmentation method to image data of different spatial resolution but with comparable radiometric specifications.

1.1 Multi Resolution Segmentation

In accordance to Baatz & Schäpe 2000 and Definiens, 2004 the multi resolution segmentation generates image segments by taking the homogeneity of color and shape into account. Thereby, all criteria can be weighted, whereas the homogeneity of shape is split into the sub-criteria *smoothness* and *compactness*:

$$h_{comp} = l/\sqrt{s} \quad (1)$$

$$h_{smooth} = l/b \quad (2)$$

with l = length of the borderline of a segment, s = size of a segment measured in pixels and b = length of the borderline of the minimum surrounding rectangle of the segment, so that the homogeneity of shape is described by:

$$h_{form} = w \cdot h_{comp} + (1 - w) \cdot h_{smooth} \quad (3)$$

with w = weight and $0 \leq w \leq 1$. The compound homogeneity of a segment then is given by:

$$f = w \cdot h_{farbe} + (1 - w) \cdot h_{form} \quad (4)$$

whereas f is the compound homogeneity and h_{farbe} is given by:

$$h_{farbe} = \sum_{c=1}^n w_c \cdot \sigma_c \quad (5)$$

with w_c as weight of channel c of an image and σ_c as the standard deviation of channel c of the pixels of a segment. Pixels or segments are then merged to create larger segments if the square root of the compound homogeneity of a new segment created by merging them is below the scale parameter SP :

$$SP \geq \sqrt{f} \quad (6)$$

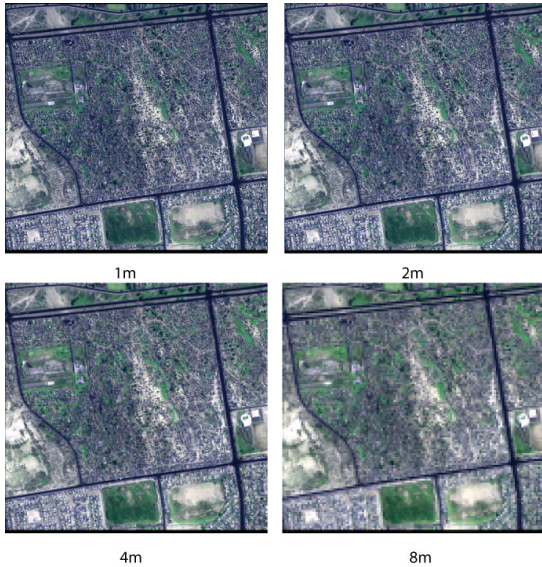


Figure 2: Resampled IKONOS data

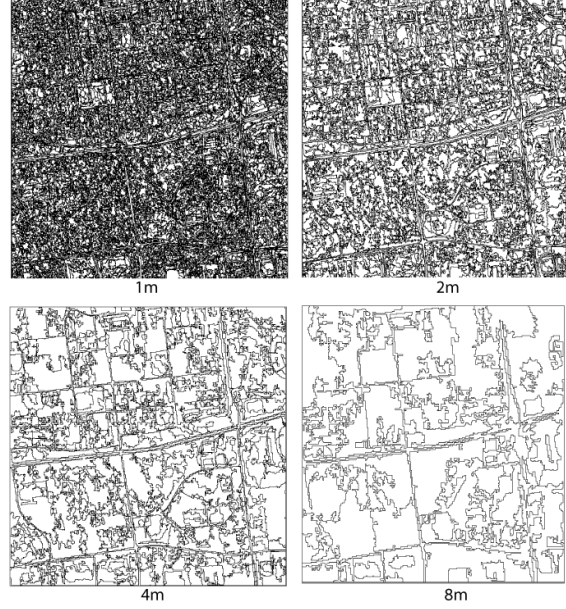


Figure 3: Segmentation results for images of different resolution using a scale parameter of 100 with $w_c = 1.0$ and $w_{comp} = w_{smooth} = 0.5$.

With respect to images of different resolutions this means, that segments of comparable size in terms of pixel size but not of metric size are generated. However, when keeping the scale parameter at the same value but increasing or decreasing the resolution (i.e. the pixel size) at the same time, objects with different shape are generated. This behavior can be observed, when resampling the original image data to different resolutions and applying an identical SP to the resampled images (see Figure 2, Figure 3 and Table 1).

resolution	mean area [m ²]	mean border length [m]	mean length [m]
1m	634.61	319.58	52.70
2m	3006.11	817.33	121.30
4m	12975.73	1708.33	241.18
8m	51151.16	3220.21	427.28

Table 1: Mean values of some shape properties of the segmentation in Figure 4.

As observable in Table 1 the mean values of the segments' area, border length and length are increasing with the pixel size. Moreover, the mean areas are increasing by approximately factor 4.0, whereas border length and length are increasing by a factor at approximately 2.0. Both factors correspond to the increase of pixel size and decrease of resolution respectively. This means due to the constant maximum allowed heterogeneity defined by the scale parameter (here $SP = 100$), segments are metrically raising with the pixel size. However, in order to keep rule sets re-applicable on data sets with differing spatial resolutions, the scale parameter obviously has to be adapted.

1.2 Adapting the Scale Parameter according to differing resolutions

For the case that h_{farbe} , h_{comp} and h_{smooth} are weighted by the object size - i.e.: the number of pixels of an object, as described

in Baatz M. & Sch pe, A., 2000 – in order to obtain in image data of higher resolution r_{hr} image objects of similar metric size as in image data of lower resolution r_{lr} with the scale parameter SP_{lr} , the scale parameter for the image data with higher resolution SP_{hr} can be determined by multiplying SP_{lr} with the ratio of the resolutions which we call zoom factor $z = r_{lr} / r_{hr}$:

$$SP_{hr} = SP_{lr} \cdot z \quad (6)$$

1.3 Sensitivity analysis

Although the average object size can be compensated notionally by the zoom factor and therefore objects of comparable size in images with different resolutions can be generated, in order to estimate how far which object properties are affected by differing resolutions we carried out some empirical analysis with resampled imaged data as outlined in chapter 1.1. We were therefore resampling the original IKONOS image data to resolutions of 2m, 4m, 8m, 16m and 32m. In a next step we were applying for each scene a hierarchical multi resolution segmentation (MRS) with 10 segmentation levels, whereas the levels were generated bottom-up. For each level of segmentation the scale parameter was increased by $SP_{r,i}(n) = 2 \cdot SP_{r,i}(n-1)$ with $n = 10$ levels and $i = 6$ images. This corresponds to an increase of the SP by a zoom factor of $z = 2.0$ (see Table 2).

r	Segmentation level									
	1	2	3	4	5	6	7	8	9	10
Scale parameter										
1m	32	64	96	128	160	192	224	256	288	320
2m	16	32	48	64	80	96	112	128	144	160
4m	8	16	24	32	40	48	56	64	72	80
8m	4	8	12	16	20	24	28	32	36	40
16m	2	4	6	8	10	12	14	16	18	20
32m	1	2	3	4	5	6	7	8	9	10

Table 2: Resolutions and scale parameters used for sensitivity analysis.

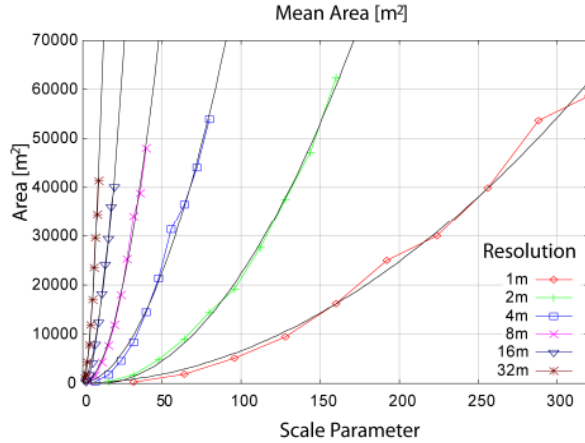


Figure 3: Mean object sizes for segmentations with adapted scale parameters.

These sequences of segmentation then led to objects of sizes and shapes as displayed in Figure 3, Figure 4 and Figure 5.

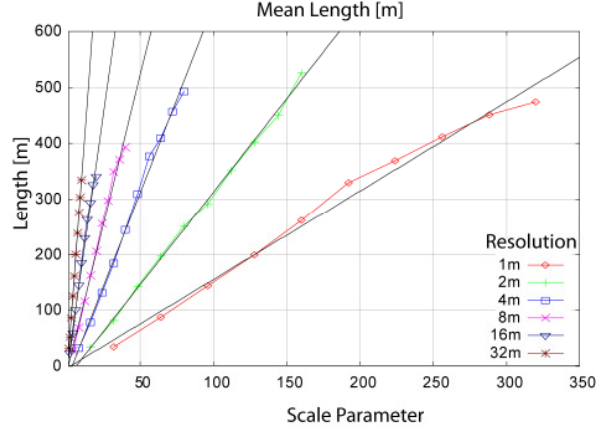


Figure 4: Mean length of objects for segmentations with adapted scale parameters.

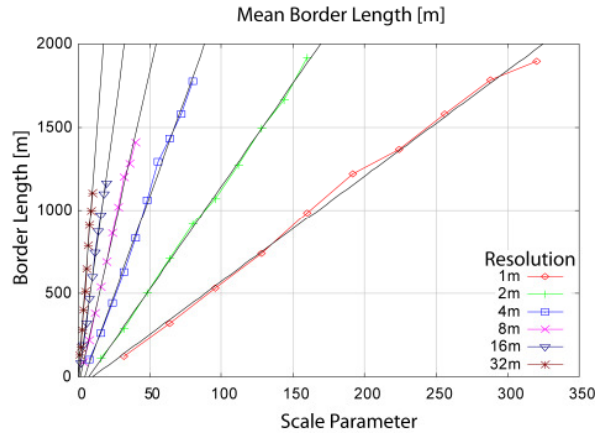


Figure 5: Mean border length of objects for segmentations with adapted scale parameters.

These empirical results seem to confirm our theoretical thoughts from chapter 1.2. However, in order to estimate how far the design of rule bases could be affected by this behaviour we were then observing the behaviour of some object properties out of the categories colour and texture, whereas the latter relates to texture measurers based upon properties of sub-objects within the segment-hierarchy. For the case, functional dependencies (including uniformities) between image resolution - i.e. segments created with an adapted scale parameter - and values of the segments' properties are observable, this would give an indication that a rule base to be transferred should only consist of such functional adaptable properties. Vice versa, properties for which no such functional dependency can be observed should be avoided in the rule base design. As Figure 6, Figure 7 and Figure 8 outline, the properties *Ratio of Channel n* and *Asymmetry of Sub-Objects* behave more or less independent of the underlying resolution within the resolutions 1m to 8m, whereas the properties *Mean No of Sub-Objects* and *Mean Difference of Sub-Objects in NIR channel* behave logarithmic as well as the *Standard Deviation of Channel n*. In contrast, the spectral mean values do not show a recognisable functional dependency. This indicates, that these properties are not appropriate to be used in transferable rule bases.

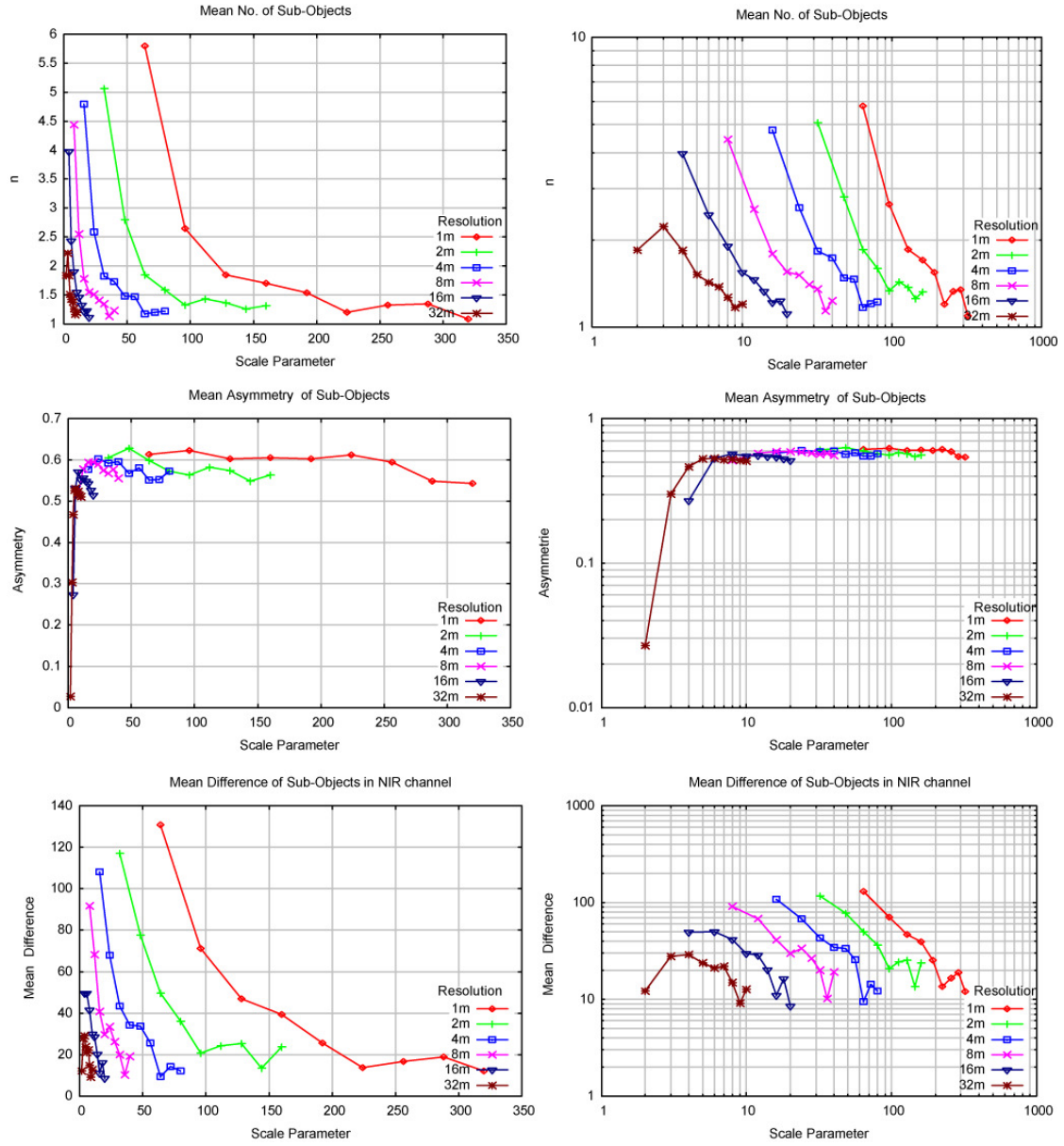


Figure 6: Behaviour of texture properties *Mean No. of Sub-Objects*, *Mean Asymmetry of Sub-Objects* and *Mean Difference of Sub-Objects in NIR channel* for different image resolutions for segments with accordingly adapted scale parameters as displayed in Table 2. Left linear scaling, right logarithmic scaling.

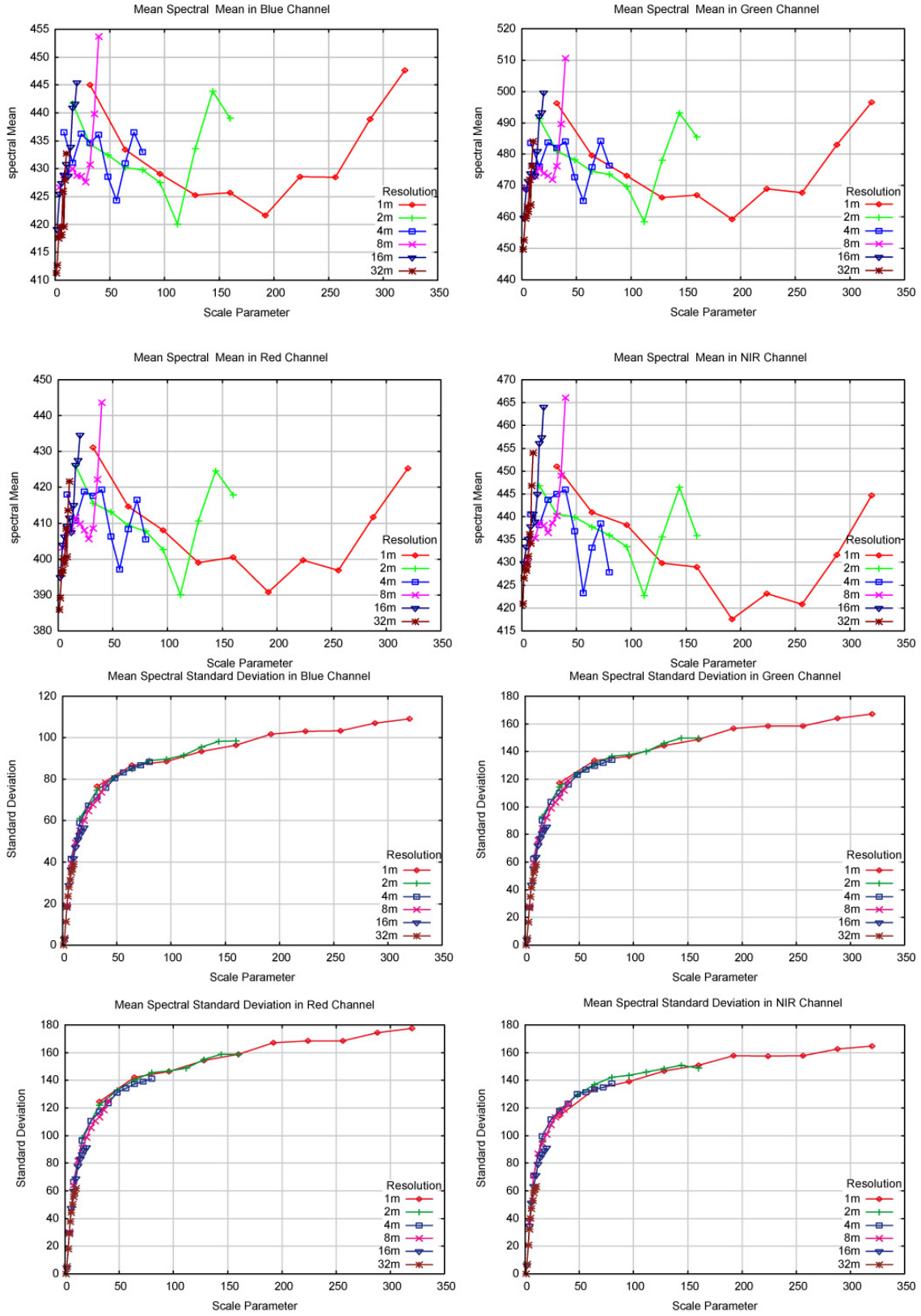


Figure 7: Behaviour of mean values for colour properties *Mean of channel* and *Standard Deviation of channel* for different image resolutions for segments with accordingly adapted scale parameters as displayed in Table 2.

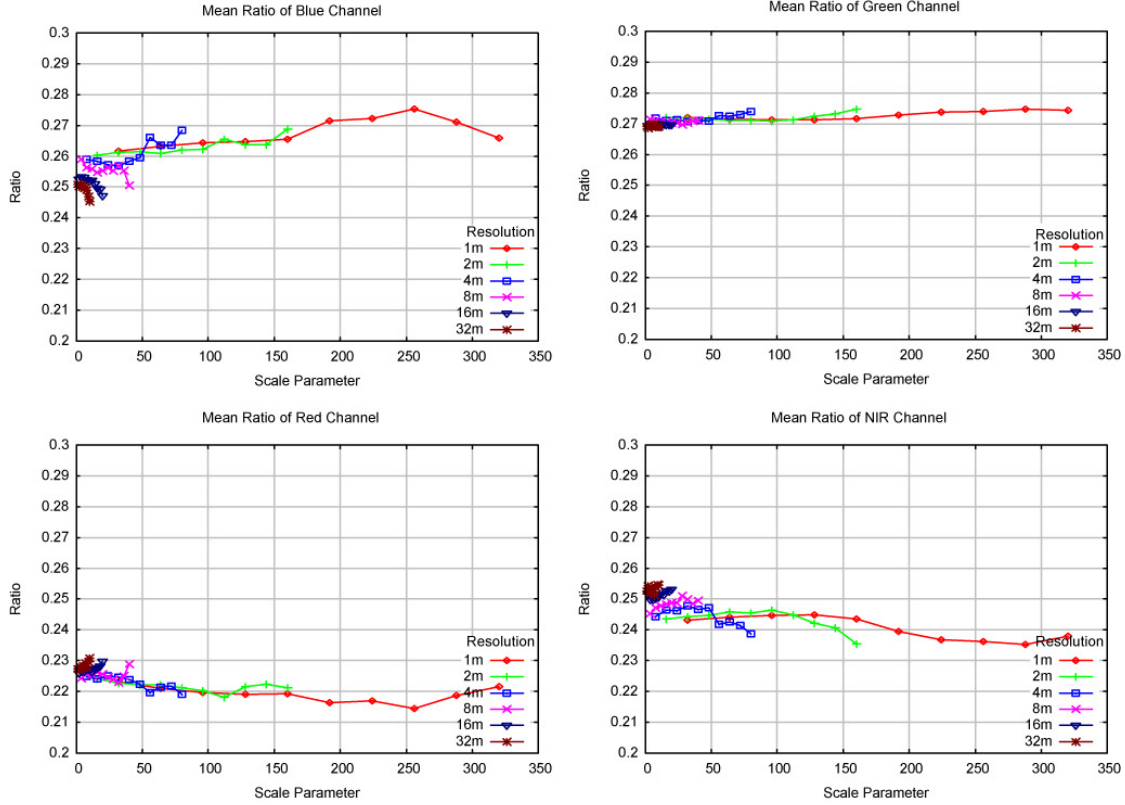


Figure 8: Behaviour of mean values for *Ratio of channel* values per segment for different image resolutions for segments with accordingly adapted scale parameters as displayed in Table 2.

2. APPLICATION EXAMPLE

In order to determine how far the adaption of an initial image segmentation as described in chapter 1.2 helps to reduce the effort of adapting an initial rule base to be re-applied on comparable image data of different resolution, we were investigating a rule base to outline informal settlements as described in Hofmann, P., 2005 and Hofmann, P., 2006. This rule base contains several properties which are similar to the ones displayed in Figure 6, Figure 7 and Figure 8. The rule base was originally developed on an IKONOS scene of Cape Town (South Africa) and should be re-applied on a QuickBird scene of Rio de Janeiro (Brazil). Both sensors are radiometrically similar but the resolution of QuickBird is at 0.64m, which would lead to a zoom-factor of $z = 1.44$. The original segment-hierarchy was a two-level segmentation

	Overall Accuracy	classification stability for informal settlement	
		inside reference	outside reference
IKONOS Cape Town	0,80	0,92	0,84
QuickBird Rio de Janeiro without adapted segmentation	0,35	0,89	0,84
QuickBird Rio de Janeiro with adapted segmentation	0,68	0,94	0,89

Table 3: Accuracies for original classification in KONOS scene and adapted and non-adapted segmentations in QuickBird scene.

using *SPs* of 10 and 100. Consequently, for the QuickBird scene the *SPs* 14 and 144 were applied. We were then comparing the necessary amount of rule base adaption to obtain best possible results for an adapted segmentation of the QuickBird scene and a segmentation with directly transferred *SPs*. We ascertained not very much difference between the rule base for the adapted segmentation and the directly transferred. Moreover, most differences were more ascribable to differences that are not caused by different imaging conditions but by different structures of housing and architecture. However, the results of the accuracy assessments indicate that the adapted segmentation led to improved results (see Table 3).

3. CONCLUSION AND OUTLOOK

The paper present demonstrates how segmentation parameters (here: the scale parameter of the multi resolution segmentation) can be adapted to obtain comparable segmentation results in image data of different resolution and comparable radiometric properties. Generating segments with comparable properties is vital in order to transfer rule bases for image analysis, e.g. from IKONOS to QuickBird. In chapter 1.3 we have demonstrated for selected segment properties how far they are affected by a systematic adaptation of the scale parameter and in chapter 2 we gave an example of how far this adaptation method could enhance the classification results for a transferred rule base. However, there is still research necessary to investigate the influence of different radiometric properties of the sensors on the generation of comparable image segments. Additionally, other imaging conditions which can affect the generation of

segments are not yet investigated, such as different conditions of illumination and atmosphere. In the context of rule base design the article present demonstrates, that some segment properties change proportional to differing image resolutions, while others do not. Thus, the usage of properties can affect the transferability of rule bases accordingly.

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