SCALING ISSUES IN VALIDATION OF ABUNDANCE MAPS DERIVED FROM HYMAP DATA OF AN URBAN AREA

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ABSTRACT:
For the analysis of hyperspectral data of urban areas linear spectral unmixing can be applied. With such methods abundances of urban materials can be derived. Validation of the abundances is important but not straight foreward. Area-based validation is the most suitable approach. However, the spatial scale of the validation area influences the measured accuracy, especially in heterogeneous urban areas. The aim of this study is to analyze which spatial scale of the validation area is most applicable to validate the abundances in urban areas. The abundances derived from a HyMap data set of Munich are validated with manually classified reference data of fourteen building blocks at different scales. It is shown that the average absolute difference in abundance between the unmixing result and the reference is almost 20 % lower at building block level than on the basis of a pixel-by-pixel comparison. However, errors of location at low spatial scales can be balanced out on higher scales and overestimating the accuracy. Depending on the application, the minimum size of the validation area is recommended to be 3x3 pixels or larger to avoid underestimation of the accuracy because of co-registration errors between the hyperspectral data set and the reference data.

KEYWORDS: spectral unmixing, validation, spatial scale, urban area, HyMap

1. INTRODUCTION

For material identification in urban areas, linear spectral unmixing of hyperspectral data is a suitable approach (Herold *et al*. 2003). In preparation of further use, e.g. in the context of urban planning, the unmixing results need to be validated. However, validating sub-pixel data is not straightforward. The RMS error only represents the quality of the mixing model and not the thematic assignment of classes. The use of a standard confusion matrix is not possible, since more then one class can be assigned to each pixel. In several studies validation measures for sub-pixel classifications have been developed, but such measures are often difficult to interpret (e.g. Silvan-Cardenas & Wang, 2008). Often the most suitable approach is to perform an area-based validation. The aim of the study presented here is to test, which scale of the validation area is most applicable to validate the abundances in urban areas. Small validation areas are desirable because they account for spatial errors in the unmixing results, but they are also sensitive to co-registration errors. With large validation areas co-registration errors become insignificant, but the location of the assigned abundances is not taken into account and validation can result in artificially accurate outcomes because errors of omission and commission keep each other in balance.

2. DATA AND METHODS

A hyperspectral data set of Munich, recorded with HyMap (Cocks *et al.* 1998) in June 2007 with 4 x 4 m spatial resolution, is atmospherically corrected and geo-referenced (Figure 1) (Habermeyer *et al.* 2005). Next the spectral linear unmixing approach described in Roessner *et al.* (2001) is applied to a subset of 3x5 km to derive material abundance maps (Figure 2). 14 reference building blocks are digitized and classified based on simultaneously recorded 3K aerial photos (Kurz *et al.* 2007) and field surveys. The reference data set has a spatial resolution of 50 cm. Abundances of both HyMap and the reference data set are compared for validation areas at different scales (building block, 1 pixel, 3x3 pixels, 5x5 pixels).

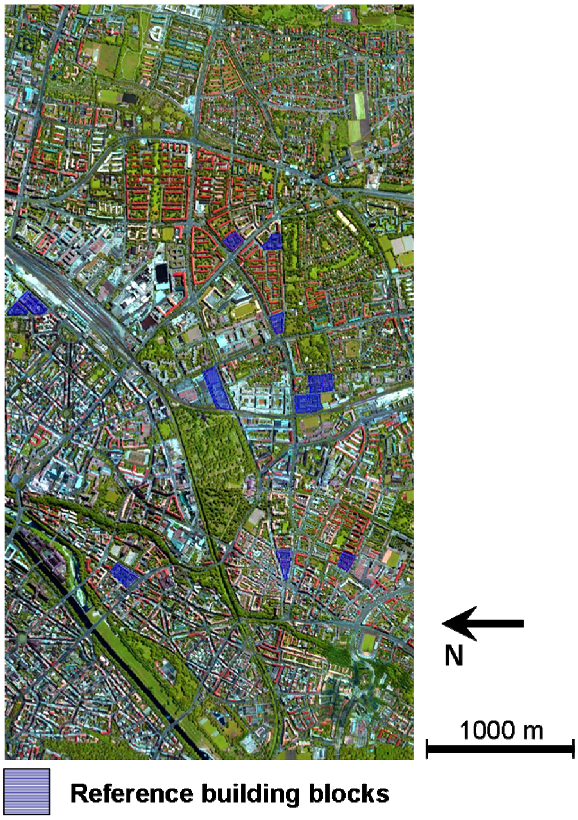

Figure 1: HyMap false color composite with reference buidling blocks highlighted in blue color.

3. RESULTS

In Figure 3 histograms of the difference between the calculated abundances and reference abundances for the different reference areas are shown. The comparison of each class in each validation area is included as one sample in the histogram. When using a validation area of 1 pixel there are 8700 samples available, whereas the validation at building block level only includes 14 samples. The building blocks have an average size of 586 pixels.

In Figure 4 the average absolute difference per abundance category of 10% is shown for roofing tiles. It can be seen that for the three smallest validation areas the difference increases towards higher abundances.

To have a closer look on the effects of scale on the measurement of the accuracy of cover fractions, the building block depicted in Figure 5 will serve as an example. In Figure 6 a comparison between the calculated abundance image and the reference image for roofing tile is presented for the different validation areas in this block. The absolute average difference for the whole building

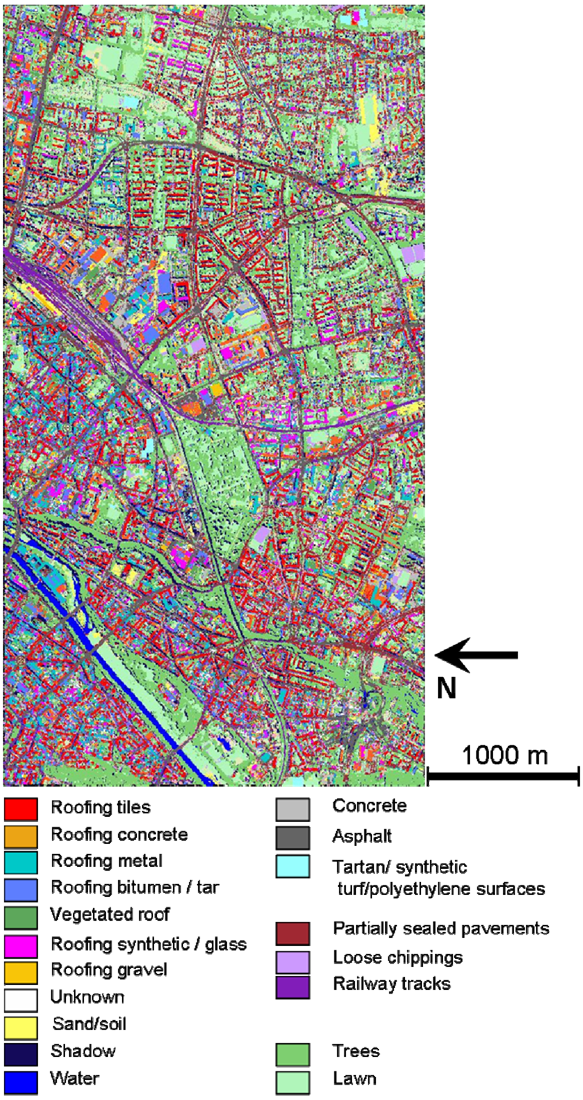

Figure 2: Unmixing result for the dominant class

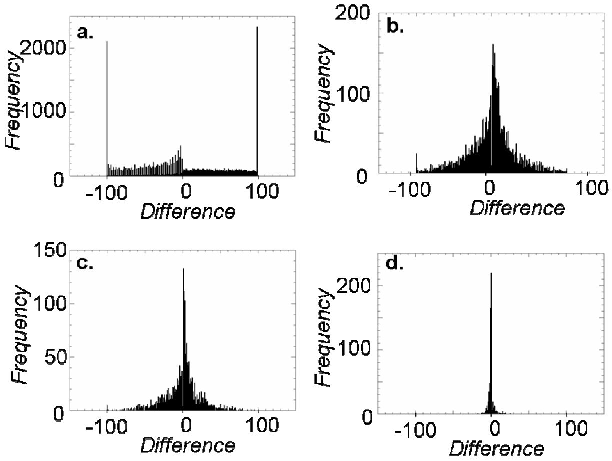

Figure 3: Histogram of the cover fraction difference between the unmixing result and the reference based on validation areas of 1 pixel (a), 3x3 pixels (b), 5x5 pixels (c) and building blocks (d)

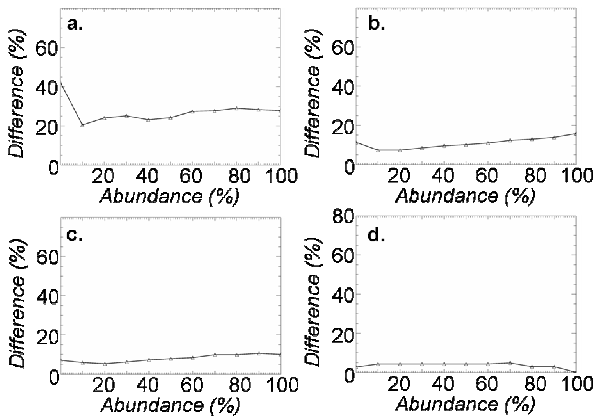

Figure 4: Average absolute difference per 10% abundance classes for validation areas of 1 pixel (a), 3x3 pixels (b), 5x5 pixels (c) and building blocks (d)

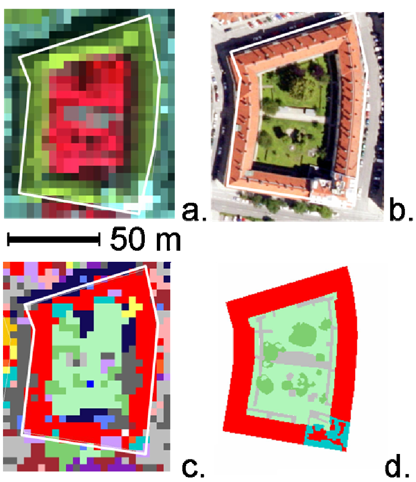

Figure 5: Exemplary building block: a) Hymap (CIR), b) aerial photograph, c) unmixing result (dominant class, legend see Fig. 2), d) reference (legend see Fig. 2)

block for roofing tiles ranges from 4.0 %, 8.5 %, 15.0 % to 23.3 % for building block validation area, 5x5 pixel validation area, 3x3 pixel validation area and 1 pixel validation area, respectively.

When looking at the abundance of trees (Figure 7) there is only a small difference of 0.9 % when validating at building block level. However, when comparing at pixel level, the difference comes up to 11.3 %

4. DISCUSSION

Figure 3 shows that the overall difference is reduced when the validation is performed on the basis of larger areas. This fact is also visible in Figure 4 when solely looking at the roofing tile class. Also, this figure illustrates that the difference increases for larger cover fractions. This can be expected because absolute differences are measured. A difference of 10 % of a low abundance corresponds with a small absolute difference, whereas a difference of 10 % of a high abundance value corresponds with a large absolute difference. Still the presentation of the results in absolute abundance difference instead of percentage is preferred. Reason for this is that for a small abundance of e.g. 5% in the reference area and 10% abundance in the unmixing result, the difference in percent becomes 100 %. This does not do justice to the quality of the results.

Figure 6 illustrates why the difference is so large for small validation areas. The co-registration error between the hyperspectral data and the reference data of 1 pixel causes many differences in abundance. This, in turn, leads to a low accuracy value, although most users would regard this cover fraction map of roofing tile as quite accurate. In many applications a co-registration error of one pixel is accepted. However, in urban areas this often not good enough, even at high spatial detail such as the 4 x 4 m pixel size of the data used in this study. The reasons for this are the

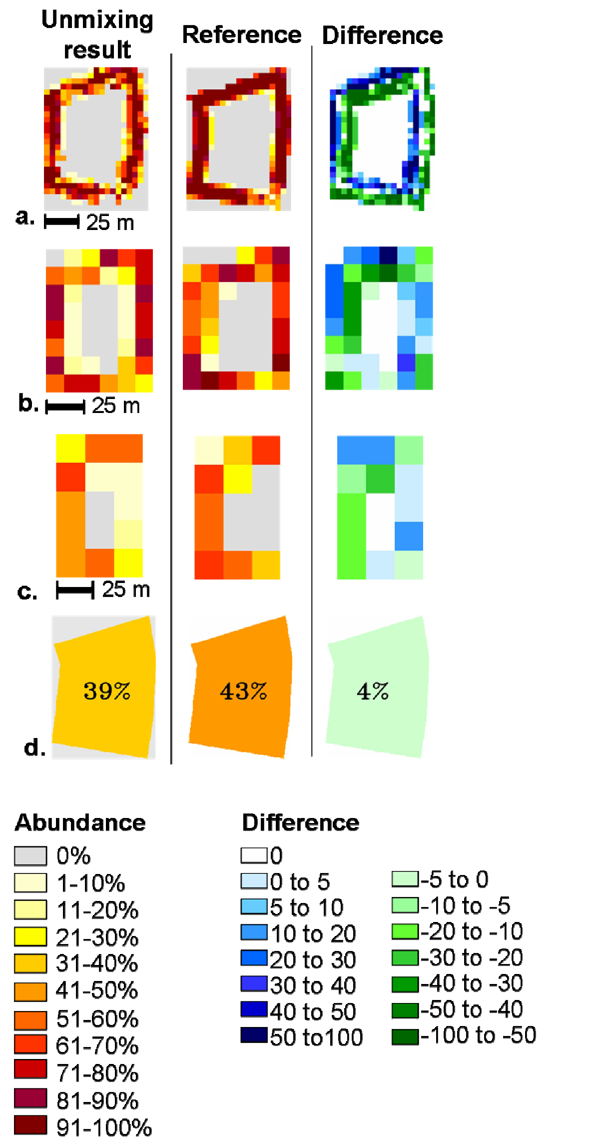

Figure 6: Comparison between the abundance of roofing tiles in the unmixing result and the reference for the validation area of 1 pixel (a), 3x3 pixels (b), 5x5 pixels (c) and building block (d)

crisp borders and the relatively small size of urban objects. Depending on the size and orientation of a building, a co-registration error of 4 m (1 pixel) can mean that two-third of the building are missing. This co-registration error has less influence on the accuracy if larger validation areas are used in an area-based validation of cover fractions. Co-registrations errors are balanced out when evaluating at a larger area. However, this can also improve the accuracy artificially, as is shown in Figure 7. Here the average absolute difference calculated on the basis 1 pixel validation areas is more representative for the accuracy of the cover fraction map. The locations of the derived abundances of trees are not identical to the reference. Still the absolute difference at building block level is small, because the overall abundance is almost the same. This effect is confirmed by the normal distribution of the differences around zero as can be seen in Figure 3.

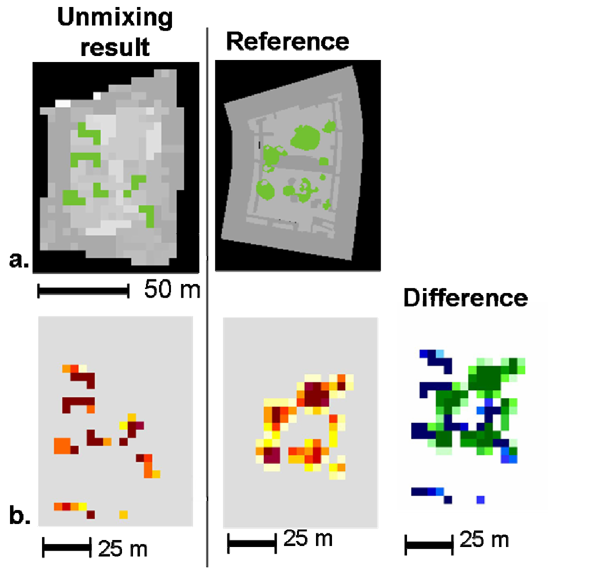

Figure 7: Comparison of tree abundance with a) abundance of trees for the whole block coming up to 5.7 % for the unmixing result and 6.6 % for the reference, and b) comparison of abundance with 1 pixel validation areas (legend see Fig. 6).

5. CONCLUSION

In the research presented here, the influence of spatial scale on the outcome of an area-based validation of cover fractions was analyzed. It is shown that small validation areas are very sensitive to co-registration errors, which advocates for using large validation areas. However, when comparing at building block level, the accuracy can be artificially high. An underestimation of the cover fraction on one side of the building block, which can be noticed in a pixel by pixel comparison, can be balanced out by an overestimation on the other side of the block. The most suitable scale of the reference area depends on the application: if the results are used for analysis at building block level, this level suits best for validation. If the unmixing results are used at pixel or building level, a 3x3 pixel reference area will be most suitable. This size of validation area is less sensitive to co-registration errors than a single pixel validation area, but still takes spatial orientation into account.

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ACKNOWLEDGEMENTS

The authors kindly acknowledge Dr. Karl Segl of GFZ for providing the unmixing algorithms. The research was funded by the BMBF funding priority REFINA.