# MONITORING THE DYNAMICS OF INFORMAL SETTLEMENTS IN DAR ES SALAAM BY REMOTE SENSING: EXPLORING THE USE OF SPOT, ERS AND SMALL FORMAT AERIAL PHOTOGRAPHY.

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## 1 ABSTRACT

Dar es Salaam is exemplary for cities in the developing world facing an enormous population growth. In the last decades, unplanned settlements have tremendously expanded, causing that around 70 percent of the urban dwellers are living now-a-days in these areas. Tools for monitoring such tremendous growth are relatively weak in developing countries, thus an effective satellite based monitoring system can provide a useful instrument for monitoring the dynamics of urban development.

An investigation to asses the ability of extracting reliable information on the expansion and consolidation levels (density) of urban development of the city of Dar es Salaam from SPOT-HRV and ERS-SAR images is described. The use of SPOT and ERS should provide data that is complementary to data derived from the most recent aerial photography and from digital topographic maps.

In a series of experiments various classification and fusion techniques are applied to the SPOT-HRV and ERS-SAR data to extract information on building density that is comparable to that obtained from the 1992 data. Ultimately, building density is estimated by linear and non-linear regression models on the basis of an one ha kernel and further aggregation is made to the level of informal settlements for a final analysis. In order to assess the reliability, use is made of several sample areas that are relatively stable over the study period, as well as, of data derived from small format aerial photography. The experiments show a high correlation between the density data derived from the satellite images and the test areas.

## 2 INTRODUCTION

Dar es Salaam has been a small town before independence in 1961, as during the colonial period, the urban development was faced with restrictions on the movement of the indigenous population (Kombe 1995 and Rakodi 1997). After independence the city experienced a tremendous expansion; it currently has annual population growth rates above 7 percent (Sliuzas et al. 1999), underlying on one side a rapid expansion of built-up areas and on the other side a strong consolidation of the already existing residential areas. Recent population estimations suggest that the city's population is around 3 million persons (Sliuzas et al. 1999).

The situation in Dar es Salaam is like in many other agglomerations in developing countries, land can be either obtained formally or informally, especially the informal sector provides much more land to land seekers than the formal one (Burra 1997). The percentage of people living in such areas had increased in the last decades rapidly. In 1960s only between 30 and 39 percent lived in squatter areas, in 1975 it increased up to 55 percent, in 1992 it was estimated to be at least 60 percent (Kombe 1995). Nowadays, around 70 percent of the inhabitants live in unplanned or self-regulated settlements (Sliuzas et al., 1999).

Basically, squatter areas could be assumed to be land occupied without authorisation but, in the case of Dar es Salaam the majority of urban dwellers in such areas have acquired land through buying (Hoek-Smit 1991 and Kombe 1995). The policy in Tanzania since the 1970s had mostly been tolerant or even supportive, as well as, in the few cases of occupying land illegally (Kombe 1995). The 'typical houses' in these areas are detached single storey houses, mostly built in a seemingly haphazard way without apparent plot boundaries (Kyessi 1994). The majority of these settlements began as peri-urban villages. In general, many squatter settlements in Dar es Salaam are strategically found along major arterial roads, around industrial complexes, around or near planned residential areas and near institutional areas (Kyessi 1994). For the early 1990s Kyessi (1994) estimated that about 42 of these settlements existed, while nowadays over 50 of these settlements exist (Hashim, 1999).

Highly dense residential areas tend to cause problems on one side for the inhabitants, as the living conditions deteriorate (e.g. caused by pollution and social problems) and on the other side as it reduces the manageability of the area (e.g. supply with sanitation). So information about density of housing is an essential topic for urban planners in order to counteract such development. For the few planned areas in the city, information about the growth processes is normally available. But, most development happens in unplanned areas. This situation is basically caused by the missing capability of the city's authorities to allot a sufficient amount of plots according to the demand. Consequently, most of the people planning to settle get the land from the informal sector. This reflects the fundamental need for information, which can be used as an impact for the local planning authorities. It also emphasises the urgency of advanced and less time consuming methods for monitoring the development of the city. This fast proceeding urbanisation strains the limited resources of the planning authorities. It made the central government unable to provide sufficient social and community services, physical infrastructure and economic opportunities for the urban dwellers (Mandwa 1997).

Several previous studies have dealt with the measurement of densities in urban areas. Forster (1993) showed a high positive correlation between building density and radiometric variability, while other research concentrated on the classification of the degree of sealed surfaces (e.g. Sptizer/Heinz 1997, Achen 1993 and Netzband 1998). By concentrating on the classification of sealed surfaces an elementary problem is avoided, namely, the difficulty to distinguish between similar spectral signature of roofs and pavement, that causes in general a high classification inaccuracy but, in doing so does not lead to information on the level of building density (Kuffer et al. 2001). But, for urban application land-use classifications are more relevant than land-cover (Sliuzas et al. 1999) as they do not only describe the spectral characteristic of an object (e.g. water, stone, vegetation or soil) but also how it is used (e.g. agricultural area, residential area, industry). Normally, the spectral signatures of land-use classes in urban areas have a high variance and tend to overlap, so it is difficult to distinguish them. The investigation of building densities using remote sensing would imply, that the spectral signature of buildings could be distinguished from other urban (e.g. roads) and non-urban classes (e.g. bare soil). As the variance of the class buildings can be rather big several methods and data sources were used in this study.

The structure of residential buildings in Dar es Salaam is quite uniform, the city is dominated by single storey Swahili type of construction, that normally consists of 4 to 8 rooms (Mwarika 1991 and Wells et al. 1998). The non Swahili buildings which can also be found in the unplanned areas have more than 6 rooms and are of varying shape with functions ranging from residential, commercial to mixed commercial and residential (Mwarika 1991). The most common materials for the roofs are corrugated iron sheets. Particular the uniform roof material is of great benefit for the detection of areas covered by buildings.

The possible densities, which can be measured from space are limited as e.g. only the roof area but, not the area of a building can be detected in satellite images. Consequently, only the roof-coverage-density can be measured. In most cases one pixel is not entirely covered by a building, as buildings tend to be smaller than 20 by 20m, so only ‘pseudo-building-pixel’ (pixels that have a dominant share of roofs) can be detected.

## 3 METHODOLOGY

The main data sources for the classification were a multispectral and a panchromatic SPOT scene, recorded in May 1998 and two different ERS-2 scenes of the same year. All images cover the city area and a large part of its hinterland. Some problems rose due to the time gap between the data acquisition. In absence of recent ground-truth data high-resolution small format aerial photos (SFAP) were at hand for three parts of the study area, one low density area and two high density areas. The SFAP images, which were made using a Minolta 35 mm camera at a flying altitude of 500-800 m, were geo-referenced and resampled[1]. For the three test areas the new and modified buildings were manually digitised and a roof-coverage density map, comparable to that of the 1992 situation, was generated. In order to generate a second set of reference data, a set of so-called “relatively stable areas” in which little construction was thought to have occurred since 1992, were delineated. These areas included both formal and informal areas. Assuming that the buildings in these areas have undergone little change.

| Image Data | Type | Date | Characteristics |
|---|---|---|---|
| SPOT-HRV | Multispectral<br>Panchromatic | 18/05/1998 | Incidence angle 18.2 deg., 20m resolution<br>Incidence angle 18.2 deg; 10m resolution |
| ERS-2 | Radar | 18/05/1998<br>14/12/1998 | Ascending path, 10m pixel size |
| SFAP | Aerial Photos | 28/10/97<br>03/12/99 | Flying height approx. 500-800m, variable scale |

Table 1: Image data sources

For analysing the roof-coverage density changes it was important to decide on which level of aggregation the density mapping should be performed. It would have been illusionary to expect that a roof-coverage density on a 20m-pixel size level could be classified. Of course, before calculating the roof-coverage density, the classification will be based on single pixels. For calculating the actual roof-coverage density a spatial unit of one ha (a 5 by 5 pixel kernel) seemed to be appropriated. The resulting roof-coverage density values ranged consequently from 0 to 25, with 0 implying no roof coverage and 25 implying 100 percent roof coverage. But, still on this level it was difficult to make reliable statements about density changes, thus a more aggregated unit was needed. As the level of settlements are getting more and more notice and importance in the planning process (shifting from a top-down to a grass-root approach), it seemed to be appropriated to make the analysis of density changes on this level. Intending on one hand to investigate which unplanned settlement was faced with density changes and on the other hand to see if these changes could be quantified.

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[1] The georeference was made with the direct linear georeference available in the ILWIS package, utilising a DEM also derived from the 1992 topographic data.

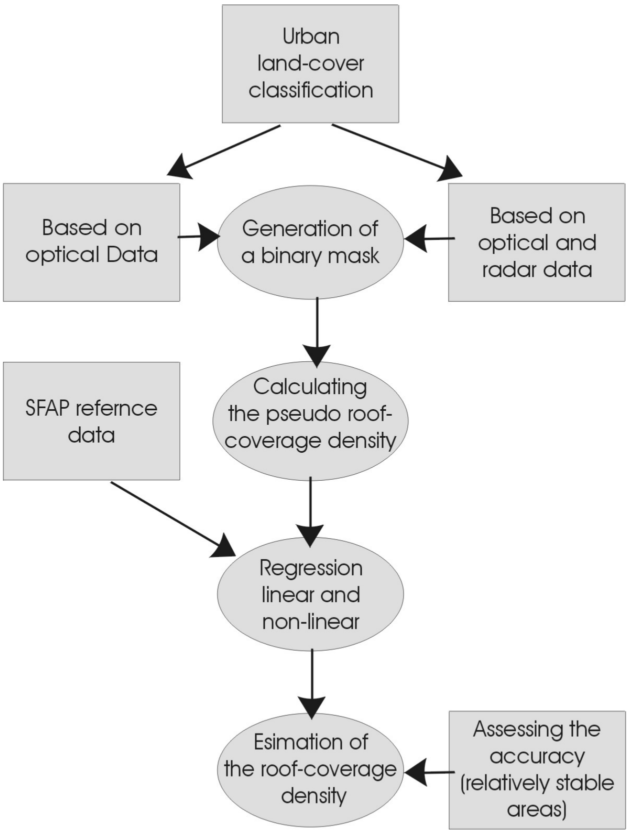

Figure 1: Scheme of applied methodology

In order to develop a method of a density classification it seemed appropriate to test first on which level of accuracy buildings can be spectrally distinguished from pavement and other land-cover classes (e.g. bare soil) by a classification. Already previous studies showed the difficulty of distinguishing buildings from other urban land-use (e.g. roads) or land-cover classes (e.g. bare soil) in the spectral domain (e.g. Sliuzas et al. 1999; Netzband and Meinel 1996 and Hashim 1999). The possible benefit of improving the classification by using radar images was tested as they showed in general a quite good differentiation of urban space and other classes (e.g. bare soil) due to the strong reflectance of iron roofs and the corner reflection. This could be used to eliminate the problem of classification errors, e.g. in areas of shallow water and riverbeds, which appeared in previous classifications of the SPOT-XS image. First the ability of detecting areas of buildings in the ERS images was investigated by utilising the level slicing[2] technique of two scenes. And finally, a multiple-layer classification was performed combining the radar data and the optical data.

The obtained land-cover classes were next transformed to a binary image of 0 = non-building and 1 = building. Consequently, the roof-coverage density was calculated inside a 5 by 5 pixel kernel. In order to improve the result a regression model was calculated for estimating roof-coverage density. This was based on calculating the regression function between the SPAP updated reference areas and the classifications. These regression functions could be then used for transforming the previous classifications into a new roof-coverage density map on the settlement level.

Estimating the density implied that each pixel classified as a certain density class had a similar composition of features, which is of course not realistic. Particular problems rose for pixels of high densities, as the estimation did not allow an estimated value of 100 percent. But, these high values exist in reality, ignoring them is only possible as they are in the case of Dar es Salaam exceptional. Considering this methodology from a ‘pixel-based’ point of view it is very problematic. But, as the main interest of this study was to estimate density changes on a settlement level the method became more reliable, as on aggregated level like settlements an average content of a pixel could be assumed.

Two different sets of ground-truth data were generated; one using a digital data set of all buildings for the major part of Dar es Salaam of the year 1992. This data set was used to generate a roof-coverage density map. For the selection of relatively stable area in terms of construction of new buildings local knowledge was used. Like this several areas were selected that could be later on used to assess the accuracy of the density classification. The areas were also selected according to different characteristics. Some of them were low densely some in very high densely built-up areas, some areas were in planned settlements others in unplanned. This should help later on evaluate different types of areas.

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[2] According to the DNs distribution (histogram) a certain threshold is detected to divide the image into intervals or parts (Lillesand and Kiefer 1994).

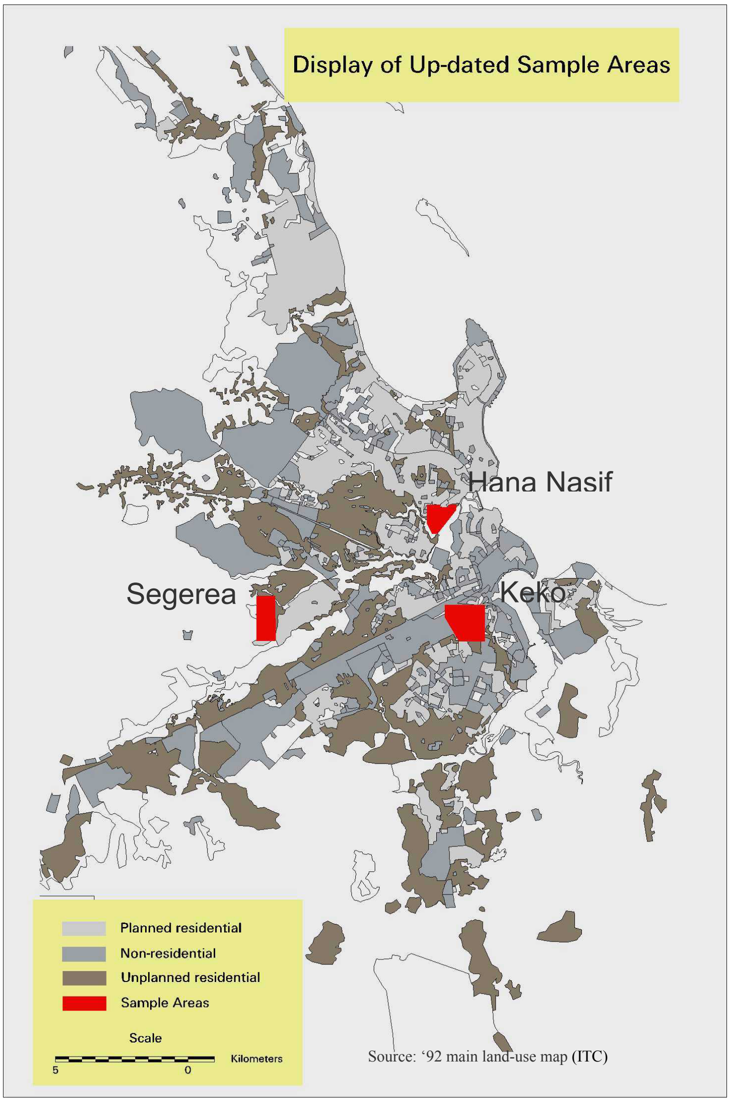

Figure 2: Updated reference areas (Data source: main land-use classification ITC)

The second set of reference data was generated by using the SFAP. Several sets of SFAP were used to update three sample areas in the existing building map (see figure 2). Two areas (Hana Nasif and Keko) are unplanned settlements and one (Segerea) is mainly planned and low density. The sample areas of Keko and Hana Nasif (see figure 3) are pretty high densely built-up.

In general it has to be mentioned that this data replacing ground-truth data underlay a small inaccuracy, e.g. for the case of buildings covered by trees the outline could only be approximated also in some very oblique parts of the image the shape of the buildings and the respectively digitised area was difficult to approximate. Despite these problems, the overall accuracy was high.

Figure 3: Part of Hana Nasif (Data source SFAP, ITC)

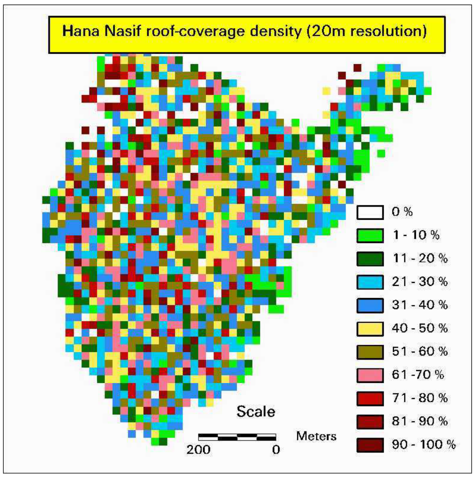

Figure 4: Roof-coverage density of Hana Nasif

## 4 RESULTS AND DISCUSSION

For a first investigation of the ability of the ERS-data to detect buildings they were analysed separately from the SPOT scene. Only if areas of buildings can be detected in these images it might improve the overall accuracy in a multiple-sensor approach. Two different ERS-2 images were available for this study but, one (of May 1998) had an area of disturbance in a part of the scene, the disturbance was blocked out.

Principally, the images offered a good detection of built-up areas. Of particular interest was that roads (especially the major roads) could be better detected. This observation was important as the previous classification using the multispectral SPOT image was faced with this problem. Also the high densely built-up areas are separable from the less densely built-up areas. One problem of the ERS images were that areas of similar densities, which differed in the layout of the roads, were not classified accordingly. This could be observed in particular for two areas. The CBD and a neighbouring central area (Mchafukoge) have very similar densities of roof-coverage only the main directions of the streets differ.

In order to investigate an appropriate starting point for the level slicing, the two histograms of the original images were taken into consideration.

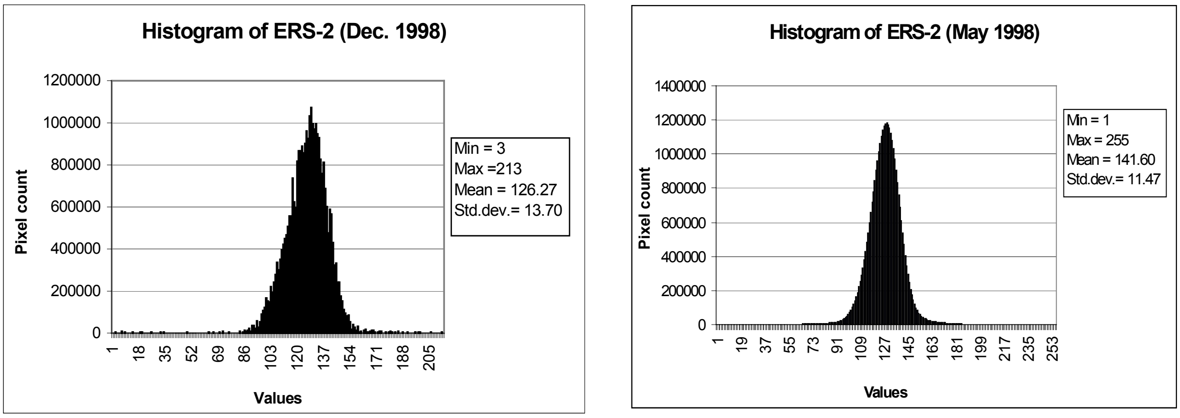

Figure 5: Histograms of the ERS-2 images (October and May 1998)

Both histograms have a very similar shape (see figure 5). Analysing the range of the values of the 'pseudo-building' pixel (using the data for the relatively stable areas) it confirmed that in both cases the values were above the mean. In order to use both images the pixel values got multiplied and divided by the multiplied standard deviation. The newly obtained image had now values ranging from 0.003 up to 2.853 (see figure 6). In order to examine the range of values indicating buildings the data was again compared to the '92 roof-coverage data of the relatively stable areas. The starting point of the values was analysed to be close to the mean with a light tendency of being a bit higher. In order to not randomly choose a value the mean plus twice the standard deviation was used. So the choice was made to set the threshold respectively, all values below were classified as 'non-building' and all values above were classified as 'pseudo-building' pixel.

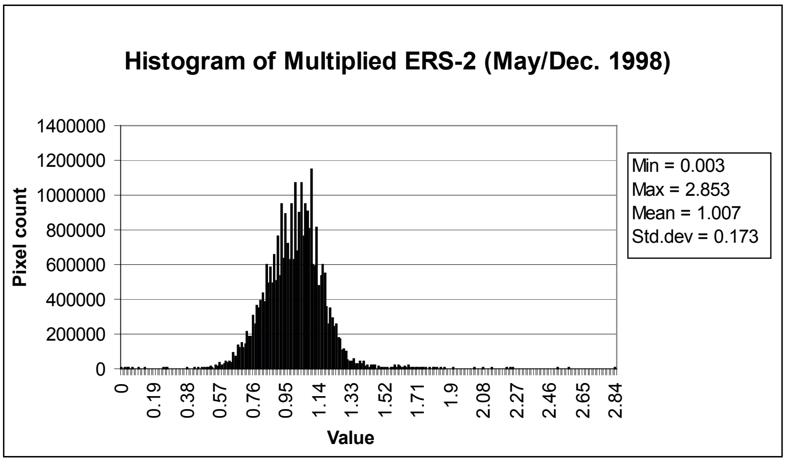

Figure 6: Histogram of the multiplied ERS-2 images (May/Dec. 1998)

For calculating the density the same approach was used as discussed above. But, this time a 10 by 10 pixel kernel was applied to calculate the density (to obtain an one ha kernel). In order to obtain comparable data the result was transformed into the system of values ranging form 0 (0 percent roof-coverage) to 25 (100 percent roof-coverage).

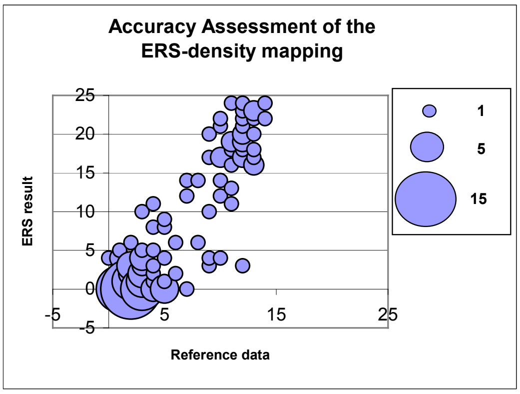

Figure 7: Accuracy of the level slicing

The scatter plot of the result is visualising the correlation between the two data (see figure 7). The correlation coefficient was with 0.89 quite high. From this point of view it seemed that the ERS data are useful for indicating the roof-coverage density. One main limitation of this method was the different density values depending to the layout of buildings and roads. This problem occurred particularly in the planned areas as the roads follow a main direction. In the unplanned areas this effect tended to be less dominant because of their haphazard development pattern.

Thus, ERS-2 images are able to detected areas of buildings. Also several authors pointed out that the combination of SPOT-HVR and SAR data improved the classification accuracy (e.g. Palaganas 1993 and Beha et al. 1996). The expected values of the two ERS-2 images were calculated using an approach based on the work of Beha et al. (1996)[3]. In difference to the method of Beha et al. (1996), only two images were used for calculating the new image of the expected values. First the two global regression coefficient of the two images were calculated:

$$a = \sum_{i=1}^{n} (x_i - \mu_x) * (y_i - \mu_y) / \sum_{i=1}^{n} ( x_i - \mu_x)^2$$

and

$$b = \sum_{i=1}^{n} (x_i - \mu_x) * (y_i - \mu_y) / \sum_{i=1}^{n} ( y_i - \mu_y)^2$$

where $x_i$ are the pixel values of the first images and $y_i$ the pixel values of the second image, $m_x$ the mean of the first images and $m_y$ the mean of the second image. These coefficients were as a next step used to calculate a new image by multiplying the values of the image by the coefficients.

$$z = a\, x_i + b\, y_i$$

where z is the expected value and $x_i$ and $y_i$ the values of the two images.

The layer of the expected values was added to the three layers of SPOT-XS and to the layer of the SPOT-Pan image. In order to have the same nominal resolution for all five layers the SPOT-XS images was resampled to 10m. Hence, a ML classification was performed. The result showed a very good ability to distinguish between bare soil and pavement from areas of buildings (see table 2) compared with the ML-classifier using just SPOT-XS (see table 3).

Table 2: Confusion matrix of the classification (multiple-layer approach)

| | Water | Shallow water | Bare soil | Buildings | Vegetation | Grass | Cut grass | Pavement | Total | User Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|
| Water | 3692 | 72 | 0 | 0 | 0 | 0 | 0 | 0 | 3764 | 98,09 |
| Shallow water | 14 | 1821 | 0 | 0 | 0 | 2 | 20 | 0 | 1857 | 98,06 |
| Bare soil | 1 | 0 | 743 | 1 | 0 | 0 | 17 | 1 | 763 | 97,38 |
| Buildings | 7 | 0 | 3 | 206 | 0 | 0 | 2 | 0 | 218 | 94,50 |
| Vegetation | 0 | 0 | 0 | 0 | 2430 | 9 | 0 | 0 | 2439 | 99,63 |
| Grass | 10 | 0 | 6 | 0 | 115 | 314 | 29 | 0 | 474 | 66,24 |
| Cut grass | 41 | 5 | 14 | 0 | 24 | 5 | 1231 | 0 | 1320 | 93,26 |
| Pavement | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 128 | 129 | 99,22 |

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[3] Beha et al. showed that the classification accuracy of buildings is significantly improved by using the expected values. In the original approach three images were used for calculating a new image of the expected values.

| Data | Buildings | Bare soil | Cut grass | Grassland | Pavement | Shallow water | Vegetation | Water | Total | User Accuracy |
|---|---|---|---|---|---|---|---|---|---|---|
| Buildings | 282 | 1 | 9 | 0 | 4 | 4 | 0 | 0 | 300 | 94,00 |
| Bare soil | 35 | 149 | 1 | 0 | 1 | 0 | 0 | 0 | 186 | 80,11 |
| Cut grass | 24 | 2 | 278 | 4 | 0 | 0 | 4 | 13 | 325 | 85,54 |
| Grassland | 0 | 0 | 6 | 122 | 0 | 0 | 51 | 0 | 179 | 68,16 |
| Pavement | 70 | 0 | 0 | 0 | 41 | 2 | 0 | 0 | 113 | 36,28 |
| Shallow water | 6 | 0 | 6 | 0 | 0 | 419 | 0 | 9 | 440 | 95,23 |
| Vegetation | 0 | 0 | 1 | 8 | 0 | 0 | 531 | 0 | 540 | 98,33 |
| Water | 0 | 0 | 0 | 0 | 0 | 23 | 0 | 895 | 918 | 97,49 |
| Total | 417 | 152 | 301 | 134 | 46 | 448 | 586 | 917 | | |
| Prod. Accuracy | 67,63 | 98,03 | 92,36 | 91,04 | 89,13 | 93,53 | 90,61 | 97,60 | | |

Table 3: Confusion matrix of the the initial ML-classifier (SPOT-XS)

In order to avoid the disturbing influence of other classes two masking operations were applied before performing the classification. First, using the NDVI all pixels of a NDVI higher than 0.1 were blocked out (Loveland et al. 1991 and Bähr 2001). Second, in order to avoid the misclassification of areas of buildings as water-bodies, the ‘92 land-use map was used for blocking them out (small rivers are not included in the ’92 land-use data). Blocking out the disturbing land-cover classes (water and vegetation) reduced also the classes for the new classification. Now only samples of the classes buildings, grassland, pavement, cut grassland and bare soil had to be used. Based on the reduced training samples a ML-classifier was performed.

The improvement by using the expected values of the ERS-2 images can be clearly observed in figure 8, showing the CBD and parts of neighbouring settlements. The multiple sensor classification did not misclassify in the most cases main roads and bigger areas of bare soil as buildings. The difference in the vegetation (between the two plotted maps) is due to slightly different approaches[4]. Very similar for both methods are that nearly the entire area of the CBD is classified as buildings, roads are not detected in such high density areas. In the case of the ML-classification of the SPOT-XS image the misclassification of roads and other open spaces as buildings caused this overestimation. In the case of the multiple sensor ML-classification it was due to the overruling strong corner reflection in the ERS images, which are influencing a bigger area than the actual size of a building.

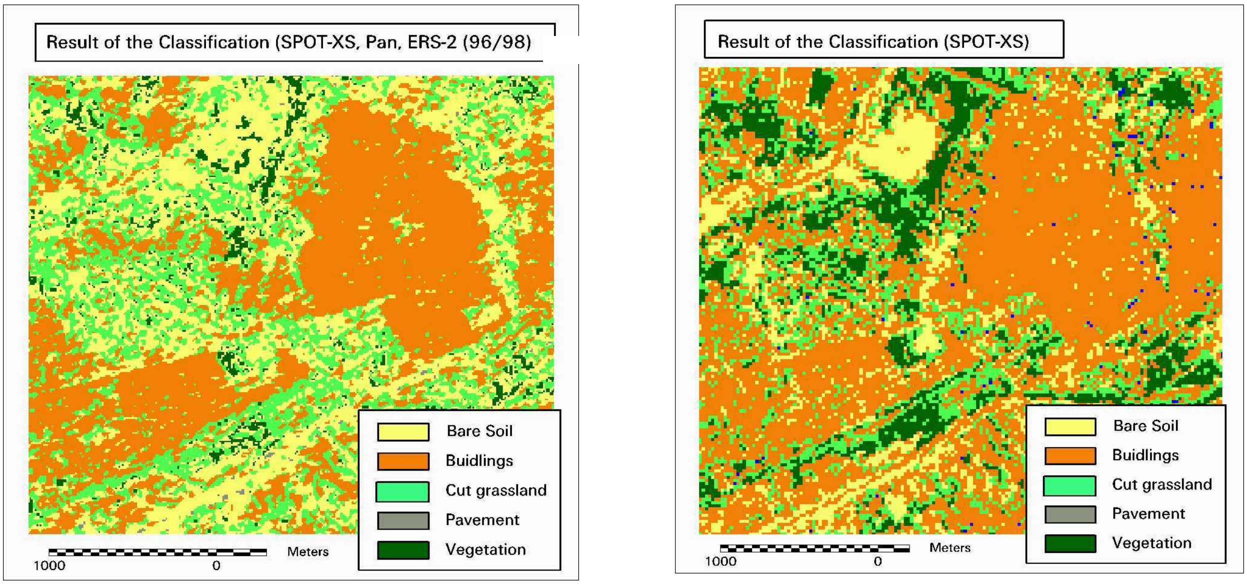

Figure 8: Comparison of the different classification of the CDB

Another aspect, which can be observed, is that river valleys classified in the SPOT image as areas of buildings were now less misclassified. But, still in some cases pixels of water or shallow water were classified as buildings.

Next, again the accuracy assessment is was applied for the multiple sensor approach. The resulting correlation coefficient was with 0.95 very high. Also here the roof-coverage density was strongly overestimated. So it was still not possible to quantify density changes.

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[4] In the case of the ML-classification of the SPOT-XS image no mask operation of the NDVI was used

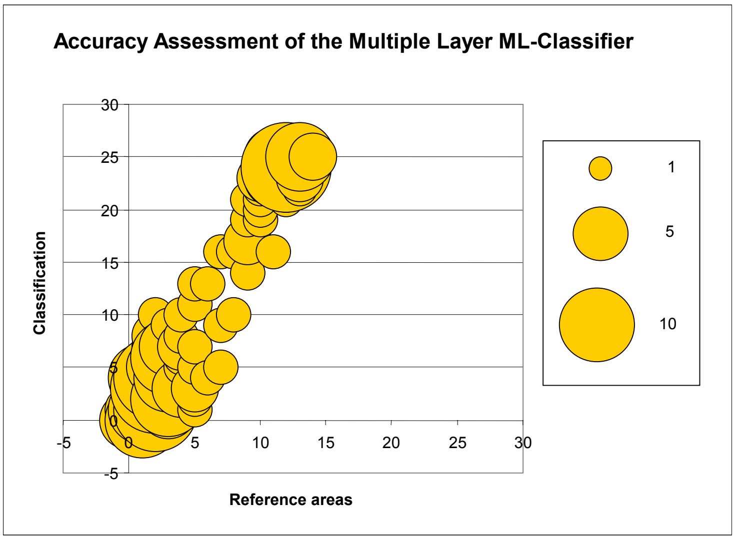

Figure 9: Multiple sensor image (SPOT-XS/Pan and ERS-2 May 98/ Dec. 98)

The result of the classification was promising enough to see if the actual density could be estimated by a regression model. Based on a linear and a non-linear regression model the density classification was once again estimated. The better result had the linear model using the following equation:

$$y_i = 1.9819\, x_i - 0.9551$$

where $x_i$ are the estimated pixel values and $y_i$ are the pixel values of the classification.

**5**

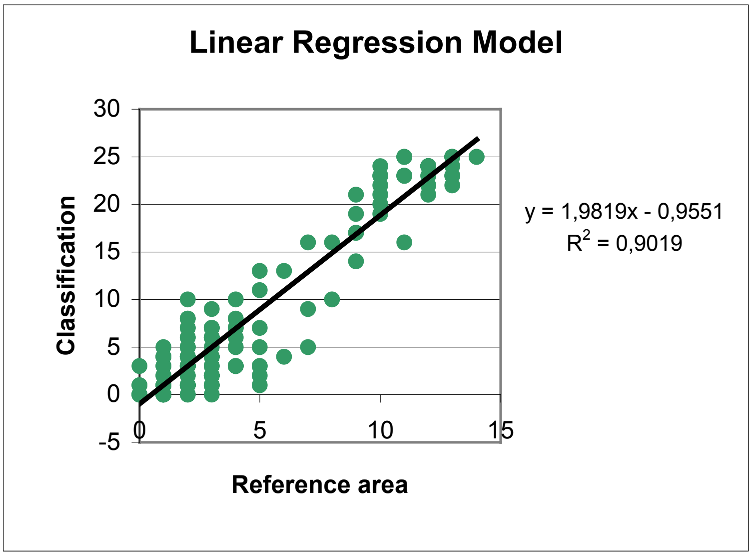

Figure 10: Regression model of the multiple-layer approach

Considering the result on the level of settlements it can be observed that in the case of the low-density settlements the multiple sensor approach is underestimating the density substantially. So it seemed that for these areas the classification is not performing very well. This phenomenon can be explained by disturbance of tree-cover in the low-density settlements but, also by the fact that pixel which are not containing a dominant share of roofs are not classified as 'pseudo-building' pixels. For the case of the medium density settlements the results were in the most cases relatively reliable. In the case of the high-density areas the density is overestimated. Table 4 shows the averaged result for all areas (the areas which are effected by the disturbance in the May '98 scene were excluded). The result is far from being perfect but a difference of 0.94 can be considered as being quite stable.

| | '92 data | Estimation |
|---|---|---|
| Average Density of Stable Areas | 6.91 | 7.85 |

Table 4: Comparison between estimation and '92 data

This result opened the possibility to make statements of the actual scale of density changes in unplanned settlements. Of course, these changes could not be quantified on a level of exact percentages only the scale of these changes could be analysed (see figure 11). As discussed above the low-density areas are outstanding, here reliable statements about the scale of density changes could not be made. It can be assumed based on the results of the assessment using the relatively stable areas, that the scale of changes in medium and high-density areas can be quantified.

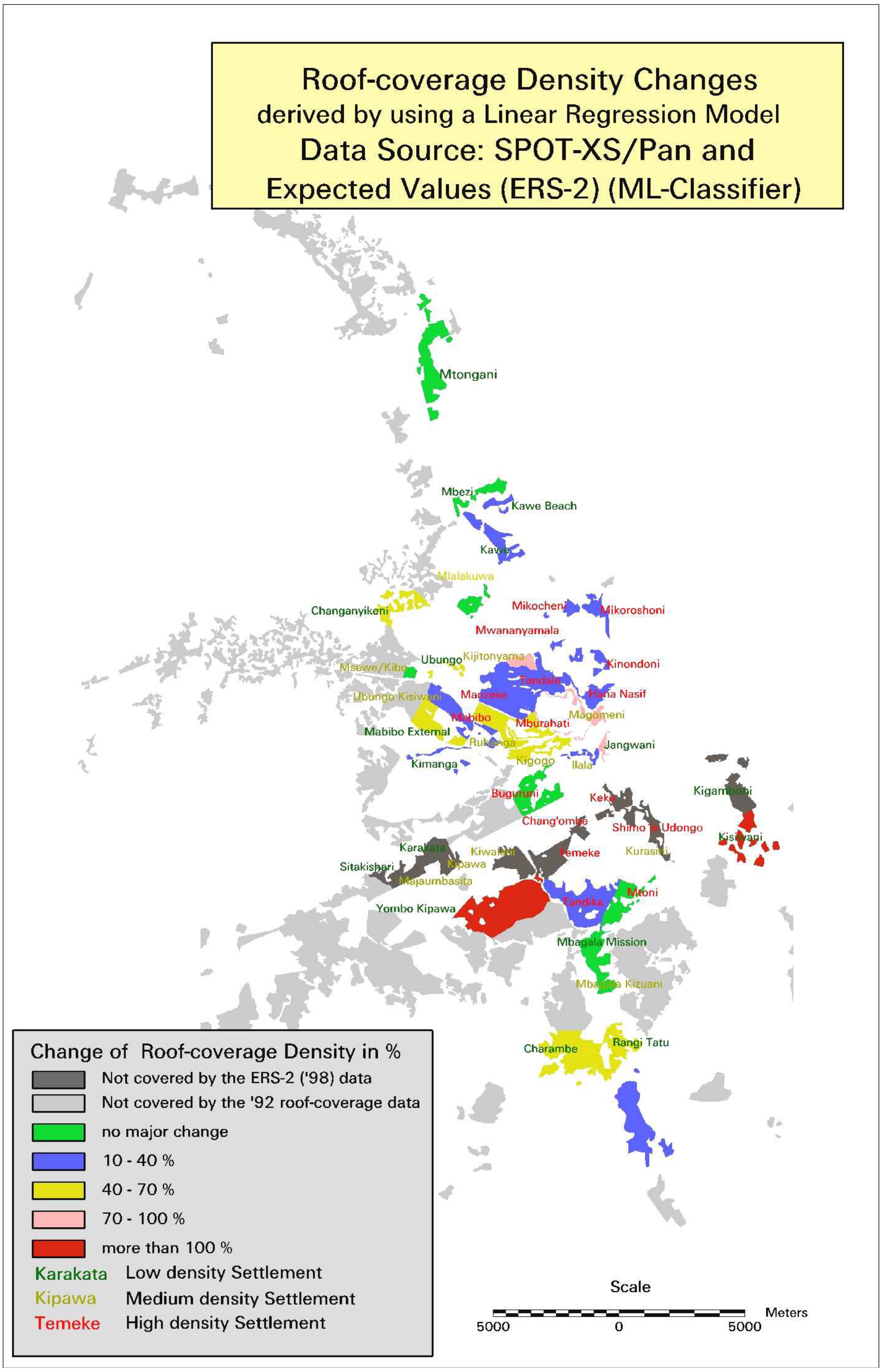

Figure 11: Density changes of informal settlements

## 6 CONCLUSIONS

As discussed previously, urban planning in Dar es Salaam is a difficult task due to the tremendous growth of population and the consequently expansion of unplanned settlements. In order to manage this situation reliable data of the present situation are essential.

It was not possible by using optical data to accurately classify areas of buildings, as they were confused with areas of bare soil, shallow water and pavement. A further problem that occurred was that buildings in Dar normally are smaller than one SPOT-XS pixel, to classify roof-areas would imply to classify on a sub-pixel level, which cannot be achieved by standard classification algorithms. So only “pseudo-pixel”, pixels that are containing at least a dominant share of roofs, could be spectrally classified. The accuracy of an urban land-cover ML classification, particularly the classification of buildings, bare soil and pavement could be significantly improved by additionally using the expected values of two radar scenes in combination with a SPOT-XS and SPOT-Pan image. The main condition for improving the results by using the expected values of two ERS-2 images are that they are timely close related.

One basic problem, which the additionally use of the expected values of two ERS-2 images could not solve was the overestimation of roof-coverage densities of high-density areas and the underestimation of low-density areas by the classifications. In the case of the optical data it referred to the misclassification of mainly bare soil and pavement as buildings and secondly, the problem that entire pixels were classified as a building, no percent values on a sub-pixel level was possible. In the case of using radar data the overestimation was also caused by the missing possibility to classify sub-pixel percentage but, mainly also by the overruling strong corner reflection of buildings.

As roof-coverage densities could not be directly classified, the only possibility was to use reference data for estimating the density. As reference three SFAP updated areas were used. Applying a linear regression model the density was estimated. The verification of the result caused small difficulties as it only could be compared to the relatively stable areas of a roof-coverage density map of the year ’92. The actual stability only could be assumed which caused inaccuracy. The results of these estimations showed that particularly low-density areas could not be reliable estimated. Density changes on a settlement level can be in the cases of medium and high-density settlement analysed, and also the scale of these changes could be approximated. But, in at this stage it seems not to be possible to quantify these changes reliable.

## 7 ACKNOWLEDGEMENTS

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