Detecting and Characterizing Settlement Changes in Developing Countries Using VHSR Data: Case of the Coastal Area of Benin

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Abstract In many developing countries, coastal areas show high dynamics of settlement structures, which are hardly regulated by regional planning and therefore give rise to a series of risks. Most of all, increasing settlement density and spread in areas close to the shoreline and into wetland areas appear worrying against the background of climate change and sea level rise. In our study area, the coastal zone of Benin, settlements are spreading into agricultural areas as well as near-natural zones, towards the lagoon and are threatened by coastal erosion. To enable regional planners to take these threats into account, process monitoring respectively modelling based on remote sensing data is needed. Due to very small land use structures and the necessity of detecting individual buildings, very high spatial resolution (VHSR) data has to be used. However, like in other developing countries, VHSR data availability is poor. Furthermore, process analysis and modelling based on approaches for industrialized countries are not feasible due to strong differences in the appearance of villages respectively suburban areas in Benin. Individual buildings are sometimes even difficult to detect by eye, nonetheless, to achieve large-scale information, automation is indispensable. We exemplify these issues for the coastal area of Benin by an approach based on both

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manual and segment-based (semi-)automatized building detection. We use the results to analyze the settlement process and model its further evolution by data driven modelling.

1 Introduction

In developing countries, there is a great need to detect spatial processes like changes in the settlement structure. Remote sensing can be used to describe the spatial extents of these processes. The derived information can consequently be used for simulation or modelling and can serve as decision base for further planning. We exemplify these issues for the coastal area of Benin in Western Africa. Like most coastal zones worldwide (Department of Economic and Social Affairs (DESA) 2007), it is the most densely populated area of the country (Institut national de la statistique de l'analyse economique (INSAE) 2004) and yet migration destination (e.g. Doevenspeck 2005; Teka 2010). Very high settlement dynamics, characterized by high building activities within and around settlements together with land seizure of formerly near-natural areas as well as agricultural areas characterize this process. Our study area is close to the administrative and economical capital, Cotonou. Several studies deal with processes in the coastal region (e.g. Domingo 2007; Teka 2010). However, unlike for other areas of the country (Doevenspeck 2005; Judex 2008), migration processes and their implications have been barely analyzed in their spatial extension for this area.

The combination of inordinate settlement processes referred to as urban sprawl by Zhang (2004) according to Bhatta (2010), and land seizure in areas near to the shore line and into wetland areas give cause for serious concern. These processes need to be detected, analyzed and monitored in order to enable regional planners to face these challenges. Remote sensing and GIS are indispensable methods for accomplishing these tasks.

There are two objectives of this study: Firstly, we want to provide a methodology needed to detect and describe vectored processes of change in the settlement structure of a village in the coastal area of Benin based on remote sensing data. A reliable detection and description of these processes is an indispensable requirement to analyze and model them. Here, we want to refine our methodology presented in Sturm-Hentschel et al. (2011). Secondly, we will make an initial attempt to model further settlement growth based on the multi-temporal building detection.

In the study area, building densification and spread can be observed. They need to be spatially determined and quantified. To detect urban sprawl synoptically, in many studies the area of impervious surface is analyzed (Epstein et al. 2002; Jat et al. 2008). Yet, in developing countries, even in urban areas, dwellings are often the only impervious objects–open soil and vegetation are found in between dwellings. Hence, an approach based on detecting impervious surface is not adequate. Pesaresi et al. (2009) present studies working with texture. Due to similar sizes and structures of buildings and fields—those approaches fail in our study area. Since buildings and fields are partially mixed, the very first step is to detect individual dwellings in order to analyze the process. Automatic extraction of objects like roads and buildings in natural environments is one of the challenging issues in photogrammetry and computer vision. Many approaches published on the detection of individual dwellings are based on computing features that take into account pixels neighbourhoods. The extended morphological profiles used herein are one type of these features, however many alternatives exist (e.g. features based on wavelets, local intensity gradients, empirical mode decomposition). Some of these approaches yield quite promising results. However, many approaches consider small subsets of images that exclusively show the urbanized area. The number of available classes in such subsets is limited. Thus, there are few classes buildings can be confused with. In contrast to that, our approach is based on entire images that consist of urbanized, vegetated and agricultural area. Outside the urbanized area, many open soil segments are found that are very similar to roof segments from urbanized areas. Therefore, the problem of confusion between these roof segments and open soils arises. Thus, approaches focused on detecting dwellings in scenes that exclusively show urbanized areas can not be applied directly. An approach needs to be developed that is able to detect dwellings within the multitude of classes present in datasets that consist of urbanized, vegetated and agricultural areas. The interested reader may be referred to e.g. Hinz (2008) for getting more detailed information about current issues and challenges of automatic object extraction. It must be noticed, however, that almost all approaches on automatic object extraction rely on quasi-perfect data in terms of resolution, overlap, revisit time etc. But, like in many developing countries, data availability is poor in our case. Therefore, the situation changes dramatically. For the area where we implemented our approach, only the scan of a grey-scale aerial image from 1995, a Quick Bird scene taken in 2002 and a RGB aerial image of 2007 were available. The heterogeneity of both the appearance of houses as well as the data available makes multi-temporal process identification a challenging task. Thus, different strategies on data interpretation need to be employed. Furthermore, the limited number of points in time renders process modelling an even bigger challenge–both issues will be tackled in our report.

Our approach is based on manual detection in order to achieve a high level of accuracy and certainty for smaller areas and on (semi-)automatized detection to provide means to gather information for larger areas. Classification results will be presented for both approaches and a comparison will be given. The manual results serve furthermore as reference for quality assessment of the automatized detection as well as for process analysis and modelling.

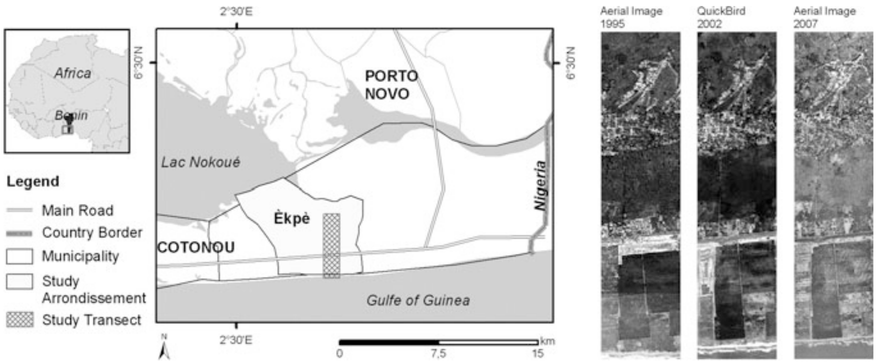

Fig. 1 Study area

2 Study Area

Our study area is situated in the coastal zone of Benin in Western Africa, situated at the Gulf of Guinea. The coastal area is geomorphologically a graded shore line with numerous recent and ancient lagoons that follow coast parallel structures in approximate west-east direction. Sandy ground and marsh alternate. The littoral is situated in the zone of tropical-summer humid climate (Weller 2002) and is characterized by two rainy seasons (April to July and October to November; Adam and Boko 1993).

Both rainy seasons implicate flooding, especially of the (ancient) lagoons. The study area represents one of the most densely populated areas of Benin (Institut national de la statistique de l'analyse economique (INSAE) 2004). It has shown very high settlement dynamics during the past years (Sturm et al. 2007; Vogt et al. 2007).

We chose the district Èkpè as our study area, a growing suburban region east of Cotonou, the administrative and economical capital. We apply our approach on a north–south transect (1,200 m × 4,850 m), which cuts several land use units. The northern and southern parts are characterized by dry sandy ground and are used apart from settlements (village of Djéffa in the north) mainly for agriculture in the north and plantations in the south. The middle part is characterized by an ancient lagoon, today marshland. The south bound is faced by the Gulf of Guinea and threatened by coastal erosion.

3 Data Base

We worked on a multi-sensorial time series using the scan of a gray-scale aerial image (March 1995, scale 1:30,000), QuickBird data (December 2002) and a color aerial image (March 2007, scale 1:20,000), see Fig. 1. The ground sampling distance (GSD) of the gray-scale aerial image scans of 1995 is about 0.30 m, of the color aerial image of 2007 about 1.3 m; the used pan sharpened QuickBird bands of 2002 have a spatial resolution of 0.6 m. The aerial images of 1995 and 2007 are georectified based on the pan sharpened QuickBird dataset of 2002 and resampled to its GSD of 0.6 m. As one can see, our study represents an example of poor and heterogeneous data availability typical for least developed countries as mentioned above.

4 Methods

We base our approach on detecting individual buildings. The data situation, which is typical for developing countries, is not optimal for automatic detection: Dwellings in the study area show diverse shapes and sizes as well as manifold roof colors due to diverse roof materials such as new metal, corroded metal, asbestos or organic materials. Furthermore, the roofs seem to fuse with the surrounding surface: bright roofs with bright sand, darker roofs with dry vegetation. In order to have a certain and accurate base for modelling as well as for assessment, we choose to firstly classify dwellings manually, before we make an automatic attempt. The main reason for working towards an automatic building detection is to provide methods for analyzing the entire coastal area of Benin. After detecting individual buildings, we compute grid-based density estimation and analyze the density change over time. The settlement outlines we detect by a support vector approach. Based on these detected outlines, we model the change in time with a data-driven geometrical modelling approach.

4.1 Manual Building Detection

To analyze and quantify the change in the settlement structure in the coastal area of Benin we need to detect buildings. Due to the diverse shapes and manifold colors of the dwellings, we accomplish this task by manual classification at first. Buildings were digitized on-screen at a scale of 1:1,000, using the ArcGIS software. The obtained digitalization serves on the one hand as input for process analysis and on the other hand as data base for quality assessment of the automated building detection. Manual detection of dwellings assures reliable and high detection rates. However, it is very time consuming and consequently not a feasible solution for regions much larger than the study area. Thus, developing automatic detection methods is a crucial prerequisite in analyzing the entire coastal area.

4.2 Semi-Automatized Building Detection (User Defined Features)

As VHSR coverage of Benin is very heterogeneous–within the area of Èkpè, we already had to use three different sensors–a least common denominator needs to be found. Therefore, we exploit the only information present in all images–spectral intensity and geometry. Another reason for refraining to use the spectral information is that the spectral signature of dwellings is also very heterogeneous. Due to the limited spectral information, the shape of dwellings is the most important feature to detect buildings. Therefore, we segment our data, using the region growing algorithm (see Baatz and Schäpe 2000), implemented in the used eCognition Developer 8 software. As training and control areas we use such segments that overlap to at least 50 % with manually detected buildings.

In Sturm-Hentschel et al. (2011), we had only used the Bayes quadratic discriminant classifier (QDA) to classify buildings. Yet, we experienced that apart from the QDA, the Parzen classifier (based on Kernel density estimation) and the Fisher classifier (Linear discriminant analyses) produced the most accurate results for the test area used in Sturm-Hentschel et al. (2011a). For mathematical foundations see Duda et al. (2001). As the building detection needed for process analysis is a hard task, relying on a single classifier may not be the best option. We therefore tried to enhanced our approach by not only using one of the tested classifiers but now combine the results from the QDA, Parzen and Fisher classifiers by ensemble classification (Briem et al. 2002). Ensemble classification (*E*) attempts to integrate classification results by various single classifiers to a joint decision in order to yield higher accuracy rates. Various methods have been proposed (e.g. fuzzy majority voting, bagging, product combiner; see Briem et al. 2002 and Gomah et al. 2010). For our data, a very simple method yielded the best results: In the Pattern Recognition Toolbox (PR Tools) for Matlab, the decision values of each single classifier are scaled to [0,1]. Then, the product combiner multiplies the decision values of the single classifiers to a new vote. While this method is very simple, in preliminary tests it outperformed fuzzy majority voting and bagging on our data. Additionally to the ensemble classification (*E*) (see above), we tested and compared knowledge based classification (*KB*) and the newly integrated Optimal Box prototype (*OB*)–both in the eCogonition Developer 8 software. The latter classification approaches are based on samples (house vs. non-house segments) as well. The *KB* approach uses samples indirectly through analyzing the histograms of a variety of features, choosing proper features and adjusting the membership functions. *OB* generates membership functions automatically by searching the best separating features based upon sample training (Definiens 2009). Unfortunately, further information about the separation method can not be found in Definiens documentation.

Table 1 represents the chosen features. Within the *KB* approach, one set of features with their respective membership function was used for all dates. During training the histograms of all dates were compared synchronously. For *E* and *OB*,

Table 1 Used features for classification ("⊙": used; "-": not used) (*-intensity of pixels in segment)

	Ensemble classification (E)	Knowledge based classification (KB)	Optimal box classification (OB)		
	For all points in time	For all points in time	1995	2002	2007
Features based on spectral information:					
Mean*	⊙	–	⊙	–	–
Median*	⊙	–	–	–	–
Variance*	⊙	–	–	–	–
Minimum*	⊙	–	–	–	–
Maximum*	⊙	–	–	–	–
Value of segment after mean-shift	⊙	–	–	–	–
Max*-min*	⊙	–	–	–	–
No of grey values in segment	⊙	–	–	–	–
Features based on geometrical/shape information:					
Area (A)	⊙	⊙	⊙	⊙	⊙
Shape index	–	⊙	⊙	–	⊙
Lenght/width	–	–	⊙	⊙	⊙
Length (L)	–	⊙	⊙	⊙	⊙
Length of bounding box	⊙	–	–	–	–
Width	–	⊙	⊙	⊙	⊙
Width of bounding box	⊙	–	–	–	–
Equivalence diameter	–	–	⊙	–	⊙
L/4*((A)^(1/2))	⊙	–	⊙	–	⊙
L/A	⊙	⊙	⊙	⊙	⊙
Borderlength	⊙	–	⊙	–	⊙
Length of longest edge (polygon)	–	–	–	⊙	–
Extent	–	–	–	⊙	⊙
Radius of largest enclosed ellipse	–	–	–	–	⊙
Density	–	–	–	–	⊙
Asymmetry	–	–	–	–	⊙
Compactness	–	⊙	–	–	–
Number of edge pixels in segment (after canny operator)(n)	⊙	–	–	–	–
n/A	⊙	–	–	–	–

training was realized for the 2002-data. The used features and respective membership functions were afterwards transferred to the 1995- and 2007-data. For *OB*, these results were additionally compared to the outcomes of training with the 1995 data and 2007 data respectively.

In Sturm-Hentschel et al. (2011), we had developed and evaluated our first approach on a small subset of the images (in the north of the transect; village of Djéffa). There, automatic detection provided reasonable results. Both spread and densification could be assessed in general terms. Now we use the developed methods on the entire transect. Due to the heterogeneity of our data, a lack of robustness of the classification methods has to be feared.

4.3 Automatized Building Detection (Morphological Features)

The features used for semi-automatized detection were defined based on a user's appraisal, e.g. the size of the bounding box was computed and used since we considered it to be relevant for distinguishing buildings from background. However, human recognition on features adequacy for the classification process may be limited. Thus, it may be helpful to compute extra features for classification with an automatized algorithm which aims to introduce contextual information. Therefore, a second approach for automatized detection is employed. This approach is based on morphological profiles. Morphological profiles have been proposed by Benediktsson et al. (2005) mainly for the analysis of VHR data in urban datasets. The key idea is to extract features describing the spatial context of pixels to have a classification based on spectral and spatial features. The simplest method to complete this task would be to compute e.g. a median filtering applied to each channel. However, median filters are not shape-preserving, objects are simply blurred. Although they introduce spatial context into classification, the performance of classification could decrease since major objects are mixed up with minor objects. In contrast to that, it would be desirable to introduce spatial operations which completely preserve major objects and completely delete minor objects. This task is completed by morphological profiles. They apply the two key morphological operators (opening and closing) to the image channels and combine them to erosion and dilation operators. For this task, they use a structuring element (e.g. a disk) of a certain size. A structure is preserved if it completely fits into the structuring element; otherwise it is merged to the next bigger structure in which it is contained. Note that openings isolate bright objects while closings isolate dark objects in the image. Since an operation based on only one structuring element is hardly sufficient to cover the diversity of urban datasets, a whole series of structuring elements with different sizes is employed. Therefore, to an image *Im*, a whole series of closings *Cl* and opening *Op*, are computed based on structuring elements λ with different sizes (i.e. $\lambda 1,\ldots,\lambda n$). The resulting morphological profile would then be:

$$MP = \{Cl\lambda n, \ldots, Cl\lambda 3, Cl\lambda 2, Cl\lambda 1, Im, Op\lambda 1, Op\lambda 2, Op\lambda 3, \ldots, Op\lambda n\}.$$

Hence, a whole series of new features is computed which introduce the spatial context of an object in a certain neighbourhood around each pixel defined by structuring elements. These features preserve objects considered as major objects w.r.t. the current filter size while deleting smaller objects. From there, a shape preserving spectral-spatial classification is made possible. After computing the morphological profile, classification will be performed using support vector machines (SVMs, Vapnik 1992) since they have proven to be capable classifiers for spectral-spatial classification based on morphological profiles. An example is found in Tan and Du (2010).

4.4 Detecting the Settlement Outlines

As the goal of this study was to describe the change in settlement structures, merely detecting dwellings was only the first step. One approach to detect urban sprawl relies on the detection of the settlement boundary. To do this automatically, we use support vector domain description (SVDD)–which is usually used for classification. SVDD (Tax and Duin 1999) is designed to find enclosing boundary lines around data. In order to find a well-generalized boundary, it cuts off outliers–which would be single buildings far outside the settlements in our case.

4.5 Grid-Based Density Analysis

Settlement changes are not only characterized by sprawl of buildings but also by densification. On the results of the building detection, we perform grid based quantitative change detection. We aim to identify the areas of altered settlement structure. To achieve this goal we perform a grid based density analysis. We compute a grid with a size of 50×50 pixels (30×30 m^2). For each of the three points in time (1995, 2002, and 2007) we obtain an estimate for building (area) density for each year using the manual results. From these, we assess the change in settlement density by subtracting these density results from one another, estimating the densification during the periods 1995–2002, 2002–2007 and the entire period 1995–2007.

4.6 Data-Driven Modelling of Urban Sprawl

After detecting dwellings and the settlement boundary for the three points in time, we attempt to model the settlement spread. Yet, as mentioned above, the available data is very much constrained, so that we refrain from modelling density changes. Given only three points in time, modelling of processes is a hard task. Besides that, appropriate socioeconomic background is not fully explored up to now, like a lot of other information about driving and restricting factors. Nonetheless, a rough image of the dynamics is possible by a data driven, geometrical modelling, which presumes homogeneous spatial conditions. We take the normal of the boundary line in 1995 as a nucleus for our model. From there, we draw lines passing each point of the boundary outlines in 2007 (see Fig. 2). We calculate the distance d from the intersections of the lines with the boundary of 1995 and 2007. We divide this distance by the number of years (12) that passed between the points in time. Then, we interpolate starting from the 2007 line for 5 years along the direction of d. As a result, we obtained a large number of interpolation points. From these, we calculate a smooth prediction outline using the SVDD again.

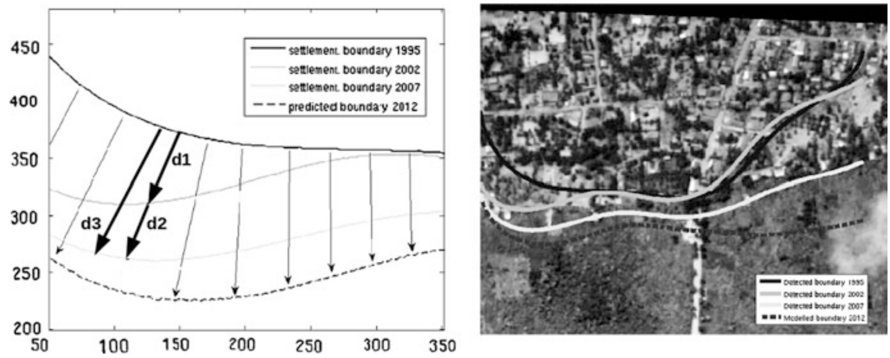

Fig. 2 Data driven modelling approach (*left* geometrical concept; *right* result, using the derived dwellings)

The result thus represents a geometrically motivated prediction for the year 2012. The blue, cyan and yellow lines represent the settlement boundaries, mentioned above, while the dashed red line represents the boundary of the data driven model for 2012 (5 years prognosis).

Of course, this is only to prognosticate the situation which would result assuming no spatial or temporal change in the urban sprawl–an assumption that is certainly incomplete.

5 Results

5.1 Comparison of Manual and Automatized Building Detection and the Resulting Settlement Outlines

Figure 3 shows (a) the manually, (b) and (c) semi-automatically detected dwellings with user defined information and (d) automatically detected dwellings with morphological information for the three points in time as grey-white dots and the respective settlement outline of the settlements produced with SVDD as a broad white line. Comparing the results, it becomes obvious, that the semi-automatic approaches based on user defined information classify too many segments of vegetated areas in the centre and the south of the scene falsely as buildings. The main reason for the high amount of false-positives is caused by confusion between open soil, vegetation and buildings of similar shape. For instance, segments in between the plantations in the south show building-like forms because of the patchiness of the plantations. The automatized approach based on morphological information also shows too many false positives, although to a smaller extent than the first semi-automatized approach. Obviously, many areas that either represent open soil within the settlement are classified as dwellings. On the other hand, it

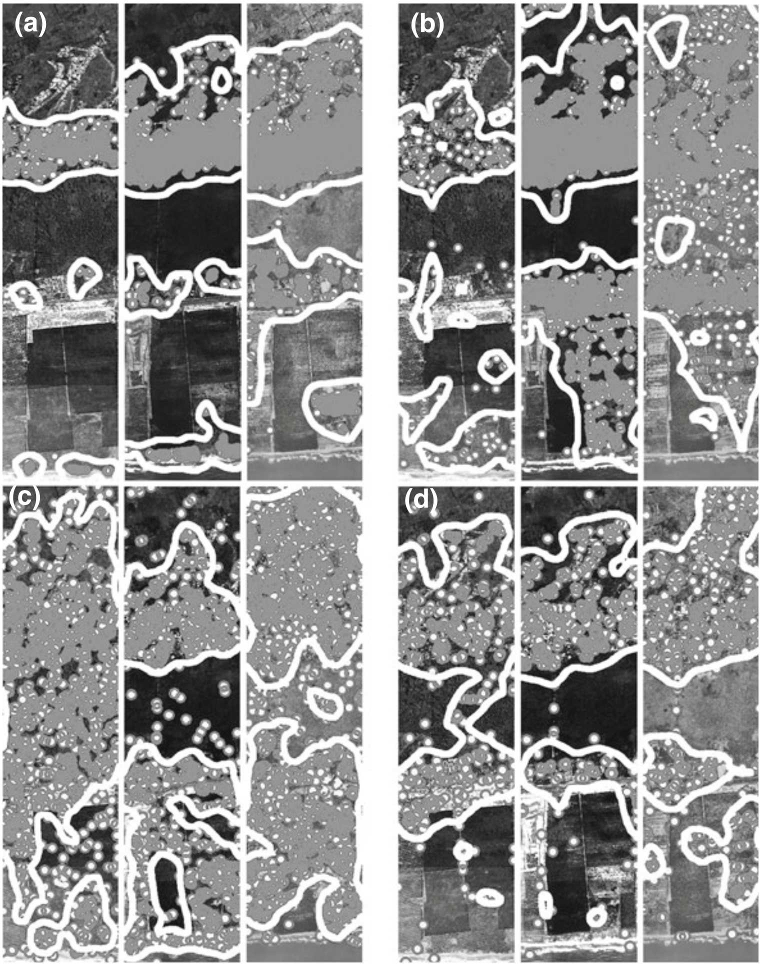

Fig. 3 Example of detected dwellings (*grey circles*) and boundaries (*white lines*) **a** manually. **b** by ensemble classification. **c** by knowledge based classification. **d** by automatized classification using morphological profiles (*left* 1995, *centre* 2002, *right* 2007)

should be noted that the major part of false positives by the *E* and *MP* approaches are found within settlements. From there, both approaches can give hints of human settlement activities although they may not perfectly allow for a building detection yet.

In respect of the spatial processes, the manual results show clearly an augmentation of dwellings and a spread of the settlements. The northern area, still left open in 1995, is being more and more populated in the following points in time. Dwellings are being erected in between the small fields. The boundaries of the areas north and south of the ancient laguna (in the middle of the images) come very close to this area; in fact, a number of houses is already situated within the wetland. This indicates that there might be a threat of wetland vegetation (brush up to forest) being cut down when open spaces for new dwellings become scarce, or areas used for agriculture are being altered. In the south, dislocation of buildings can be noticed, caused by coastal erosion (Vogt et al. 2007). The northward spread of settlements of the village in the upper part and increase in size of the settlement patches in the centre can be observed in the automatized detection results as well, however, they are to a large extent disguised by the false-positives.

At this point, it can be concluded that the promising result for the Djéffa subset (Sturm-Hentschel et al. 2011) can not be enhanced and applied so far to the entire transect. Although morphological information has helped to reduce false positives automatized approaches still lack robustness. For this reason, density analysis and modelling have been computed on the manual results exclusively.

5.2 Quantitative Quality Assessment

Quantitative quality assessment was realized by using pixel-based measures. As control areas we used such segments that overlapped at least 50 % with manually digitized buildings.

The ensemble classification (*E*) based on user-defined features produced results that were quantitatively not satisfying (Table 2). High OAC values are yielded; however, one has to keep in mind that the major part of segments relates to non-building segments. Therefore, the non-building class vastly biases the OAC. One important performance measure for our task is the true-positive rate which is only moderate for all three points in time. For our task, performance measures which rely on a combination of completeness and correctness should be taken into account. F-Score and Youden's Index are such measures. Both are unsatisfying for the classification results. From there, although the ensemble-classification may give a first overall impression of the process, it should not be used for quantitative analyses or further processing (input for modelling). For every date, the knowledge based (*KB*) approach showed better results than the Optimal Box (*OB*) approach (Table 2). Further improvements might be necessary for that prototype, developed by Definiens. The *OB* does not even provide the best possible result: For 2007 e.g. 2002-*OB*-training transferred to the 2007-data provided a better result than training on the 2007-data itself. Altogether, Fig. 3 and all PPV values for *KB* and *OB* in Table 2 show that too many segments are wrongly classified as building. Concerning the SVM classification based on morphological profiles (*MP*), similar conclusions as for *E* can be drawn. While the OAC may seem convincing, F-Score and Youden's Index certainly are not. However, it can be stated that the results produced with morphological profiles are higher than the ones produced with user-defined features. This indicates that the relevant features for separation of buildings and non-building may be produced by automated algorithms and should be taken into account.

Table 2 Quality assessment (OAC = overall accuracy; FS = F-score; YI = Youden′s index; TPR = true positive rate; TNR = true negative rate; PPV = positive predictive value; NPV = negative predictive value)

	OAC	FS	YI	TPR	TNR	PPV	NPV
E 1995	0.98	0.26	0.38	0.39	0.99	0.19	0.95
KB 1995	0.88	0.03	0.55	0.68	0.88	0.02	0.99
OB 1995(*tr*.'02)	0.77	0.02	0.59	0.82	0.77	0.01	0.99
OB 1995	0.80	0.02	0.68	0.88	0.80	0.01	0.99
MP 1995	0.92	0.06	0.88	0.96	0.92	0.03	0.99
E 2002	0.98	0.26	0.38	0.39	0.99	0.19	0.99
KB 2002	0.93	0.13	0.74	0.81	0.93	0.07	0.99
OB 2002	0.87	0.08	0.87	0.99	0.87	0.04	0.99
MP 2002	0.94	0.16	0.85	0.91	0.94	0.08	0.99
E 2007	0.98	0.17	0.15	0.16	0.99	0.18	0.99
KB 2007	0.82	0.09	0.63	0.81	0.82	0.05	0.99
OB 2007(*tr*.'02)	0.67	0.06	0.62	0.95	0.67	0.03	0.99
OB 2007	0.61	0.05	0.58	0.98	0.60	0.03	0.99
MP 2007	0.90	0.17	0.80	0.89	0.90	0.09	0.99

5.3 Density Analysis

The settlement density and the density changes between the respective points in time are shown in Fig. 4. The images in Fig. 4a show spatially heterogeneous distributions of the dwellings. White indicates "no area covered by dwellings". Bright values show low settlement density, while dark values indicate higher settlement density. The highest density reaches 30 % areal coverage of a grid cell (black). The density change maps (Fig. 4b) reveal heterogeneous densification tendencies. Orange areas represent an increasing density, while blue ones represent a decrease.

As can be seen, the village in the north of the scene has become denser in the center and significantly increased in size between 1995 and 2007. The northern part of the village has not been very densely settled–an indicator of settlement sprawl. The same accounts for the settlement spread in the centre of the scene. The settlement at the shoreline in the south has been dislocated northwards between 1995 and 2002 as well as between 2002 and 2007, which is due to transgression of the shore line towards the north caused by coastal erosion.

5.4 Modelling the Settlement Spread

Figure 5 shows the geometrically modelled settlement spread and its prevision for 2012. Note that the settlement spread is stronger in some areas than in others (spatial anisotropy). In some areas, the urban sprawl accelerated between the two periods 1995–2002 and 2002–2007, while in others, it slowed down (temporal anisotropy).

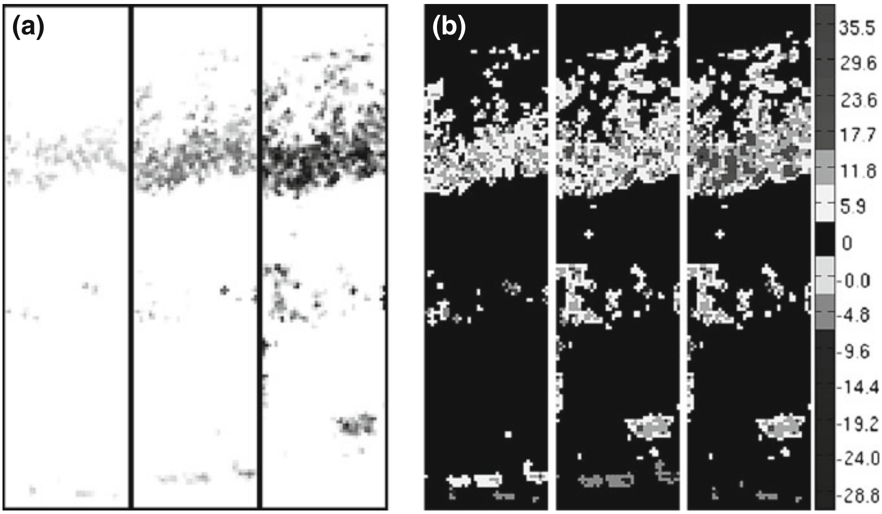

Fig. 4 **a** settlement density (*left* in 1995; *middle* in 2002; *right* in 2007) and **b** density change (*left* 1995–2002; *middle* 2002–2007; *right* 1995–2007)

If this prognosis is correct, the southbound land seizure caused by the northern settlement would implicate a severe loss of wetland vegetation. The most notable change would be a strong settlement spread towards the north of the scene, implicating a loss of agricultural areas as already observed in 2007. Furthermore, the settlements in the centre and the south east of the scene could significantly increase in size. The wetland area in the centre could decrease in size through settlement spread from the north and the south. However, these results can not be considered a reliable prognosis by themselves. While we believe that settlements will spread further into the agricultural areas in north of the scene, it is questionable to which extent people will settle in the wetlands in the future. At the shore line, no prediction line is found, since the model is not built for settlement dislocation.

We reckon that this prognosis should be used only as additional input data for a process oriented modelling as it can be derived quite easily from the classification results directly. A next step towards a process oriented modelling would be the integration of densification into the model.

6 Discussion

It could be shown, that the results perceived by manual detection serve well for further settlement analysis. While the (semi-)automization delivered for the village of Djéffa in the north of the transect good results (quality 91–97 %; detection 94–98 %; Sturm-Hentschel et al. 2011a), it did not perform well for the entire transect. Therefore, we refrained from using the detection results for an analysis

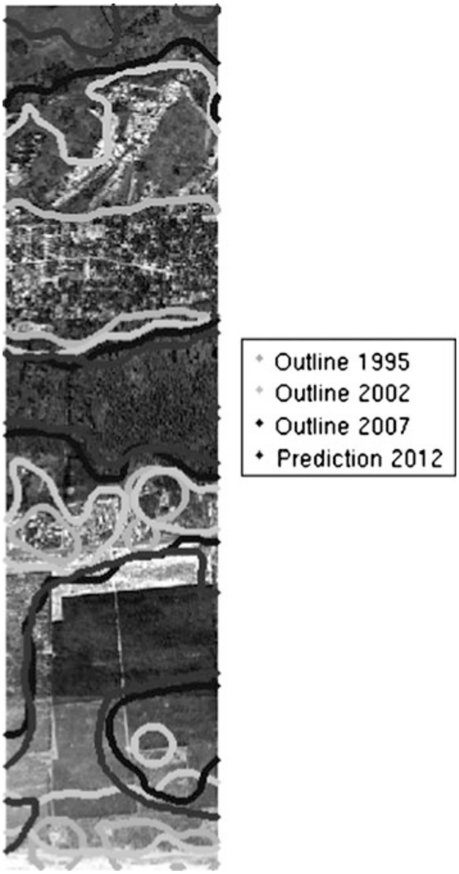

Fig. 5 Data-driven modelling of the settlement spread

of density change and modelling of settlement spread. Many segments that show open soil are fused with buildings or rooftops show different shading. Therefore, the segmentation is strongly affected by both over- and under-segmentation (Fig. 6).

As we use geometrical features besides intensity for building detection, a good segmentation is a crucial prerequisite for reliable detection. As mentioned above, we trained our classifier on the scene of 2002 only and used it for the other scenes as well. Of course, this approach has a number of limitations. Nonetheless, to train one classifier on each scene would not fulfil all the requirement of efficient transferability to other scenes taken in the coastal area.

The results for modelling the settlement spread we presented here are the outcome of a strictly data-driven geometrical approach. Data-driven modeling does not account of the factors that cause the change. They are merely represented implicitly by the boundaries detected. However, we do not have the necessary data (like e.g. land tenure, settlement behaviour and its drivers, digital terrain model, vegetation) to develop a modelling approach based on the processes themselves. It needs to be questioned whether urban sprawl will continue to follow the

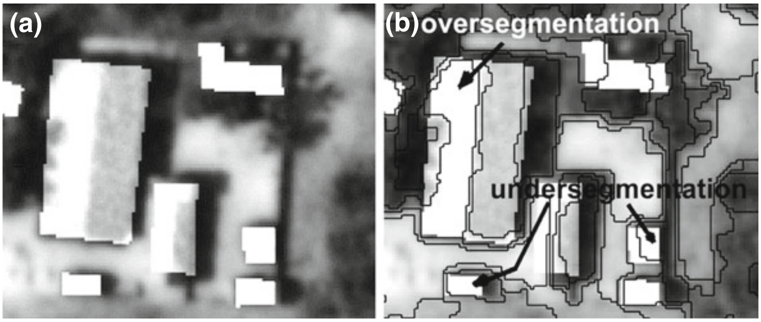

Fig. 6 **a** Image with manually digitized references and **b** segmentation result, showing over- and under segmentation (*white* digitized building reference; *black lines* segment borders)

tendency of 1995–2007. Which factors favor densification, which ones favor spread? Especially the spread into wetland area is difficult to estimate. Regarding informal conversations with settlers, financial causes seem to force people to settle into these risky areas. Yet, in order to understand these processes better, driving factors are being studied up to date.

Until now, automatized detection of dwellings is not achieved yet. Both, user-defined and morphological information is useful to describe the general tendencies (i.e. the centroid of settlements etc.). However, both approaches produce too many false-positives to be helpful in a quantitative assessment of urban sprawl. Since up-to-date classification methods were used, the second crucial point besides segmentation seems to be the features. Both types of features used are seemingly not fully able to achieve separation of buildings and background. More work has to be undertaken to find suitable features therefore. On the other hand, we believe that automatized building detection based on morphological profiles can help to capture the general tendencies of urban sprawl. This is particularly true for tasks that require a coarse image to be made available quickly. One has to keep in mind that the high precision of manual classification depends on time-consuming processing and could only be achieved by various field trips that created the users ground knowledge. One important aspect to keep in mind when considering the results of both automatized approaches–based on user-defined and based on morphological features–is the semantically different nature of the features used. The user-defined features aim to characterize the dwellings themselves (e.g. their size, length, width etc.). In contrast to that, morphological features aim to pronounce the relationship between dwellings and their spatial context.

7 Conclusion and Outlook

Semi-automatic and automatic building detection in data such as ours has not achieved the accuracy and reliability of manual classification so far. Using morphological profiles to describe the context around the individual building has admittedly reduces false positives. Nonetheless, the performance is still unsatisfying for quantitative tasks. Since the approach based on user defined features includes features of the buildings and the morphological features are focussed on the surroundings of the buildings, an attempt to combine both could be beneficial. For manual classification, human cognition using indicators such as shadow helps to identify a dwelling even if part of it fuses with the surroundings. Therefore, manual detection seems still indispensable for analyses that require reliable results, when working on a data base like ours which is typical for many areas in developing countries.

Anyway, an enhancement of the automatized approach is needed in order to at least estimate settlement processes for larger areas. Therefore, concerning the automation of process analyses much more research efforts need to be made. Since any kind of automatized approach will work on segments, an adequate segmentation result is needed. For instance, if a dwelling is split up by over-segmentation or merged with an adjacent tree by under-segmentation, any kind of feature which aims to describe dwellings size or outline will deteriorate its performance. A poor segmentation result will therefore be the first step of error propagation that impoverishes the performance of the final result. As shown above, the segmentation result achieved up to now is far from being sufficient due to the special characteristics of villages in Benin (irregular building shapes, large areas covered with open soils or man made materials, lack of impervious surface etc.). Concerning segmentation of dwellings in relatively noisy images as presented in this study, approaches by (Ohliger et al. 2010) concerning region-based active contours might be one option to be tested.

For this study, we applied a straightforward and simple approach, detecting buildings in each scene separately. In the future, we will focus more research efforts on automization to be able to perform quantitative analyses based not only on manual but also automatized results. Crucial prerequisites hereby will be an enhanced segmentation result, more descriptive features for buildings and background and a fusion approach for user-defined and morphological features.

Regarding settlement modelling, the results of the data-driven approach should be used only as additional input data for a process oriented modelling as they can be derived from the classification results directly. Further socio-economic studies can contribute to a more processes oriented modelling.

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