Delimiting Central Business Districts – A physical approach using remote sensing

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Abstract—**Central Business Districts (CBDs) are an apparent structural type of large cities. Although the conceptual definition of CBDs is mostly functional, this urban structure type has characteristic physical features. The paper presents a conceptual framework to map these CBDs using physical parameters. We identify physical parameters from the published literature and statistically designate the CBD from a 3-D city model by the example of the test site La Defense, Paris, France. From it, we develop a method to detect CBDs from a combination of large-area Cartosat-1 high resolution digital surface models for the entire spatial extent of mega city Paris. Accuracy assessment shows that CBDs are detected with an accuracy of 83.3% and are spatially delineated with an overall accuracy of 83.7%.**

I. INTRODUCTION

One of the most visible features of global cities and their supremacy in national economies are Central Business Districts (CBDs). Although settled as a geographic concept, the CBD is difficult to define. Definitions of this mental construct are qualitative such as the CBD is “the nucleus […] of an urban area that contains the main concentration of commercial land use” [1] or a “unique area of massive concentration of activities and focus for the polarisation of capital, economic and financial activities in cities” [2]. Thus, several authors describe CBDs as areas marked by various qualitative indicators relative to the surrounding urban environment [3]. This shows that the CBD is defined not only by an individual building, but by the structure of the surrounding urban morphology. Furthermore, studies on the temporal development of CBDs provide recent discussions about the decline of existing CBDs in favour of new business districts in peripheral locations [4]. Hence, business districts remain important for the distribution of functional spaces within cities.

In the recent past, various indicators of urban centrality have been used to approximate a cartographic delineation of CBDs: Authors have used demographic [5] and economic [6, 7, 8] variables to measure centrality. However, these variables are only indicators and they are often not available on the requested scale.

The unique capability of Earth observation is the provision of independent and area-wide data sets on the physical characteristics of the land surface. Thus, various studies based on EO-data focused on the derivation of urban structural types (USTs). Examples are based on methods such as spatial metrics [9], object-based classification using decision trees [10] or supervised classification [11]. In addition, authors aimed at the delineation of particular USTs such as slums [12]. However, most approaches remain on the stage of case studies and are limited in terms of spatial coverage. Although some quantitative descriptions of the physical appearance of CBDs exist [13], no study towards spatial delineation of this particular UST using earth observation is known. In this context, we address several specific questions:

(1) Which physical parameters from the published literature can be used to delineate CBDs as an urban structure type?

(2) Which remote sensing datasets are suitable for the delineation of CBDs based on physical parameters?

(3) How can CBDs be delineated from these datasets?

(4) What is the accuracy for spatial delineation and detection?

II. TEST SITE AND DATA

For this study, we selected mega city, Paris, because it contains a city internal CBD and additional CBDs are distributed across the city. Paris is currently the third largest European city with 10.6 million inhabitants. The test site La Defense is well documented in literature as an internal edge city [14]. It was developed to protect central Paris from modern office development and embrace the demands of international business in 2000 featuring one of the most concentrated areas of high-rise buildings in Europe.

In this study we integrate geodata from different sources: (1) freely available building footprints and street networks from the OpenStreetMap project to derive a realistic 3-D model of the test site La Defense, Paris; (2) an urban footprint classification for the entire mega city from Landsat ETM+ imagery [15]; (3) a high resolution digital surface model (DSM) derived from stereo scenes provided by Cartosat-1 (IRS-P5).

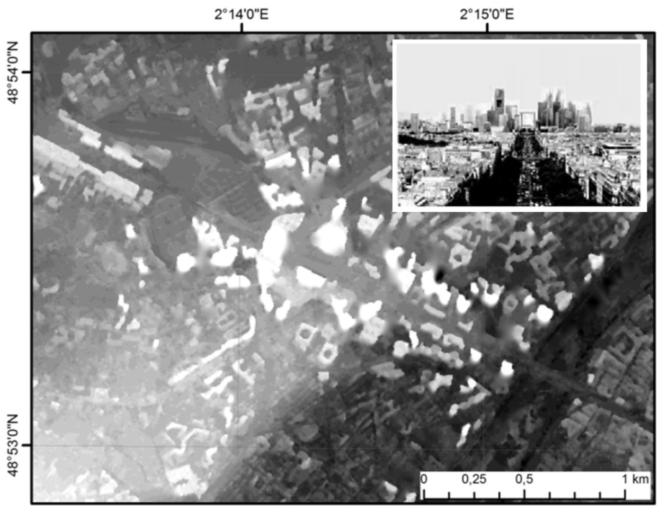

Fig. 1 Cartosat-1 DSM and photo impression [17] of La Defense, Paris

The satellite is equipped with two PAN cameras sensitive in the 500-850nm spectral wavelength region. Featuring a geometric resolution of 2.5m, its sensors simultaneously acquire images in stereo mode. Due to the relatively large swath width of 26km large urban agglomerations can be fully captured during one or two paths. With these specifications, Cartosat-1 provides HR stereo imagery which is derived from fully automated semi-global matching [16] resulting in surface representations of 5m grid spacing. The unique advantage of Cartosat-1 stereo scenes is the large-area coverage at a relatively high spatial resolution, allowing for the detection of significant physical urban structures such as CBDs in relation to the large-scale built environment (Fig. 1)

III. METHODOLOGY

The methodical workflow presented consists of five major steps: (1) Physical parameterisation of the CBD from the published literature, (2) compilation of a 3-D city model for the test site La Defense, (3) statistical delineation of CBDs from Non-CBDs based on the 3-D city model, (4) classification of CBDs from the Cartosat-1 DSM, and (5) the evaluation of detection and delineation accuracy.

1) *Phyisical parameterisation of the CBD*

The traditional concept of CBDs is rather descriptive. However, their physical appearance differs significantly from the surrounding USTs. Although physical definitions in literature are rather vague and pre-defined thresholds do not exist, we aim to derive physical indicators from the qualitative statements that describe the physical face of CBDs.

In urban geography, the CBD is described as the part of the city which features peak land values and employment densities and thus, the highest buildings [1, 17]. In this context, the *maximum building height* presents a distinct indicator for the CBD and can be supplemented by the *maximum building volume* which is commonly highly correlated. Further qualitative statements imply that the CBD is an aerial unit formed by a group of buildings, not by an individual object [3]. Thus, average values of the aforementioned measures present a logical addition to the parameter set. Another parameter commonly used for urban structuring is *building density* [18]. Although CBDs are generally not recognized to be more densely built-up than other parts of the city, they do feature a unique *density of high-rise buildings*, known as the skyline [19]. Finally, high *floor space densities* have been found to be a typical physical feature of CBDs [13].

2) *Compilation of the reference 3-D city model*

For the development of the methodology a highly resolved physical reference is needed: For the test site La Defense a building inventory from OSM exists. However, the data set is neither complete nor fully consistent. Therefore, the associated building footprints were updated with Google Earth©. Systematic height estimation was conducted for buildings not attributed with height information in OSM. Herein, Google StreetView© which provides aerial views of building façades on street level was employed. Beyond this, a street layer is integrated to determine statistical reference units, here the block level (Fig. 2).

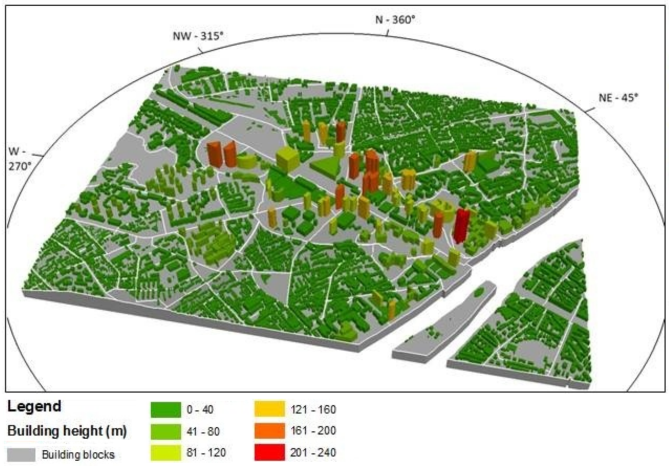

Fig. 2 3-D city model for La Defense, Paris

3) *Statistical designation of CBS vs. Non-CBDs*

For physical differentiation of the CBDs from the surrounding urban environment, cluster analysis based on the aggregated physical building parameters on block level – *average and maximum building height, average and maximum building volume, density of high-rise buildings, and floor space densities* - is used. This step is based on the central hypothesis that CBDs show significant differences regarding their morphology compared to other urban structures. We use a standard unsupervised hierarchical clustering algorithm based on Euclidean distances to differentiate two clusters within the set of observations. These clusters can be thematically described as the classes *CBD* and *Non-CBD* on block level and allow for the identification of typical thresholds between these classes for all physical input parameters.

4) *Classification of CBDs from HR Cartosat-1 DSMs*

Detection and delineation of CBDs is based on the urban footprint product from Landsat and HR Cartosat-1 DSMs. This method was implemented using an object-based image analysis and consists of three steps: (a) morphological pre-processing, (b) hierarchical segmentation, and (c) a fuzzy-logic based classification.

a) Due to the geometric capabilities of Cartosat-1, the DSMs do not provide a high-detail reference for a physical analysis on the level of individual buildings, but are suitable for the delineation of CBDs based on the dimension of their physical features relative to the surrounding urban environment on pixel level. Thus, a morphological filtering module was implemented to obtain an accurate measure of the above-ground building volume. The filtering process is based on a morphological opening [20] to produce a normalized DSM (nDSM), i.e. a surface representation of the building volume above-terrain, and consists of the sequential execution of a kernel-based minimum (erosion) and maximum (dilatation) filter on pixel level of the DSM to derive a digital terrain model (DTM) [11]. Consequently, the nDSM is calculated as the difference between the DSM and the DTM.

b) The following, top-down segmentation (Fig. 3) is executed using the nDSM and the urban footprint layer. The urban footprint level (L1) reduces the spatial extent for segmentation of the nDSM. Below, the aggregation level (L2) presents the spatial scale of statistical reference units. Against the background of transferability of the approach, square reference units of 200m cell size where chosen (2).

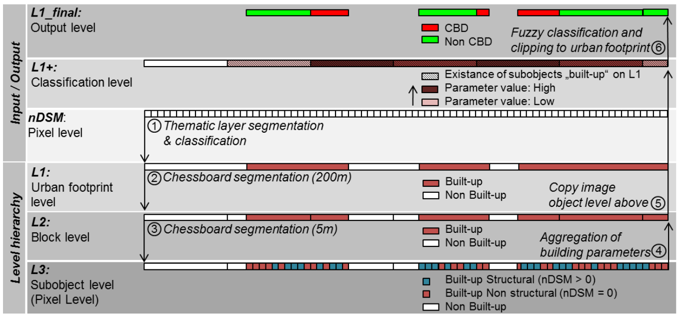

Fig. 3 Hierarchical segmentation scheme

The third sub-object level (L3) equals the pixel level and is classified into pixel objects that represent urban structures and terrain pixels. Subsequently, this multi-level approach allows for the straight-forward aggregation of physical parameters on block level (L2) from individual pixel values by the use of relational features between those levels (4). In this connection, the area classified as built-up on L1 presents the reference for area-dependent measures such as *floor space density*, whereas sub-object terrain pixels represent the physical above-ground building volume. By transferring the aggregation level (5), a separate classification level (L1+) is created which contains all aggregated physical parameters as well as a reference to the urban footprint level.

c) Finally, a fuzzy-logic approach is used to classify CBDs on block level (L1+) based on the defined characteristic physical parameters (cp. III. 4.). Fuzzy sets, i.e. classes with continuous grades of membership, combine membership values to derive the final classification result. For this purpose, it is referred to the class thresholds on building and pixel level identified from the structural analysis of the 3-D city models, as these values represent the comprehensive physical differences of the class *CBD* compared to the surrounding's urban morphology. Due to the holistic approach of parameter combination, class change-overs are not distinct but exhibit a fuzzy transition between the two classes defined by distinct lower and upper thresholds. The basic scheme of fuzzy-logic classification applied here consists of two rules combined by a logical minimum (AND) operator. (1) The a priori knowledge about the urban footprint extent is employed as a criterion of exclusion by using the existence of sub-objects classified as built-up on urban footprint level as a hard thresholding rule. (2) Physical parameters aggregated on block level from pixel level are combined via a second minimum operator. In between the identified lower and upper thresholds of the transition range, the CBD membership value increases according to a fuzzy sigmoidal membership function from zero to one; thus, returning an individual membership value for each parameter. To combine these values, again, hard thresholding is used based on the logical decision that all reference units must at least meet the lower threshold of the transition range for each parameter to be classified as CBD. Finally, the classification result is clipped to the urban footprint extent (6).

5) *Evaluation of detection and delineation accuracy*

Last, the accuracy of CBD classifications is assessed in two different manners: (a) spatial delineation and (b) detection accuracy. (a) Spatial delineation aims at quantifying the spatial precision of CBD detection at the city-internal test site. The accuracy is assessed by standard pixel-based confusion matrices for the two thematic classes (*CBD*/*Non-CBD*) with regard to the statistically designated building blocks from the analysis of 3-D city models. (b) In contrast, the spatial detection accuracy reflects the correctness of large-scale CBD localization for the entire mega city. For this purpose all blocks classified as CBDs are visually compared to the urban structures presented by Google Earth imagery and 3-D models to quantify the producer accuracy. However, this procedure does not allow for the calculation of the user accuracy.

IV. RESULTS AND VALIDATION

1) *Statistical designation and threshold identification*

By applying the two-class unsupervised clustering process to the 3-D city model, comprehensive quantitative thresholds for object-based CBD delineation from the Cartosat-1 DSM are approximated. Thus, substitutes for the selected physical parameters were derived not only from object level but also from pixel level of the 3-D model (Fig. 4). Although some of these substitutes only present proxies and are associated with a certain information loss, they reflect the typical physical features of CBDs.

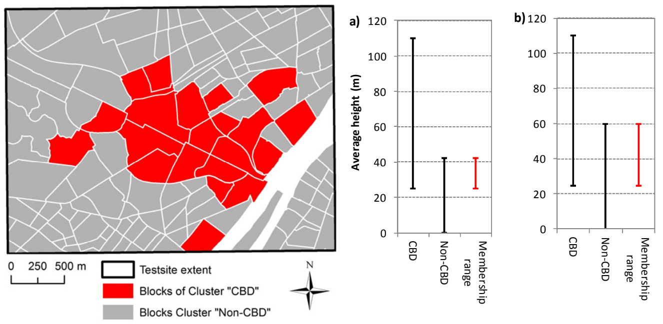

Fig. 4 Clustering results for the CBD on block level (left) and example range plot exemplifying the absolute and the transition range (red) of average height derived from a) building and b) pixel level

Due to the complexity of urban morphology, the physical parameters were combined. As a consequence, the between-class transition of parameter values is not entirely disjunct which is exemplified in figure 4 by the average height parameter, encouraging the decision for a fuzzy-based classification approach. Overall, the uniform criteria derived from the analysis of 3-D city models should allow for a transferable and thus, comparable localization of CBDs on urban footprint level.

2) *Spatial delineation accuracy*

The spatial delineation accuracy is assessed to determine the spatial precision of the CBD classification from Cartosat-1 data by comparison to the statistically designated areas by dissimilarity clustering from the 3-D city model. With an overall accuracy of 83.7% and a Kappa-Index of 0.56, high general classification accuracy is reached (Tab. 1). However, delineation results feature decreased user and producer accuracies for the class *CBD*. These shortcomings in terms of spatial precision result predominantly from the choice of square units as spatial classification unit. This emphasizes a distinct problem of scale inherited in the designation of suitable statistical reference units for parameter aggregation.

Although the delineated areas are not found to be overly precise regarding their form, CBDs are generally correctly delineated from the surrounding urban environment.

Tab. 1 Accuracy assessment of the final CBD classification for the test site La Defense, Paris

	CBD	*Non-CBD*		
Producer accuracy	67.69%	88.93%	***Overall accuracy***	83.70%
User accuracy	66.56%	89.42%	***Kappa-Index***	0.56

3) Area-wide detection and it's accuracy

The spatial detection accuracy presents a check whether the blocks classified as CBDs reflect the typical physical feature of CBDs based on a visual comparison. Overall, 45 of 54 blocks detected across Paris reflect structures in line with the physical features of La Defense resulting in a user accuracy of 83.33% and an error of omission of 16.67%. These values confirm the transferability and the comprehensiveness of the presented method across the entire mega city. The aerial classification result is displayed in figure 5.

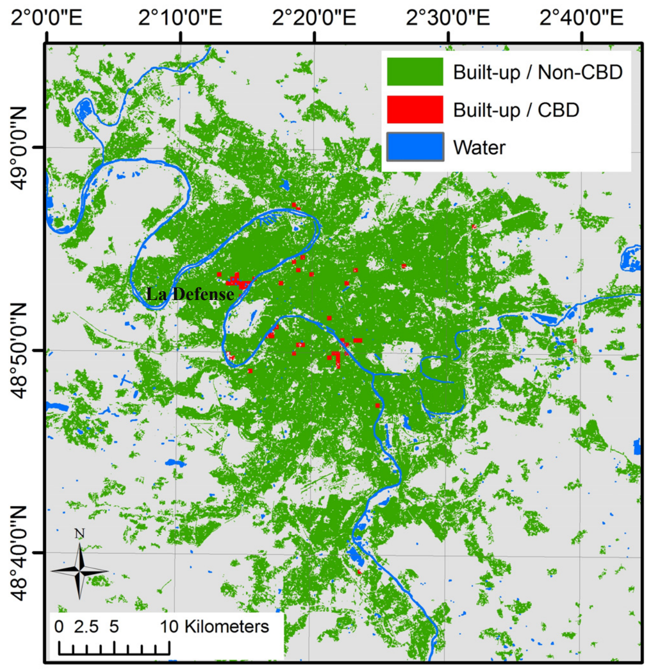

Fig. 5 Urban footprint and aerial classification result for CBDs across Paris

Examples of correctly detected blocks include the commercial center, the national library, and the shopping district at the Tour Montparnasse, as well as La Defense itself as the largest CBD featuring the strongest class memberships.

V. Conclusion

Definitions of the CBD as a mental construct are fuzzy and mostly qualitative. This study has introduced a conceptual framework to classify and define measurable physical parameters to delineate CBDs from a morphological point of view employing the capabilities of remote sensing measuring the physical face of cities.

The results allow answering the research questions addressed in the introduction. By the selected physical parameters of the built-up structure (1) and a high detail physical reference, CBDs can be physically distinguished from the surrounding urban morphology. With regard to this physical reference, we classify CBDs from HR Cartoat-1 DSMs and the area-wide urban footprint (2) based on morphological filtering, hierarchical segmentation, and fuzzy-logic classification (3) with high spatial delineation and detection accuracies (4). Thus, the presented method can provide valuable information on the structural and functional arrangement of cities.

Acknowledgement

The authors would like to specifically thank Peter Reinartz and Pablo D' Angelo from DLR for processing and providing the Cartosat-1 DSM data.

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