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It's Not Big, It's Large: Mapping and Characterizing Urban Landscapes of a Different Magnitude based on EO Data

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1 ABSTRACT

The United Nation's *"World Urbanization Prospects"* numeralise a migration process of a huge dimension – from rural to urban areas. While in 1975 only 37.7% of the world's global population were urban dwellers, in 1990 already 43.0% and today little over 50% of all earth-dwellers are living in urban areas. For the year 2050 the expected number is even 67.2% (UN, 2011). This recent and prospective urbanization trend leads to new spatial dimensions of urban landscapes.

One new trend is the spatial evolution of once polynuclei urban areas to so-called *'mega-regions'*. Because in literature clear definitions for the term *'mega-region'* are missing or at least fuzzy and only qualitative we aim to derive quantitative physical spatial characteristics possibly defining mega-regions. For this purpose we use multi-temporal and multi-source satellite data to classify urbanized areas for an exemplary mega-region – the Hong Kong-Shenzhen-Guangzhou mega-region in Southern China – for the years 1975, 1990, 2000 and 2011. Furthermore, we suggest a set of spatial features potentially characteristic for the evolution of mega-regions. In particular we apply a multitude of spatial metrics at a defined spatial unit for the entire mega-region. The result is a novel spatial approach to capture, measure and analyze new dimensions and shapes of urban landscapes.

2 INTRODUCTION

What is the shape of cities and how does it evolve? The traditional concept of the urban fabric – the 'city' in a broader sense – is defined as dense center surrounded by a more or less complex halo of lower-rise buildings and suburbs. However, the dramatic urbanization now under way constitutes one of the epochal transformations in human history. As a consequence of the before mentioned transformation process the overcoming process of spatial urbanization creates different types of settlement and respective landscape patterns. Thus spatial landscape configurations are not big anymore, they are large. Today the dynamic process of urbanization leads to a conglomeration of multi-nuclei patterns where a center is not obvious.

While spatial growth and expansion of urban areas and landscapes has long been studied at the local scale, the effects and change processes of urban expansion beyond a regional scale are virtually unknown. Especially as new dimensions and types of settlements and respective large-area urban landscape patterns are evolving. New concepts such as *mega-regions*, *urban corridors* and *city-regions* are suggested to capture the new nature of urban landscapes (UN-Habitat, 2008). It is particular characteristic for these new spatial units that they are emerging in various parts of the world, turning into spatial units that are territorially and functionally bound by economic, political, socio-cultural, and ecological systems (UN-Habitat, 2008). However, our understanding of urbanization at these scales is primarily based on United Nations population figures, but these statistics do not provide information on the distribution, pattern and evolution of the built environment (Zhang & Seto, 2011).

We use remote sensing data and techniques to provide a physical perspective on the evolving settlement patterns. Clear advantages in using remote sensing methods are the capacity for consistent mapping and periodic monitoring of large urban agglomerations such as mega-cities or mega-regions at various scales. In the following study we choose data from the Landsat programme which is an obvious and cost-effective choice as the data are freely available from USGS. Using this series of sensors allows to monitor spatial urbanization since the mid-1970s. For extending the time series we additionally opted for radar data. We use data from the radar satellites TerraSAR-X (TSX) and TanDEM-X (TDX) to delineate urbanized from non-urbanized areas (Esch et al., 2012; Taubenböck et al., 2012).

For our study we focus on the following research question by the use of large area, multi-temporal remote sensing data: Can we find specific spatial parameters which characterize the spatial configuration of a mega-region and which allow for an empirical definition of spatial mega-region attributes?

To find a systematic answer for the above mentioned research question we apply the following workflow schematically illustrated in Fig. 1. The headlines represent the structure of the paper. The study is basically oriented on the work published in Taubenböck et al. (2014).

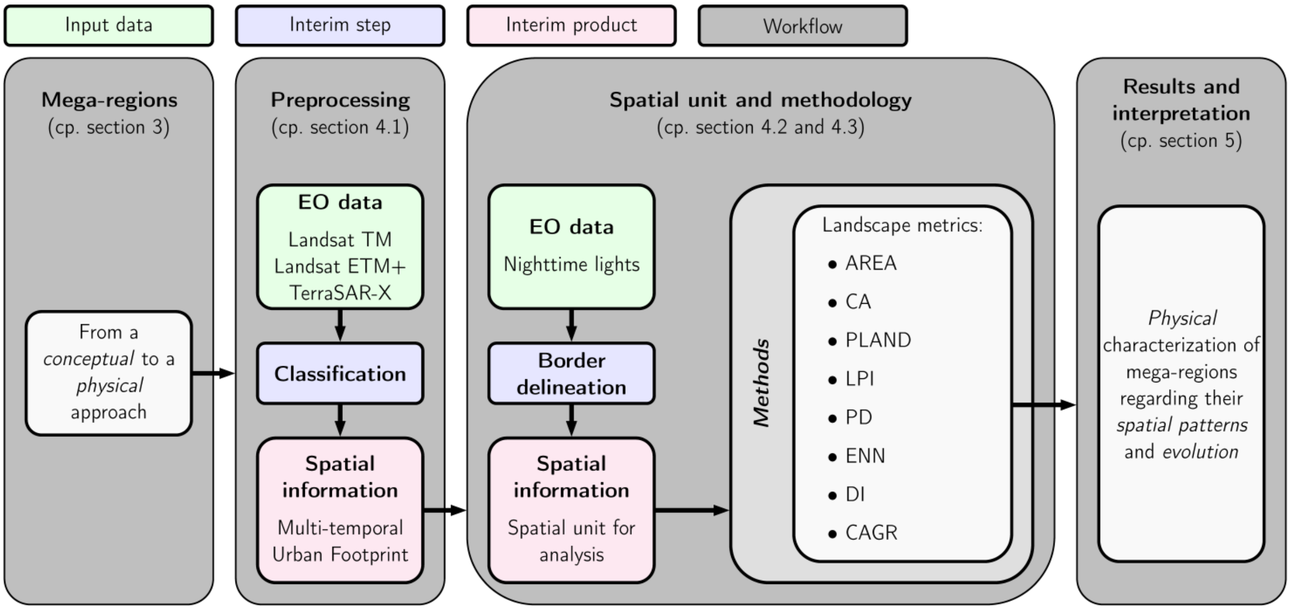

Fig. 1: Schematic overview of the workflow from a conceptual definition to the physical characterization of a mega-region.

3 THE CONCEPT OF MEGA-REGIONS AND THEIR PHYSICAL ATTRIBUTES

In literature there are many attempts to conceptualize the above mentioned new dimensions and types of settlement. In 2008 Florida et al. (2008) as well as the UN-Habitat (2008) suggested a new concept using the before mentioned term *mega-region* to capture the new nature of urban landscapes.

Mega-regions form a spatial unit territorially and functionally bound by several emerging city areas that result from the convergence growth (e.g. shared infrastructure systems) and spatial spread of geographically linked metropolitan areas and other agglomerations (Atlanta Regional Commission, 2008; Florida et al., 2008; UN-Habitat, 2008, Taubenböck et al., 2014). Further characteristics of mega-regions are the polycentric urban clustering surrounded by hinterlands with low densities regarding their settlement elements as well as the population growth which exceeds the growth of the overall population of the nations in which they are located (Florida, 2008).

Suggested examples of mega-regions in literature are the Hong Kong-Shenzhen-Guangzhou mega-region in China (home to approximately 120 million people), Nagoya-Osaka-Kyoto-Kobe in Japan (about 60 million), Philadelphia-Baltimore-Washington (named Bos-Wash) in USA (about 54 million) or Rio de Janeiro-Sao Paulo with about 43 million (Florida et al., 2008; UN-Habitat, 2008) among many others.

All of the above introduced concepts have the following properties:

(1) They classify the above introduced concept of a mega-region solely on a descriptive and qualitative level.

(2) An universal theory on their definition, location, evolution, spatial extent and delineation does not exist.

(3) Common approaches to delineate mega-regions are based on subjective perception of people or descriptive assumptions regarding land use and respective functional parameters. Nevertheless, respective resilient data sets on land use, commuting or socio-economy are very inconsistent across the globe or only available for case studies if available at all.

The central concern of this study is to overcome the qualitative stage of the conceptual definitions of mega-regions by classifying and characterizing the spatial pattern of the settlements and their evolution over time. Therefore we identify physical characteristics from the qualitative descriptions of mega-regions mentioned in the cited literature (after Taubenböck et al., 2014):

(1) The dimension of the area: several cities which are distributed over a large area beyond the dimensions of mega-cities form a mega-region;

(2) Poly-nuclei settlement pattern: cities which are formerly independent are at the mega-region stage physically linked to each other;

(3) Dynamics of urbanization: The urban growth dynamics exceed other regions or cities within the country.

4 METHODS

4.1 Classification method

We apply a backdating chronological workflow to optimize the outcome of the monitoring of spatial urbanization based on multi-sensoral EO data sets. Therefore, the classification aiming at delineating ‘urbanized’ from ‘non-urbanized’ areas starts with the latest data set, the TDX data from 2011, having the highest geometric resolution. For the TDX classification we classify VHR SAR images using a pixel-based approach. The result is a binary mask delineating ‘urbanized’ from ‘non-urbanized’ areas, a so called ‘urban footprint’ classification (Taubenböck et al., 2012; Esch et al., 2012).

For our backdating chronological workflow we use the urban footprint classification derived from TDX data from the year 2011 to support the classification of urban areas for the year 2000. The lower geometric resolution of the Landsat data as well as the related problem of mixed pixels makes it necessary to integrate the urban footprint classification from the year 2011 into our classification approach. With it we aim at reducing the possible areas for classifying urban areas in the scene of the 2000 time step to the particular spatial extension. Thus, we classify urbanized areas in the Landsat data only if the later time step confirms an urban location (Taubenböck et al., 2012). The classification of the Landsat scenes is based on an object-oriented hierarchical classification procedure, which has been elaborated by Abelen et al. (2011).

4.2 Spatial unit and methods

The spatial compositions of urban landscapes depend very much on the scale of observation. Therefore analysis and interpretation of landscape patterns are highly sensitive to the areas of interest as well as to the spatial and thematic scales. With respect to the available binary urban footprint classifications and the availability in multi-temporal resolution, we approach the spatial configuration and evolution of the mega-region in a self-defined spatial scale.

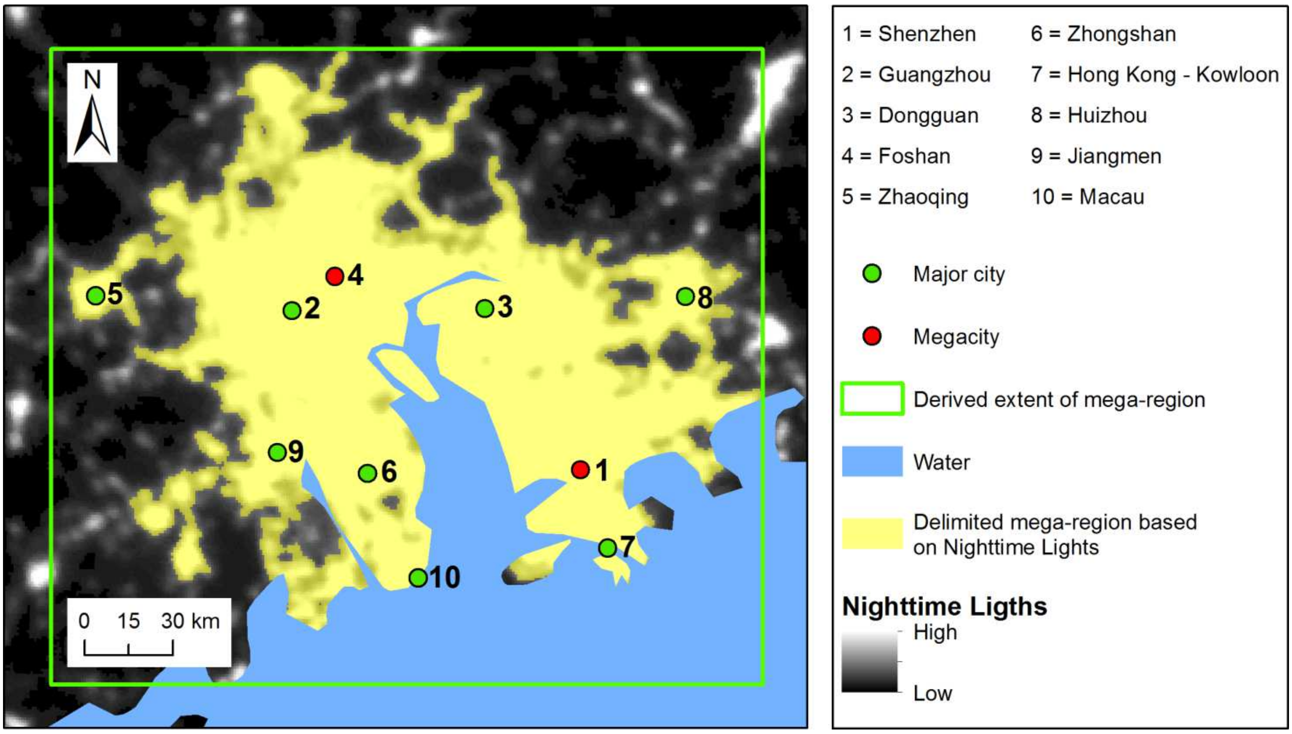

Fig. 2: Spatial delineation of the mega-region Hong Kong-Shenzhen-Guangzhou: The entire mega-region which contains 10 individual major cities of which two are mega-cities.

We use nighttime lights provided by the Defence Meteorological Satellite Program (DMSP-OLS) for a straightforward dissimilarity contrast split segmentation algorithm to differentiate between areas of light

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emission and dark areas as the light reflection inherits information on human activity (Fig. 2, NOAA, 2013, Taubenböck et al., 2014). Based on this we define a circumjacent rectangle drawn around the main body of coalescent areas of intense light emission to delineate the mega-region area (Fig. 2). We assume that the so extracted region inherits the spatial unit defining the area of interest for the entire mega-region (Taubenböck et al., 2014).

4.3 Spatial metrics for urban landscape analysis

Concerning two-dimensional urban patterns not even two spatial configurations across the globe are identical. However, it is a challenge to capture the complex patterns in a quantitative way. This is imporant for an objective identification of typical spatial features defining conceptual approaches such as mega-regions. For objective comparison beyond subjective visual inspection of the complex settlement pattern. We apply and develop spatial metrics at the defined spatial unit.

In the following we introduce the *Compound Annual Growth Rate* as well as *landscape metrics*.

4.3.1 Compound Annual Growth Rate (CAGR)

With the *Compound Annual Growth Rate* (CAGR) we aim at measuring the dynamics of spatial urban growth dependent on different time intervals (see equation 1). The CAGR is defined as annual growth rate of the considered measurement – in our case the change in urban extent between time step t_0 (i.e. 1975 in our case) and t – which can be related to different spatial units A (Taubenböck et al., 2014). Due to the approximate decadal availability of urban footprint classifications the spatial growth is interpolated per year.

$$CAGR(t_0, t) = \frac{A(t)}{A(t_0)}^{\frac{1}{N}} - 1 \qquad \text{(without unit)} \qquad (1)$$

4.3.2 Landscape metrics

One central goal of this study is to analyze the spatial landscape configuration using selected spatial metrics. These metrics have been introduced as quantitative measures of landscape configuration derived from digital analysis of thematic categorical maps showing spatial heterogeneity at specific scales and resolutions (McGarigal et al., 2002; McGarigal & Marks, 1995).

With the urban area as one thematic class of interest and with our main intention to identify typical features of the spatial urban landscape, we select complementary class-level-metrics to highlight landscape composition and landscape configuration from different points of view with respect to the class 'urban' (Riitters et al., 1995; Turner et al., 2001). We include in our analysis selected landscape metrics for the categories '*area and edge metrics*' and '*aggregation metrics*' (see table 1, McGarigal et al., 2012). We select landscape metrics based on particular hypotheses with respect to spatial changes as a consequence of urban growth processes.

Among the area and edge metrics we use the *Class Area* (CA) as a measure for the absolute urban area to define the dimension of the particular urbanized area.

The *Largest Patch Index* (LPI) gives the proportion of the total area occupied by the largest patch with respect to the entire landscape area *A* (Luck & Wu, 2002). It is a measure to define a metric, the *Modified Largest Patch Index* (MLPI), which also gives the proportion of the total area occupied by the largest patch with respect to the entire area of the class 'urban' (see equation 3). This metric is independent from the entire landscape area *A* and thus reveals the dominance of the main urban patch relative to the urbanized areas within the entire landscape (Taubenböck et al., 2014).

Among the '*aggregation metrics*' we apply the *Patch Density* (PD), which is the number of urban patches per area, as a measure of discrete urban areas in the landscape. Patch density is expected to increase during periods of rapid urban nuclei development, but may decrease if urban areas expand and merge into a continuous urban fabric (McGarigal et al., 2002; Seto & Fragkias, 2005).

For a quantitative measure on the relative location of the patches to each other we calculate two nearest neighbor metrics within the group of aggregation metrics: We calculate the *Mean Nearest Neighbor Distance* (ENN_MN). High values indicate isolation of patches, while low values indicate clustering of patches. Furthermore, the *Nearest Neighbor Coefficient of Variation* (ENN_CV) for patch distances measures relative variability around the mean of ENN (McGarigal & Marks, 1995). Thus, regularity or irregularity of the spatial patch composition can be indicated.

Beyond this, we use a *Dispersion Index* (DI) which is based on a combination of two above mentioned spatial metrics presented in Taubenböck et al. (2014): *Number of Patches* (NP) and the *Modified Largest Patch Index* (MLPI). The mathematical details are shown in equation 2 and 3.

$$NP = n_i \qquad (2)$$

with n_i equals the absolute number of patches of class *i*.

$$MLPI = \frac{\max_{j=1}^{n} a_{ij}}{CA} \cdot (100) \quad \text{(in percent)} \qquad (3)$$

The spatial dispersion index is defined as a function of NP and MLPI; we assume that in a two-dimensional feature space spanned by both parameters – NP and MLPI – an urban landscape with the complete urban area CA (class area) represented in one single coalescent urban patch is an idealistic representation of a monocentric, compact landscape; this is represented in one urban patch and thus a MLPI of 100%. If the complete urban area CA is represented by the maximum possible number of non-coalescent individual patches the landscape would be idealistically dispers.

Both parameters are weighted equally and are normalized to $NP_{norm.}$ and $MLPI_{norm.}$ while building ratios between NP respectively MLPI and CA. For that CA is first converted from hectares to pixels depending on the raster pixel size. The mathematical details for $NP_{norm.}$ and $MLPI_{norm.}$ are shown in euqations 4 and 5:

$$NP_{norm.} = \frac{NP-1}{CA-1} \cdot 100 \quad \text{(in percent)} \qquad (4)$$

$$MLPI_{norm.} = \frac{MLPI-\frac{1}{CA}}{100-\frac{1}{CA}} \cdot 100 \quad \text{(in percent)} \qquad (5)$$

All landscapes classified can be absolutely related within this two-dimensional feature space spanned by the parameters *Normalized Number of Patches* ($NP_{norm.}$) and the *Normalized Modified Largest Patch Index* ($MLPI_{norm.}$).

$$DI = \frac{NP_{norm.}+(100-MLPI_{norm.})}{2} \quad \text{(without unit)} \qquad (6)$$

If the DI approaches 0, then the pattern is compact with a low number of patches ($NP_{norm.}$) and the largest patch ($MLPI_{norm.}$) is integrating almost the entire urban landscape. This specific landscape can be interpreted as spatially monocentric. If the DI values approach 100 the number of patches is high and the dominance of the largest patch is very low, thus we are close to an idealistically, spatially dispersed landscape.

5 RESULTS

5.1 The mega-region Hong Kong-Shenzhen-Guangzhou

For testing the spatial approach and identifying spatial features which might be characteristic to define and classify an area as mega-region, we selected the *Hong Kong-Shenzhen-Guangzhou* area as representative case. This region is located in in the province of Guangdong on the South-East Chinese coast near to the piedmont and coastal plain physiographic regions, declining from the mountain areas in the north to sea level at the confluence of the Pearl River in the south (Yu & Ng, 2007).

Today two mega-cities – the provincial capital Guangzhou with 10.84 million inhabitants in 2011 and the economic hub Shenzhen (10.63 million in 2011) – are the dominating urban agglomerations (see Fig. 2); beside these two mega-cities several other large cities such as Dongguan, Foshan, Huizhou, Zhongshan, Jiangmen and Zhaoqing as well as two special administrative regions – Hong Kong and Macau – form a vast, polynuclei region with several dynamic extra-large cities and big cities of different sizes and types.

Population statistics assess that within the mega-region Hong Kong-Shenzhen-Guangzhou 120 million people are living (Oizumi, 2011). However, the population statistics mentioned above do not provide knowledge on the current physical processes.

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5.2 Spatial characteristics of a mega-region

In Fig. 3 the multi-temporal classification result for the entire mega-region Hong Kong-Shenzhen-Guangzhou is illustrated and shows us a very large and complex urban settlement pattern. It is characteristic that the city landscape stretches far beyond individual city limits to a more or less coalescent polynuclei pattern spanning roughly an area of 250 km times 220 km (Taubenböck et al., 2014). The multi-temporal classification pictures the highly dynamic process of spatial urbanization since the 1970s.

Subject	Metric	Formula	Units	Range
Area and edge metrics	AREA	$AREA = a_{ij}\left(\frac{1}{10000}\right)$	hectares	$AREA > 0$
	CA	$CA = \sum_{j=1}^{n} a_{ij}\left(\frac{1}{10000}\right)$	hectares	$CA > 0$
	PLAND	$PLAND = \frac{\sum_{j=1}^{n} a_{ij}}{A} \cdot (100)$	percent	$0 < LPI \leq 100$
	Largest Patch Index (LPI)	$LPI = \frac{\max_{j=1}^{n} a_{ij}}{A} \cdot (100)$	percent	$0 < PLAND \leq 100$
Aggregation metrics	Patch Density (PD)	$PD = \frac{n_i}{A} \cdot (10000) \cdot (100)$	Number per 100 hectares	$PD > 0$
	Euclidean Nearest-Neighbor Distance (ENN)	$ENN = h_{ij}$	meters	$ENN > 0$
Custom metrics	Dispersion Index (DI)	$DI = \frac{NP_{norm.} + (100 - MLPI_{norm.})}{2}$	percent	$0 \leq DI \leq 100$
Other metrics	CAGR	$CAGR(t_0, t) = \left(\frac{A(t)}{A(t_0)}\right)^{\frac{1}{N}} - 1$	none	$CAGR \geq 0$

Table 1: Mathematical details of the used spatial metrics for landscape quantification where aij ist the area (m²) of patch j of class i, A is the total landscape area in m² and hij is the distance (m) from patch ij to the nearest neighboring patch of the same type (class) based on patch edge-to-edge distance, computed from cell center to cell center.

It is characteristic for the time step of 1975 that individual more or less concentric city patterns with significant distances to the next larger city shaped the urban landscape. In between large and low dense rural areas separated the cities, thus a spatial connectivity was not given. This has altered significantly. Today a massive spatial urban sprawl shaping a more or less coalescent, highly complex, very large urban landscape. While in the 1970s each city can be considered spatially as a center in its own right, the pattern with today's large urban extensions and their almost totally merged shapes create a transformed, now coalescent multi-nuclei urban landscape (Taubenböck et al., 2014).

Based on the change detection we aim at quantitatively measuring the spatial urban configuration of the developing patterns for an empirical definition of possibly characteristic spatial mega-region attributes.

In general the CAGR (see equation 1) reveals very high spatial urban growth dynamics at mega-region level, with the highest dynamics in the 1990s of over 9 % (see figure 4 (left)). With respect to other studies, the mega-region grows spatially with higher dynamics (up to more than 13 times its spatial extent with respect to 1975; figure 4 (right)) than e.g. mega-cities. Indeed, in China even mega-cities such as Beijing (7 times) or Shanghai (6 times) spatially grow less dynamic, indirectly confirming the statement in chapter 3, that mega-regions grow considerably faster than other parts of the nation (Taubenböck et al., 2014 & 2014b).

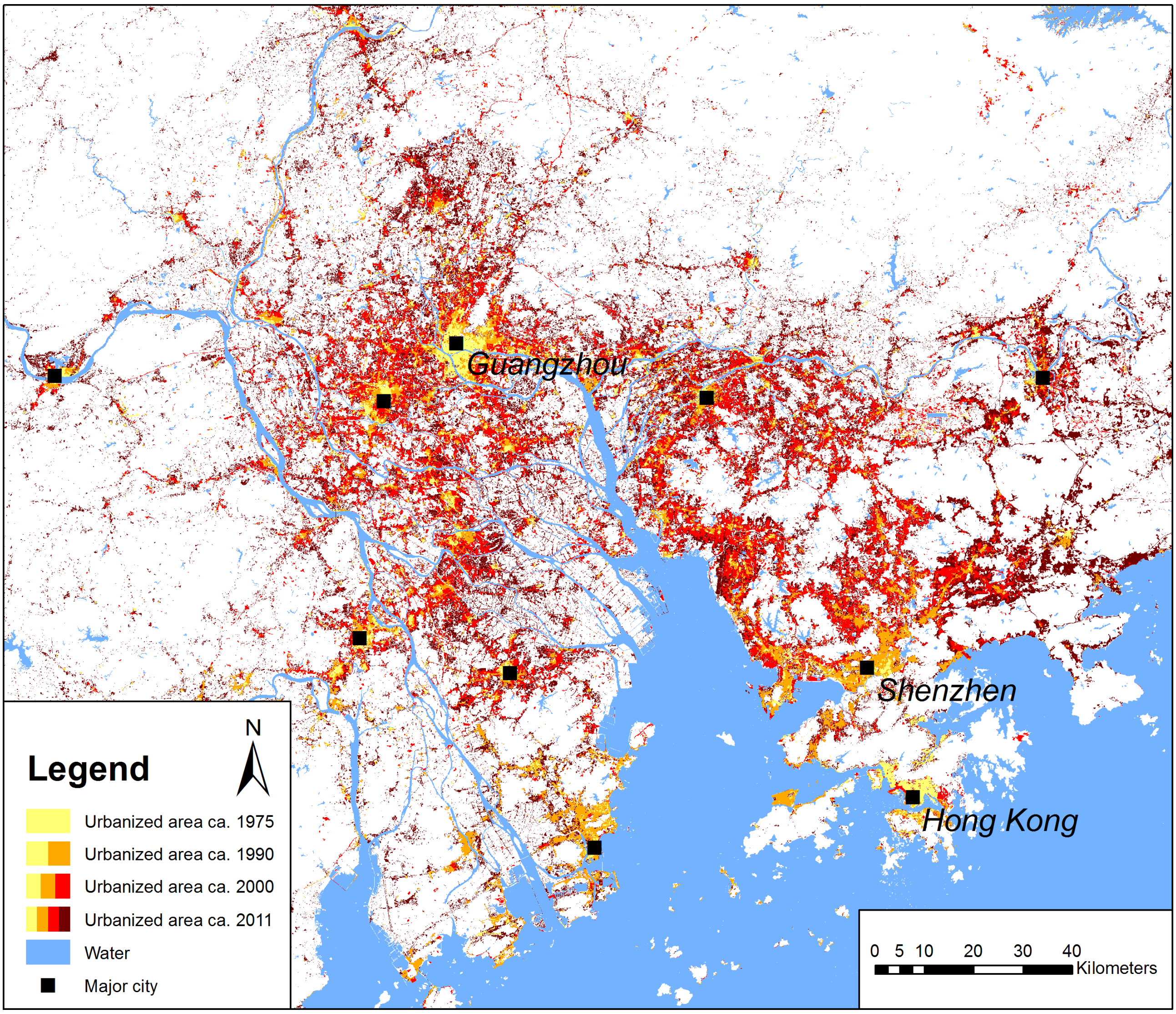

Fig. 3: Spatial development of the mega-region Hong Kong-Shenzhen-Guangzhou mapped from multi-temporal EO-data since the 1970s.

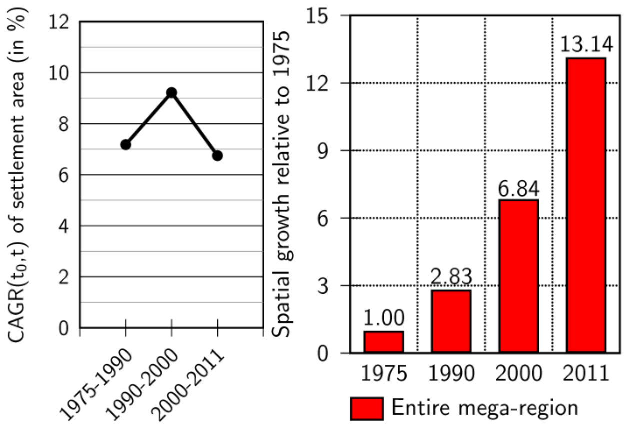

Fig. 4: Compound Annual Growth Rate (CAGR) of settlement area concerning the defined spatial extent of the mega-region (left) and the spatial growth of settlement areas for the entire mega-region relative to the urban footprint area in 1975 (right) (after Taubenböck et al., 2014).

Regarding the spatial configuration of the urban landscape we observe an continuously increasing LPI with a massive increase in the last decade (see figure 5 (left)). In general the values of LPI are low, when compared to other studies focusing on individual cities. This can be seen as a logical consequence as we deal with a multi-nuclei urban landscape. However, if the LPI calculated only on the urban footprint area (MLPI), the values of the MLPI show that coalescent processes reveal a relative dominance of a large patch (this can be

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traced back to the coalescing growth in the Guangzhou-Foshan area, where two neighbouring large cities developing a spatial focal point in the area) (see figure 3). Fig. 5 shows us that the value of the MLPI decreases from 1975 to 1990, what can be interpreted as beginning urban sprawl.

As a logical consequence of spatial urban growth combined with urban sprawl processes the PD is rising over all four time steps (see figure 5 (second from the left)). In particular, the immense increase between the years 2000 and 2011 can be lead back to intensive sprawling processes. At the same time we observe a decreasing mean nearest neighbor distance (ENN_MN) of urban patches hinting especially at densification processes of settlements in formerly low dense, spatially clearly separated areas between cities (see figure 5 (second from the right)). On the contrary the coefficient of variation of the Euclidean mean nearest neighbor distance (ENN_CV) rises permanently since 1990 as a consequence of densification process in a sprawling urban area (see figure 5 (right)).

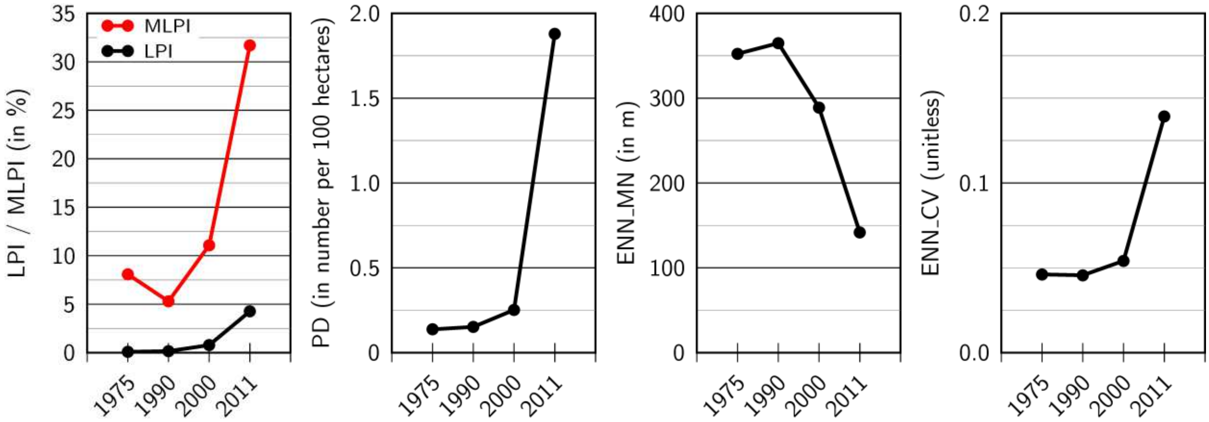

Fig. 5: Temporal development of LPI, MLPI, PD, ENN_MN and ENN_CV for the entire mega-region (after Taubenböck et al., 2014).

The dispersion index (DI) for the mega-region stays relatively constant for the years 1975 until 2000 (46.6; 47.6; 44.6) although spatial growth rates were enourmous (see figure 6). Accordingly, compaction and thus spatial weight of the largest patch within the mega-region basically balances splinter development. Since 2000 the DI shows a significant reduction (34.8) proofing a coalescent process to a multi-nuclei mega-region. Similarily, the behaviors of the city and the hinterland patterns reveal a tendency towards a more compact pattern.

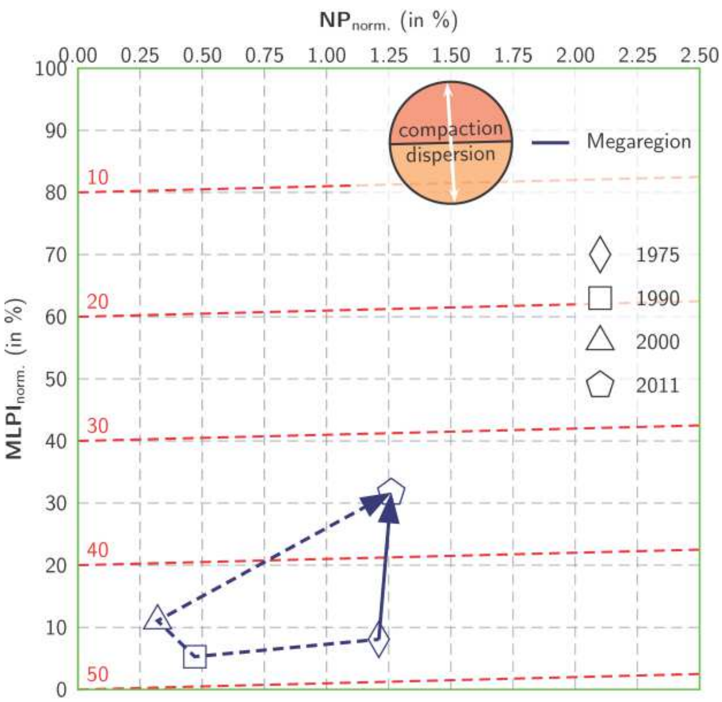

Fig. 6: The Dispersion Index (DI) as a function of NPnorm. and MLPInorm..

In Fig. 6 the y-axis as well as the x-axis are calculated relatively; this means that the Number of Patches (NP) as well as the Largest Patch Index (MLPI) are normalized spanning from 0 to 100 ($NP_{norm.}$ and $MLPI_{norm.}$) according to equations 4 and 5. The change of a pattern over time toward the lower right corner (this means an increasing number of patches and a decreasing size of the largest patch) within the two-dimensional diagram indicates a rising grade of spatial dispersion. The development of DI values vice versa toward the upper left corner in Fig. 6 indicates a more compact pattern (Taubenböck et al., 2014).

6 MAIN FINDINGS, DISCUSSION AND CONCLUSIONS

The main findings of this study refer to the research questions stated in chapter 2: Can we find specific spatial parameters which characterize the spatial configuration of a mega-region and which allow for an empirical definition of spatial mega-region attributes?

It is characteristic for our dynamically urbanizing world that new types of massive settlement types are evolving. The concept of mega-regions tries to capture this aspect by describing a large polynuclei coalescent urban area defined and bound by different systems – economic, transport, trade, settlements, political, etc.

We used multi-source remote sensing data for a consistent large area mapping and generated urban footprints for four time steps, namely 1975, 1990, 2000 and 2011. A major advantage of the applied multi-sensoral approach for long-time spatial monitoring consists in the consistently high classification accuracies between 80 and 90% (Taubenböck et al., 2012); however, it has to be mentioned that sensor changes as well as different physical aspects and geometric resolutions between Landsat and TSX/TDX data might, to a certrain degree, influence the pattern analysis.

By this spatial concept we characterize *spatial configurations of a mega-region*, which has been suggested in literature. With our suggested approach we introduced spatial features allowing for a possible *empirical definition of spatial mega-region attributes*.

In general the results confirm the identified physical characteristics from the qualitative descriptions of mega-regions from the cited literature. We observe the mega-region as an urban landscape growing far beyond an individual center. Thus, it is impossible to identify the borders between city, suburb, exurb or townscape. The dimension of the entire urban area is far beyond individual cities or respective mega-cities. Also the spatial dynamics are immense (13.14 times its spatial extent since 1975) and overcome the growth rates of mega-cities in China such as Beijing or Shanghai.

In general, we measure increasing values of the LPI and MLPI for the analyzed region. Although PD and therefore indirectly NP is increasing over time the coincidental and more intensive increase of MLPI results in a decreasing DI. This means the entire region is developing towards spatial compactness. Because of the slight but steady increase of PD we also identify a decreasing ENN_MN as well as a rising ENN_CV revealing trends of urban sprawl.

This study suggests physical parameters to define the abstract concept of mega-regions. As this approach has only been tested on one example – the Hong Kong-Shenzhen-Guangzhou mega-region in China – comparative studies to other mega-regions are critical to prove that the main findings are de facto characteristic for these large urban landscapes or if the special orographic, economic, transport, etc. situation has a higher influence on the resulting urban pattern. Beyond this, a complementary analysis of different systems such as trade or transport within the respective mega-region is of crucial importance to find a broader picture on the spatial delineation of mega-regions. Earth observation has to take its share in providing a larger data base for systematic urban analysis.

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