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Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures

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ABSTRACT

The term urban heat island describes the phenomenon of altered temperatures in urban areas compared to their rural hinterlands. A surface urban heat island encompasses the patterns of land surface temperatures in urban areas. The classical indicator to describe a surface urban heat island is the difference between urban and rural surface temperatures. However, several other indicators for this purpose have been suggested in the literature. In this study, we compared the eleven different indicators for quantifying surface urban heat islands that were most frequently used in recent publications on remote sensing-based urban heat island assessments. The dataset used here consists of 263 European cities with monthly mean temperatures from MODIS data products for July 2002, January 2003 and July 2003. We found that (i) the indicators individually reveal diurnal and seasonal patterns but show rather low correlations over time, and (ii) for single points in time, the different indicators show only weak correlations, although they are supposed to quantify the same phenomenon. Differentiating cities according to thermal climate zones increased the relationships between the indicators. Thus, we can identify temporal aspects and indicator selection as important factors determining the estimation of urban heat islands. We conclude that research should take into account the differences and instabilities of the indicators chosen for quantifying surface urban heat islands and should use several indicators in parallel for describing the surface urban heat island of a city.

1. Introduction

The urban heat island (UHI) effect describes the influence of urban surfaces on temperature patterns in urban areas as opposed to surrounding areas (Oke, 1982). Apart from arid and semi-arid areas, the UHI shows higher temperatures in urban than in rural areas (e.g., Jin et al., 2005) and depends on a variety of factors, such as latitude, height above sea level, topography, city size (Wienert & Kuttler, 2005) and atmospheric stability (Tomlinson et al., 2010). The UHI not only influences the quality of life and human well-being in urban areas (Harlan et al., 2006; Lafortezza et al., 2009) but also alters ecological functions, such as the provision of water resources and air quality (Grimm et al., 2008), and biodiversity (Knapp et al., 2010).

UHIs manifest themselves in different forms in a city and its rural hinterlands: They influence air temperatures in the canopy layer (micro-scale; roughly from the ground to tree or building height) as well as e.g. precipitation in the boundary layer (meso-scale; in the layer of the atmosphere that is still affected by the city, but above the canopy layer) (Oke, 1982). Furthermore, UHIs are distinguished for surface temperatures as well as for subsurface temperatures (Arnfield, 2003; Yow, 2007). Two main strands of research have evolved for quantifying the UHI: First, the UHI of the canopy layer is determined by measuring air temperatures (usually 2 m) above ground. This measurement is performed either on a traverse through a city or by comparing temperatures from point measurements, for instance, in the city centre versus surrounding rural areas (Arnfield, 2003; Stewart, 2011). Second, the surface UHI is derived from remote sensing data (Voogt & Oke, 2003). Whereas measurements of air temperatures above the ground directly refer to the UHI in the canopy layer, remote sensing data use the thermal emissivity of land surfaces and the derived land surface temperatures (LSTs). Remotely sensed data and above ground air temperatures are not identical, but related (Mostovoy et al., 2006; Prihodko & Goward, 1997). However, the term "surface UHI" is often used to explicitly distinguish UHIs measured using LSTs from air temperature patterns (e.g., Voogt & Oke, 2003).

LSTs have the advantage of spatially explicit datasets, compared to single measurement points or traverses. A variety of remote sensing products are also available in time series. Thus, remote sensing data are frequently used for assessing surface UHIs (Voogt & Oke, 2003; Weng, 2009) with a variety of indicators. The classical approach is to analyse the difference of urban and rural temperatures (Dousset & Gourmelon, 2003; Gallo et al., 1993; Kottmeier et al., 2007; Roth et al., 1989; Runnalls & Oke, 2000). However, the differentiation between "urban" and "rural" remains diverse and confusing (Stewart & Oke,

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2009). Lowry (1977) in his conceptual model defines rural areas as parts of a city region that are not influenced by the urban heat island; consequently the differentiation between urban and rural areas is a result of the urban heat island analysis. However, remote sensing studies often include a priori definitions of "urban" versus "rural" areas according to land cover. Researchers use a variety of methods to delineate the "urban core" versus the "rural part", including downtown districts versus selected rural districts (Dousset & Gourmelon, 2003); pixels around urban and rural weather stations (Gallo et al., 1993; Tomlinson et al., 2010 for the rural area); pixels with high imperviousness versus a buffer lying 15 to 20 km away from low imperviousness areas (Imhoff et al., 2010; Zhang et al., 2010); and areas with the highest LST versus areas with rural land cover (Roth et al., 1989).

Furthermore, several other indicators (Table 1) have additionally been developed: the *difference urban − water* (Chen et al., 2006), the *hot island area* (Zhang & Wang, 2008), the shape properties of a fitted three-dimensional Gaussian bell (Streutker, 2002) or the *magnitude* of the LST (Rajasekar & Weng, 2009). The indicators *magnitude* and *hot island area* are examples of remote sensing indicators that do not use a priori definitions of "urban" and "rural". Furthermore, the sensors used to study the surface UHI also vary (see also Table 1). Depending on the combination of sensors and satellites used, different spatial resolutions for thermal emissivity are available. Finally, not only the indicators but also the chosen seasons and time of day for assessing the surface UHI differ in the literature (again, see Table 1; Weng, 2009). A comparison of studies is further complicated by the fact that studies on the surface UHI use different spatial extents: Some studies employ a complete satellite image that covers an entire urban region (e.g., Aniello et al., 1995; Streutker, 2002), whereas others use administrative boundaries (e.g., Zhang & Wang, 2008) or a combination of administrative boundaries and the layout of remote sensing images (Rajasekar & Weng, 2009).

Given the variety of surface UHI indicators and chosen points in time reported in the literature, the aim of this study is to analyse the similarities of and differences between these indicators and to systematically compare the results for different seasons and times of the day. To achieve this, we compute and analyse the surface UHI for a large number of European cities and employ a consistent way to delineate them. We hypothesise that:

Hypothesis 1. Absolute values for the single surface UHI indicators are not constant over time but rather show similar diurnal and seasonal changes.

Hypothesis 2. Results for the European cities under study regarding a single surface UHI indicator are temporally stable, implying that measurements of different points of time lead to similar rankings of cities.

Hypothesis 3. Indicators used in the literature were all designed to measure the same phenomenon and are thus correlated for the same time step. This analysis is performed with LST datasets from MODIS, which are frequently used for surface UHI analysis (i.e. Hung et al., 2006; Imhoff et al., 2010; Jin et al., 2005; Rajasekar & Weng, 2009; Tomlinson et al., 2010; Zhang et al., 2010; Zhou et al., 2010).

The remainder of this study is organised as follows. In Section 2, the data and surface UHI indicators are described. Section 3 includes the results and discussion. Results are presented regarding temporal variations within indicators (Hypothesis 1, Section 3.1) with respect to diurnal and seasonal changes and a comparison of two summers. In Section 3.2, the temporal stability of all indicators is assessed (Hypothesis 2). Finally, similarities of the surface UHI indicators are analysed (Hypothesis 3; Section 3.3). This is carried for the total set of cities, as well as cities clustered by biome and thermal climate zone. Section 4 includes the summary and conclusion.

2. Data and methods

This study covered a total of 263 European cities (Fig. 1, see also the Appendix A for a list of all cities). These are the cities which take part in the Urban Audit initiative (Section 2.1.3), have provided spatial data on their administrative boundaries for the year 2001 plus basic statistical data such as population number, and are located on the

Table 1
UHI indicators for remote sensing data.

Indicator	Units	Quantification in this study	Related references [sensor used in the original study; temporal resolution]
Difference urban − agriculture	K	Difference in mean LST between urban area and cropland	Jin et al.(2005) [MODIS; day and night, several days]
Difference core − rural	K	Difference in mean LST between urban (administrative area) and rural (buffer of 20 km² around the city) areas	Imhoff et al.(2010) [MODIS; day and night; several days] Zhang et al.(2010) [MODIS; day and night, several days]
Difference urban − other	K	Difference in mean LST between urban area and all other areas	Dousset and Gourmelon(2003) [NOAA-AVHRR; day and night, several days] Gallo et al.(1993) [NOAA-AVHRR; day, several days] Roth et al.(1989) [NOAA-AVHRR; day and night, several days] Tomlinson et al.(2010) [MODIS; night, several days] Zhou et al.(2010) [MODIS, day and night, several years]
Difference urban − water	K	Difference in mean LST between urban area and water surface	Chen et al.(2006) [Landsat 5 + 7; several days]
Gaussian area	km^2	Area under a Gaussian surface fitted to LST, after the rural LST background has been subtracted	Hung et al.(2006) [MODIS; day and night, several days] Streutker(2002) [NOAA-AVHRR; day, several days], 2003 [NOAA-AVHRR; day and night, several days]
Gaussian magnitude	K	Maximum of a Gaussian surface fitted to LST, after the rural LST background has been subtracted	Hung et al.(2006) [MODIS; day and night, several days] Streutker(2002) [NOAA-AVHRR; day, several days], Streutker (2003) [NOAA-AVHRR; day and night, several days]
Hot island area	km^2	Area with LST higher than the mean plus one standard deviation	Zhang and Wang(2008) [Landsat 7; 1 image]
Magnitude	K	Difference between maximum and mean of LST	Rajasekar and Weng(2009) [MODIS; day and night, several days]
Micro-UHI	%	Percentage of area (without water surfaces) with LST higher than the warmest LST associated with tree canopies	Aniello et al.(1995) [Landsat 5; 1 image]
Standard deviation	K	Standard deviation of LST in the administrative area	
Gaussian magnitude empirical	K	Maximum difference between the temperatures in urban and fitted rural temperature surfaces	

LST: Land surface temperature. If not stated otherwise, all LST are measured within the administrative boundary of the respective city. For indicators related to the Gaussian bell, see Appendix B.

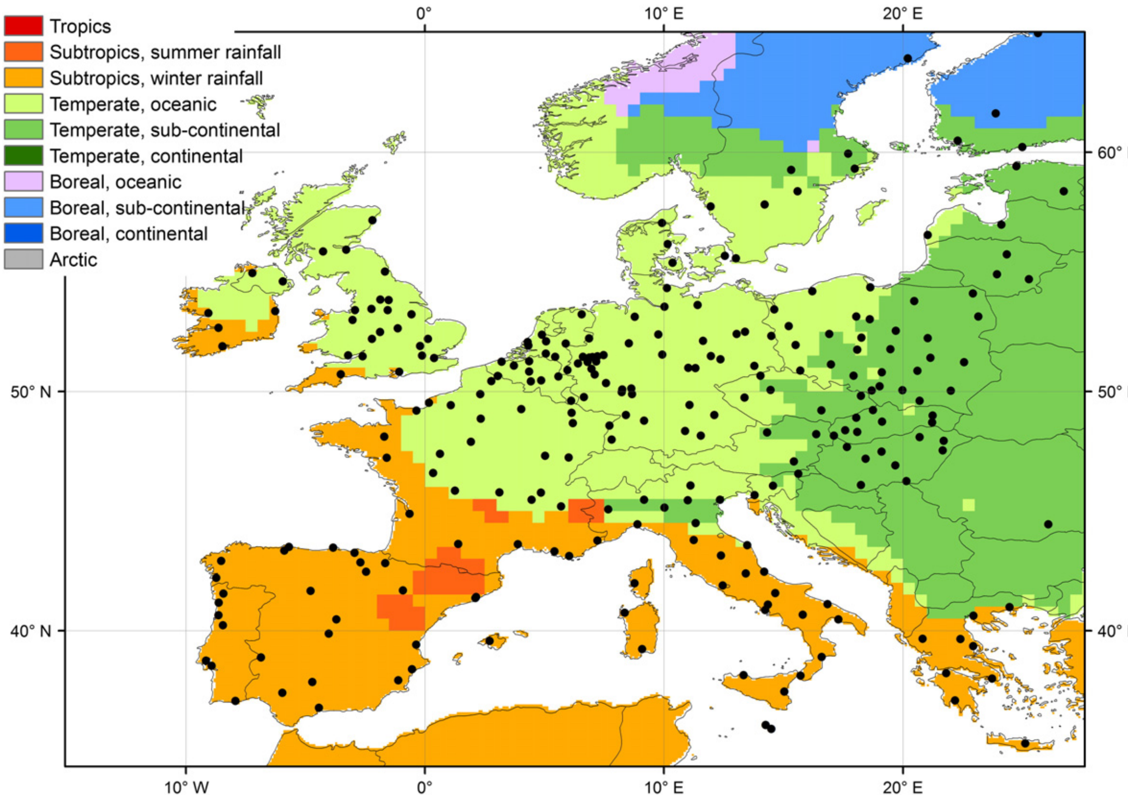

Fig. 1. Map of analysed cities with thermal climatic zones by the FAO.

European continent. Cities are delineated against one another using administrative boundaries. When quantifying a single indicator such as *difference urban — water*, we have used the MODIS land cover product (Section 2.1.2) for identifying the pixels with urban land cover or water areas. The only exception is the indicator *difference core — rural* for which the administrative boundaries were used to identify urban and rural parts (Section 2.2).

We have used LST data for July 2002 and January 2003 to represent the summer and winter surface UHI, respectively. Furthermore, we included July 2003 to also investigate a case of an extreme heat wave. Depending on the quantification of the indicator in question (Section 2.2), LST (Section 2.1.1) of different pixels were combined.

2.1. Data

2.1.1. Data on land surface temperatures

The MODIS (MODerate-resolution Imaging Spectroradiometer) instrument is located on both the Terra and Aqua NASA satellites. The Terra satellite provides images for 10:30 and 22:30 h local solar time, while Aqua conducts monitoring at 01:30 and 13:30 h. For this study, images provided by both satellites were used. The LST products Terra: MOD11A2 and Aqua: MYD11A2 were chosen with a resolution of approximately 1000 m and aggregated for eight consecutive days. We computed the monthly mean LST per pixel and time of day by aggregating the available 8-days-mean. Wan (2008) reported an accuracy of the MODIS products better than 1 K for most cases of validation, whereas Wang et al. (2008) found larger biases for vegetation at some sites. Rigo et al. (2006) compared different satellites with respect to in-situ measurements of LST in urban areas and found less than 5% differences for MODIS LSTs.

2.1.2. Data on land cover and regions

Some indicators rely on land cover (for instance by comparing urban areas with water surfaces). For these indicators, the MODIS product "land cover type" (MCD12Q1) was used with a spatial resolution of 500 m in the year 2003 and aggregated to the same spatial resolution as the LST. This data set is a derived product out of different spectral bands of the MODIS instruments. For differentiating cities into similar regions during the analysis, data on biomes and climate zones were used. The 2004 updated database of the World Wildlife Fund on terrestrial ecoregions of the world (Olson et al., 2001) provided the biomes, and the delineation of thermal climates by the Food and Agriculture Organization (FAO, 2007) was used for climatic characterisation of Europe.

2.1.3. Spatial delineation of cities

Spatially explicit data on administrative boundaries were acquired for cities participating in the Urban Audit initiative (Eurostat, 2004, 2007). The Urban Audit initiative aims at providing economic and social statistical information for analysing pan-European urban development. The Urban Audit was initialized by the Directorate-General for Regional Policy at the European Commission and has been implemented with the support of Eurostat and the national statistical offices of 27 European countries (25 member states of the European Union plus Bulgaria and Romania). Data were downloaded from the Eurostat website for the year 2004.

2.2. Surface UHI indicators addressed in this study

All of the UHI indicators currently reported in the literature (Table 1) were included in this study. For the main approach, the difference of urban and rural areas, two variations are included in this study: The indicator *difference core — rural* uses the mean LST of administrative city minus the mean LST of a 20 km buffer around the city. The indicator *difference urban — other* pixels accounts for temperature differences between urban land cover and other presumably rural land within the administrative area. Furthermore, several additional indicators have been suggested in the literature and are also included here. First, differences in the LST between urbanised land and other land cover types, such as the *difference urban —*

agriculture (Jin et al., 2005) or *difference urban − water* (Chen et al., 2006) are used. Second, surface temperatures are interpreted as forming a Gaussian bell that can be measured in terms of height when considering the increasing temperature and ground area (developed by Streutker, 2002, 2003; applied for instance, by Hung et al., 2006). Third, the total area with temperatures higher than one standard deviation above the mean is used as an indicator (*hot island area*, Zhang & Wang, 2008). Fourth, the *magnitude* (maximum minus mean) of the LST in the administrative area is computed (Rajasekar & Weng, 2009). Finally, the *micro-UHI* is the percentage of the area with an LST higher than the warmest temperatures associated with tree canopies (Aniello et al., 1995).

Finally, two simple indicators were added that are easily derived out of the indicators used in the literature: The *standard deviation* of the LSTs in a city is another indicator related to descriptive statistics and is somewhat similar to the *magnitude*. The height of the Gaussian bell was also measured empirically (*Gaussian magnitude empirical*). All of the definitions and equations used are listed in Table 1.

3. Results and discussion

Descriptive statistics for all indicators and all points in time are depicted in Fig. 2.

3.1. Temporal variations within indicators

The descriptive statistics for all indicators and points in time showed clear temporal signals. Hypothesis 1 assumes that all surface UHI indicators show the same pattern of change over time. This refers to (3.1.1) diurnal changes and (3.1.2) seasonal differences between the January and July data, as well as (3.1.3) differences between the data collected in July 2002 and July 2003 to check if all surface UHI indicators respond to the 2003 heat wave in the same way.

3.1.1. Diurnal changes

The diurnal changes for July 2002 and January 2003 are depicted in Fig. 3. To statistically test the differences between these points in time, non-parametric Wilcoxon tests were performed. The results for diurnal changes are summarised in Table 2. For most of the indicators, the surface UHI was highest in daytime (13:30 h) and lowest at night (01:30 h or 22:30 h). Only the indicator *hot island area* showed the opposite tendency of a smaller surface UHI during the day, although only a few points in time were statistically significant. Thus, Hypothesis 1 was rejected for the *hot island area*. Compared to the other indicators, the *difference core − rural* showed a smaller surface UHI in Kelvin with a lower diurnal change.

The separate findings for the surface UHI indicators are in line with the results documented in the literature. For instance, Rajasekar and Weng (2009) also reported a higher daytime *magnitude* than at night. Zhang et al. (2010) found a higher *difference core − rural* for daytime surface temperatures, Zhou et al. (2010) reported *difference urban − other* to be highest at 1:30 h, and the *Gaussian magnitude* was also higher during the day than in the night (Hung et al., 2006). Thus, the general observation of higher surface UHI values during the day versus the night holds here for most cases, while the air temperature UHI value tends to be higher during the night (Roth et al., 1989; Runnalls & Oke, 2000).

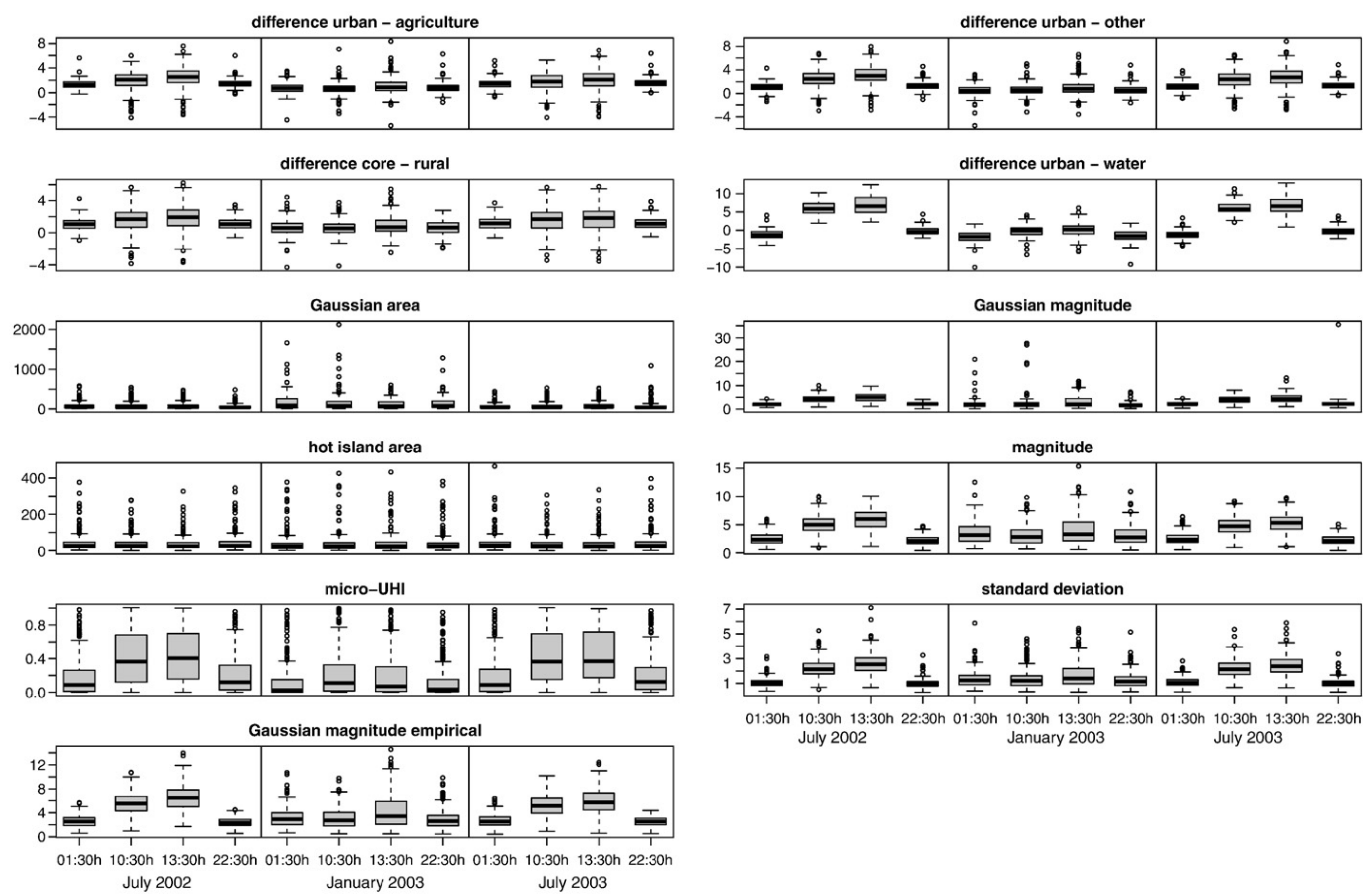

Fig. 2. Boxplots for all indicators and points in time. For each point in time, the empirical distribution of values in the 263 cities is given. The two 'hinges' are versions of the first and third quartile; the whiskers extend to 1.5 times the inter quartile range; and observations outside that range are displayed as points. For details on the indicators and their units, refer to Table 1.

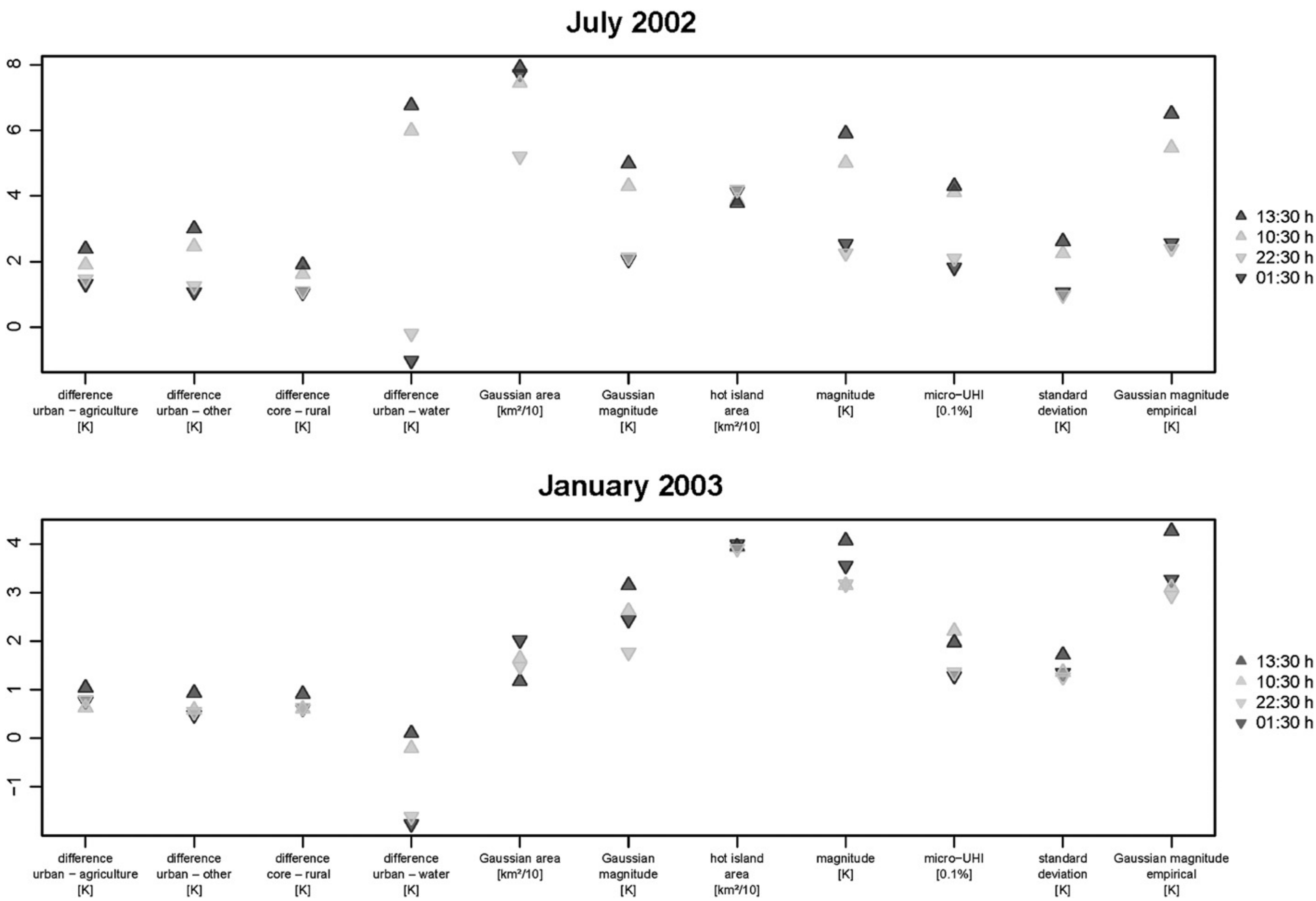

Fig. 3. Diurnal changes in July 2002 and January 2003. Mean values for each indicator in July 2002 and January 2003 are shown. Note that Gaussian area, hot island area and micro-UHI have been scaled by a factor of 0.1.

3.1.2. Seasonal changes

Seasonal changes are related to the comparisons between January 2003 and July 2002 and 2003. Except for the *difference urban — water*, all indicators showed a higher surface UHI for July than for January (see again Fig. 3). Consequently, Hypothesis 1 was rejected for *difference urban — water*. All Wilcoxon tests were statistically significant with a $p<.01$. In the literature, the winter *Gaussian magnitude* (Hung et al., 2006), the *magnitude* (Rajasekar & Weng, 2009) and *difference urban — other* (Zhou et al., 2010) were also found to be lower than in summer.

3.1.3. Changes between July, 2002 and 2003

A comparison of the surface UHI for July 2002 and July 2003 showed statistically significant differences between these two months (Table 3). For most indicators, the surface UHI was significantly larger for July 2002 in the daytime, when the surface UHI was largest during the diurnal cycle. On the contrary, the surface UHI was larger in July 2003 than in July 2002 at night. Hypothesis 1 was rejected for *Gaussian area*, which statistically significant did not follow this pattern. When considering the mean surface UHI per indicator and month, the indicators *difference urban — agriculture*, *difference*

Table 2
Diurnal changes for all indicators.

Indicator [unit]	July 2002				January 2003				July 2003			
	01:30 to 10:30 h	10:30 to 13:30 h	13:30 to 22:30 h	22:30 to 01:30 h	01:30 to 10:30 h	10:30 to 13:30 h	13:30 to 22:30 h	22:30 to 01:30 h	01:30 to 10:30 h	10:30 to 13:30 h	13:30 to 22:30 h	22:30 to 01:30 h
Difference urban — agriculture [K]	↗	↗	↘	↘	↘*	↗	↘*	n.s.	↗	↗	↘	↘
Difference urban — other [K]	↗	↗	↘	↘	n.s.	↗	↘	n.s.	↗	↗	↘	↘
Difference core — rural [K]	↗	↗	↘	n.s.	n.s.	↗	↘	n.s.	↗	↗	↘	n.s.
Difference urban — water [K]	↗	↗	↘	↘	↗	↗*	↘	n.s.	↗	↗*	↘	↘
Gaussian area [km²]	n.s.	n.s.	↘	↗	n.s.	n.s.	n.s.	n.s.	↗*	n.s.	↘	↘
Gaussian magnitude [K]	↗	↗	↘	↘	n.s.	↗	↘	n.s.	↗	↗	↘	↘
Hot island area [km²]	↘*	↘	↗	n.s.	n.s.	n.s.	n.s.	n.s.	↘	n.s.	↗	n.s.
Magnitude [K]	↗	↗	↘	↗	↘	↗	↘	↗	↗	↗	↘	↗
Micro-UHI [%]	↗	n.s.	↘	↘	↗	↗*	↘	n.s.	↗	n.s.	↘	↘
Standard deviation [K]	↗	↗	↘	↗	n.s.	↗	↘	↗	↗	↗	↘	↗
Gaussian magnitude empirical [K]	↗	↗	↘	↗	↘*	↗	↘	↗	↗	↗	↗	n.s.

Arrows indicate a statistically significant difference from one point in time to the next during the same month, as tested with Wilcoxon signed-rank tests. The direction of the arrows indicates increases and decreases, respectively. n.s.: not significant. Without asterisk: statistically significant with a $p<.01$.

* Statistically significant with a $p<.05$.

Table 3
Differences between July 2002 and July 2003 for all indicators.

Indicator [unit]	July 2002				July 2003				Significance of difference			
	01:30 h	10:30 h	13:30 h	22:30 h	01:30 h	10:30 h	13:30 h	22:30 h	01:30 h	10:30 h	13:30 h	22:30 h
Difference urban − agriculture [K]	1.33	1.90	2.38	1.47	1.42	1.71	2.02	1.56	**	**	**	**
Difference urban − other [K]	1.08	2.46	3.00	1.27	1.15	2.33	2.70	1.34	**	**	**	**
Difference core − rural [K]	1.07	1.62	1.89	1.11	1.19	1.56	1.72	1.19	**	n.s.	**	**
Difference urban − water [K]	−1.01	5.98	6.75	−0.18	−1.20	6.05	6.60	−0.17	n.s.	n.s.	n.s.	n.s.
Gaussian area [km²]	77.30	74.29	79.03	52.17	61.11	80.63	88.33	63.49	*	n.s.	**	n.s.
Gaussian magnitude [K]	2.07	4.29	4.98	2.13	2.17	4.07	4.64	2.39	**	**	**	**
Hot island area [km²]	41.58	38.56	37.80	42.03	42.43	37.23	37.18	42.81	n.s.	**	n.s.	n.s.
Magnitude [K]	2.55	5.00	5.89	2.27	2.59	4.76	5.35	2.32	n.s.	**	**	**
Micro-UHI [%]	0.18	0.41	0.43	0.21	0.19	0.42	0.44	0.22	n.s.	n.s.	n.s.	n.s.
Standard deviation [K]	1.07	2.24	2.61	0.99	1.10	2.22	2.49	1.03	*	n.s.	**	**
Gaussian magnitude empirical [K]	2.58	5.46	6.50	2.41	2.67	5.20	5.86	2.52	*	**	**	**

n.s.: not significant.
* Statistically significant with a $p<.05$.
** Statistically significant with a $p<.01$.

urban − other, *Gaussian magnitude*, *magnitude*, and *Gaussian magnitude empirical* showed statistically significant differences between July 2002 and 2003: For all indicators, the monthly surface UHI was larger for July 2002 than for July 2003. However, a comparison of the mean LST for all cities between July 2002 and July 2003 showed that there were higher temperatures in 2003 than in the previous year ($p<.01$), as in 2003, a severe heat wave occurred in Europe (Robine et al., 2008) after a warm and dry spring in parts of the continent (Dousset et al., 2011).

A relationship of higher mean temperatures accompanied by lower UHI measurements was also found by Streutker (2002); when comparing the *Gaussian magnitude* for Houston, Texas over a period of time, the *Gaussian magnitude* was found to decrease with increasing background rural temperatures. In contrast, Tomlinson et al. (2010) found a higher *difference urban − other* for Birmingham during a heat wave. Both findings of the current study as well as reported in the literature hint at a complex relationship of heat waves and the dynamics of surface UHI. The surface UHI of a given city is not only influenced by the surrounding rural land cover and its thermal admittance (Oke et al., 1991), but also by antecedent meteorological conditions. Comparative analysis of surface UHIs with different antecedent conditions should be part of future research.

3.2. Temporal stability of surface UHI indicators

Studies on the surface UHI reported in the literature use different acquisition dates for LST. To compare results from different points in time, it is necessary to assess the temporal stability of surface UHI indicators. In Section 3.1, we reported that the indicators showed statistically different surface UHI results throughout the day, between winter and summer, and between two summers. However, for the majority of the indicators, the patterns were the same, such as showing a higher daytime surface UHI and a lower winter surface UHI. Thus, the question was raised whether a higher surface UHI at a given point in time was accompanied by a higher surface UHI at another point in time, and vice versa, always in relation to the same indicator. This is reflected in Hypothesis 2 which states that results for a single surface UHI indicator should be correlated throughout time. To assess this temporal stability of all surface UHI indicators, Spearman's Rho correlations were computed for the different points in time and for each indicator individually. High correlations indicated that similar results for the given indicator were found across the different points in time and, thus, that these indicators were temporally stable. This result does not imply similarities in terms of absolute values, but rather relative similarities when ranking the cities according to their surface UHI.

Fig. 4 depicts the emerging correlation patterns. It shows that some surface UHI indicators were very unstable (and thus showed few correlations across time, e.g., *hot island area*, *Gaussian magnitude* and *difference urban − water*), whereas others were very stable (e.g., *micro-UHI*, *Gaussian area*). Stable correlations across most of the indicators were found for the daytime surface UHI (10:30 and 13:30 h) and the summer surface UHI at night (22:30 and 01:30 h). Numerous correlations were also found when comparing July 2002 and July 2003. In sum, Hypothesis 2 was rejected for numerous indicators.

The high correlations among daytime surface UHI (10:30 and 13:30 h) and among surface UHI at night (22:30 and 1:30 h) are related to the fact that the each of the two correlated points in time are only 3 h apart, so that changes in surface UHI are comparably small (see also Fig. 3). The rather low overall temporal stability of the surface UHI indicators found between night and day and between seasons might be related to the great diversity of cities included in the dataset: coastal cities were mingled with continental cities, and cities in mountainous regions were included with cities lying in a floodplain. Such topographical differences, as well as the different climate regions covered in the dataset and differing local weather conditions, likely led to differing cooling behaviours from day to night and across seasons. For example, two cities with similar characteristics except for soil moisture in their surrounding rural areas due to different climate zones or weather antecedents are likely to show different diurnal patterns of surface UHI. Coastal cities can cool down more rapidly than cities lying in a valley where the influence of cooling air from surrounding rural areas is limited.

Only a few findings related to temporal stability of UHI indicators are reported in the literature. Gallo et al. (1993) also found a low temporal stability of the indicator *difference urban − other* in biweekly data for 37 cities. The stability of *Gaussian area* indicator over time has also been documented by Streutker (2002) for Houston, Texas.

3.3. Similarities of surface UHI indicators

Hypothesis 3 aimed at identifying similarities of indicators. The similarities of the different surface UHI indicators were analysed by correlating the different indicators for each point in time individually. High correlations hint at similarities between different indicators for a given point in time and imply that they measure the same phenomenon. Again, these similarities do not imply identical absolute values but similar rankings of cities according to the different indicators instead.

3.3.1. Similarities across all cities

Fig. 5 depicts the emerging correlation patterns. Surprisingly few correlations were found, bearing in mind that all of the indicators are supposed to measure the surface UHI. The most striking observation

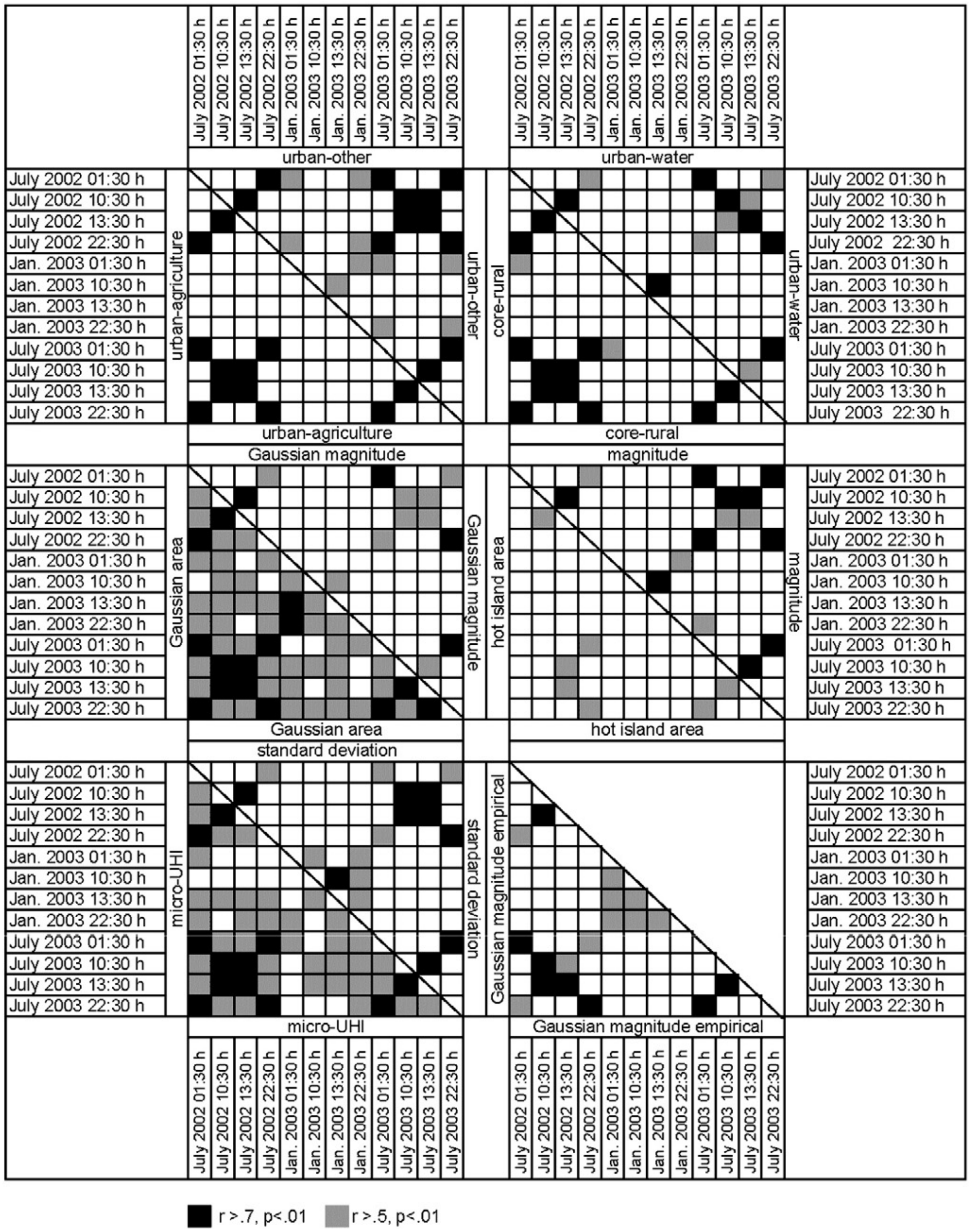

Fig. 4. Correlations over time. Shading indicates correlations (Spearman's Rho) for the given combination of acquisition dates differentiated for the indicators. urban − agriculture: difference urban − agriculture; core − rural: difference core − rural; urban − other: difference urban − other; urban − water: difference urban − water.

was the fact that no correlations higher than .5 were found between the classical indicator *difference core − rural* and the other surface UHI indicators for any of the points in time. Although it showed the same temporal patterns as the other indicators (see Section 3.2), the *difference core − rural* was at most weakly correlated with the other indicators. A likely reason for this is our use of the administrative boundaries to delineate the cities and the rural areas for the indicator *difference core − rural*. Thus, the "rural" ring around the administrative boundaries might consist of both natural or agricultural landscapes and peri-urban areas. The indicator *difference urban − other* is an alternative way of quantifying the underlying idea: For this indicator, the mean LST of urban land covers and the mean LST of all land cover types were used.

However, strong and stable correlations were found for several groups of indicators, as follows. (1) *Difference urban − agriculture* and *difference urban − other*: This relationship is due to the fact that for most cities, the land other than the urban land cover is dominated by agricultural areas. (2) *Magnitude, standard deviation* and *Gaussian magnitude empirical*: *Magnitude* and *standard deviation* are closely related, as they both rely on the statistical distribution of LST pixels in the administrative area. *Gaussian magnitude empirical* is related to these because it uses the maximum LST value in the urban area minus the fitted rural background. *Gaussian magnitude* and *Gaussian magnitude empirical* are also related, as the only difference between these two indicators is the fitting algorithm that has to be computed for the *Gaussian magnitude*. The relationship between these two indicators implies that it might be worthwhile to investigate whether the fitting algorithm could be omitted. (3) *Gaussian area* and *hot island area*: these two indicators are likely proportional to the extent of the urban area, as they measure the absolute spatial extent of the surface UHI. In contrast, the *micro-UHI* is also associated with the spatial extent of the surface UHI, though it is normalised to the total extent of the urban area and is not strongly correlated with the other spatial indicators.

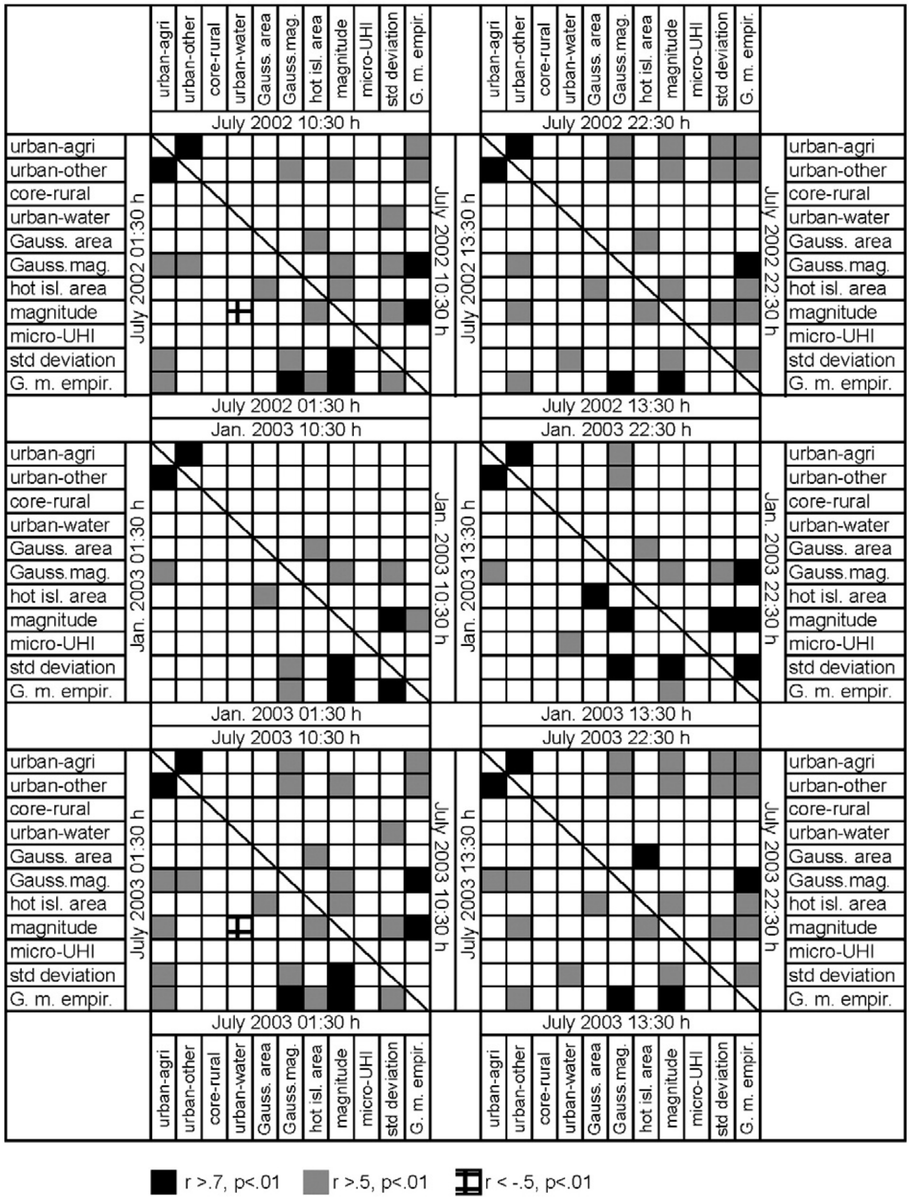

Fig. 5. Correlations between indicators. Shading indicates correlations (Spearman's Rho) for the given combination of indicators differentiated for acquisition dates. urban − agri: *difference urban − agriculture*; core − rural: *difference core − rural*; urban − other: *difference urban − other*; urban − water: *difference urban − water*; Gauss. area: *Gaussian area*; Gauss. mag.: *Gaussian magnitude*; hot isl. area: *hot island area*; std deviation: *standard deviation*; G.m.empir.: *Gaussian magnitude empirical.*

Other indicators showed lower and/or non-significant correlations. Furthermore, *magnitude* and *difference urban − water* were negatively correlated, with $r < -.5$, in both July 2002 and July 2003 at 01:30 h. Across indicators, more correlations occurred at night than during the day, and they were more frequent in summer than in winter. To sum up, Hypothesis 3 was also rejected for a number of indicators. Such relationships have rarely been presented in the literature. Only Streutker (2002) reported that the two surface UHI indicators *Gaussian area* and *Gaussian magnitude* are not correlated for the same city throughout time.

3.3.2. Similarities differentiated by biome

Recent studies (Imhoff et al., 2010; Zhang et al., 2010) on the surface UHI indicator *difference core − rural* discriminated relationships between the surface UHI and explanatory factors, such as the size of the city across biomes. Biomes are major habitat types and characterise the ecological setting of a landscape. Accordingly, we checked the similarities of the surface UHI indicators stratified by biome. Of the 263 cities investigated, 200 were located in temperate broadleaf and mixed forests, 3 in temperate conifer forests, 4 in boreal forests and taiga and 56 in Mediterranean forests, woodlands and scrub. Fig. 6a shows the correlations between the indicators differentiated for cities in temperate broadleaf and mixed forests and for the Mediterranean; the temperate conifer forest and boreal forest groups were omitted because there were too few cities included in these groups. The correlations were computed for the example of July 2002 at 01:30 h, as this point in time showed more frequent correlations in the comparison of all cities.

For the group of cities in temperate broadleaf and mixed forests, the same pattern of correlations emerged as for the whole sample, whereas slightly more correlations (and thus, more stable relationships between indicators) were found for the Mediterranean cities. These findings are mainly related to the different sample sizes in the two groups: the group of Mediterranean cities is small, and thus, the cities are more similar to each other, whereas the group of cities in temperate broadleaf and mixed forests is large, with 200 cities, and likely shows more diversity than is captured in the biome concept.

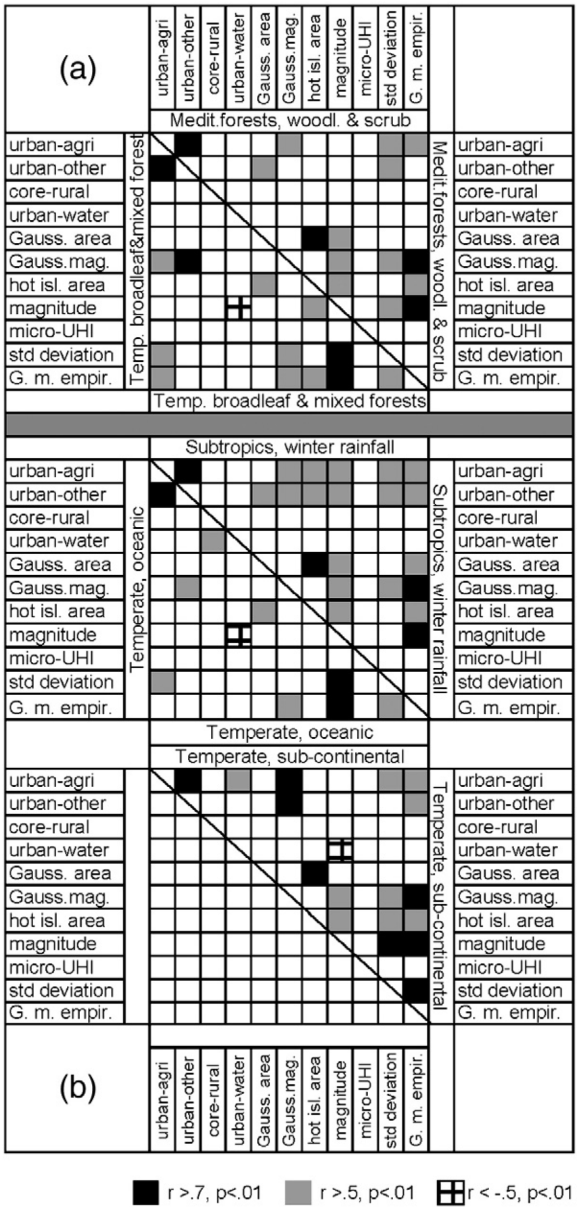

Fig. 6. Correlations between indicators differentiated by (a) biome and (b) thermal climate zone. Shading indicates correlations (Spearman's Rho) for the given combination of indicators differentiated for biomes or thermal climate zones. urban − agri: *difference urban − agriculture*; core − rural: *difference core − rural*; urban − other: *difference urban − other*; urban − water: *difference urban − water*; Gauss. area: *Gaussian area*; Gauss. mag.: *Gaussian magnitude*; hot isl. area: *hot island area*; std deviation: *standard deviation*; G.m. empir.: *Gaussian magnitude empirical*.

3.3.3. Similarities differentiated by thermal climate zones

The analysis for biomes was repeated for cities belonging to different thermal climate zones according to the FAO, also for July 2002 at 01:30 h. In the dataset, 59 cities belonged to the temperate, sub-continental zone, 126 to the temperate, oceanic zone, 75 to the subtropics with winter rainfall, and 3 to the boreal, sub-continental climate zone. Fig. 6b shows Spearman's correlations for the cities divided into the respective climate zones (omitting the three cases in the boreal, sub-continental climate zone). Differentiating cities according to climate zones revealed more and stronger correlations between surface UHI indicators, specifically for the temperate sub-continental zone and for the subtropics with winter rainfall. However, cities in the temperate, oceanic zone showed weaker correlations between the surface UHI indicators than the combination of all cities. This is the largest group, including almost half of the cities in the dataset.

3.3.4. Shortcomings of the study

Several shortcomings of the study need to be addressed: (1) validity of the MODIS product; (2) temporal constraints of the MODIS products; (3) limitations of using administrative boundaries; (4) implications of using monthly mean values; (5) concentration on remote sensing data. (1) The accuracy of the MODIS land surface product of better than 1 K (Wan, 2008) was determined for optimal conditions. Presumably, the accuracy of the MODIS product is lower for non-optimal conditions, so that a larger uncertainty needs to be assumed for the land surface temperatures. However, no indication exists that the land surface temperatures are biased in a certain direction. Accordingly, the uncertainty in the data is assumed to be randomly distributed. The extent to which these uncertainties are propagated in the surface UHI indicators depends on the quantification of each indicator: Most of the indicators build upon mean values rather than single pixel values and are thus less sensitive to such errors, while e.g. *magnitude* uses the maximum LST value and is more sensitive to extreme values. (2) The MODIS diurnal cycle does not include local noon time and thus probably does not provide peak LST. Consequently, temperature differences between land cover classes and thus surface UHI might be more pronounced than actually measured during the four points in time that are available (Section 3.3.1). This has to be kept in mind when comparing surface UHI measurements building upon different remote sensing data products and even more so when comparing surface UHI and UHI quantified with air temperatures. (3) In the study, administrative boundaries were used to delineate cities from one another. Within the administrative boundary, surface UHI indicators were computed, either taking into account LST for different land cover classes (*difference urban − water*) or the statistical distribution of LST (i.e. *magnitude*). Depending on the delineation of a specific city, it may contain sub-urban sprawl or only the core city. While concentrating on the administrative area helps combining the UHI study with statistical data such as population number or population density, the influence of delineation of the study area on the surface UHI indicators needs to be investigated in future studies as well. (4) In the present study, monthly mean values were used for each available step of the diurnal cycle of MODIS data. The intention was to create a set of LST data in which temporal variations due to changing local weather conditions are counterbalanced. While MODIS LST data are restricted to clear-sky conditions, they e.g. include different wind speeds and directions. The drawback of this aggregation approach is the inclusion of these different conditions into a single monthly data set, although the surface UHI is strongest under clear sky and very light wind. However, a finer temporal resolution might also enlarge the effect of changing wind and other weather conditions on the surface UHI and thus create more instability. This should also be analysed thoroughly in the future work and needs the combination with meteorological data. (5) A comparative analysis of remotely sensed surface UHI indicators with meteorological data on air temperature differences and local weather conditions would clearly enhance an analysis such as presented here.

4. Summary and conclusions

We compared indicators for quantifying the surface UHI. For a total of 263 European cities, the monthly mean LSTs for July 2002, January 2003 and July 2003 from MODIS data were used to compute eleven indicators: *difference urban − agriculture*, *difference urban − other*, *difference core − rural*, *difference urban − water*, *Gaussian area*, *Gaussian magnitude*, *hot island area*, *magnitude*, *micro-UHI*, *standard deviation*, and *Gaussian magnitude empirical.* Most of the indicators showed similar temporal changes, with the surface UHI being highest in the daytime during summer (Hypothesis 1). The surface UHI was lower for July 2003 than for July 2002 during the day, but larger during the night, while the mean LSTs for the cities were higher in 2003 during the heat wave. To analyse the temporal stability of the surface UHI indicators, correlations were computed for each indicator across points in time (Hypothesis 2). The temporal stability of indicators was rather weak. Thus, the surface UHI measured during the daytime was not strongly correlated with the surface UHI measured at night for the same indicator across European cities. The same holds true for measurements in summer and winter. Furthermore, the surface UHI indicators showed only limited comparability due to low correlations between the indicators for the same point in time (Hypothesis 3). Although differentiating cities according to regional biomes did not increase the relationships found between indicators, a few additional correlations were found when distinguishing among thermal climate zones; e.g., European cities in the temperate sub-continental climate zone and in the subtropics with winter rainfall showed a greater number of relationships between indicators.

Two main conclusions can be made from the results of this study, as follows. (1) Time matters. Although the indicators showed similar patterns throughout the day and across seasons, the findings for the surface UHI, as quantified by a single indicator, were not strongly correlated over time for the cities under study. Thus, for instance, one city might have a high surface UHI in the daytime compared to all other cities, but a lower surface UHI at night compared to all other cities. Accordingly, a comparison of the surface UHI among such a large set of diverse cities might lead to different rankings for different points in time, as topographical as well as climate characteristics and local weather conditions likely influence the temporal dynamics of the surface UHI. (2) The indicator matters. Although all of the indicators are supposed to measure the surface UHI, only a few indicators showed strong correlations for a single point in time. Therefore, it is extremely important to remember the specific way in which the surface UHI was measured when comparing studies on the same city or on different cities.

It might be worthwhile to use more than one indicator when describing the surface UHI to capture its various aspects. This study provides preliminary suggestions for indicator selection, as follows. (a) Only one indicator out of an indicator group with strong relationships needs to be considered, e.g., *difference urban — other* (omitting *difference urban — agriculture* to also include urban areas with only small agricultural parts); *magnitude* (omitting *standard deviation*, *Gaussian magnitude* and *Gaussian magnitude empirical*); and *Gaussian area* (omitting *hot island area*). (b) The indicators *difference core — rural* and *micro-UHI* are more closely dependent on the specific spatial delineation of the urban area and, thus, need to be investigated further. (c) The indicator *difference urban — water* is only available for cities with large water surfaces; it shows low stability and could, thus, also be omitted at least for cities without large water bodies. Generally speaking, researchers should check carefully if the surface UHI indicator is applicable for a specific case study. For instance, the Gaussian fitting procedure is likely to produce unstable results in a rough terrain.

Another aspect to consider is the spatial delineation of the urban area under study and its rural counterpart. Although working with administrative boundaries has the advantage of matching socio-economic data, it depends on the way the delineation is carried out in different countries. Future research should also investigate the stability of surface UHI indicators to modifications in delineating a case study region and for varying spatial and temporal resolutions of LST data. More research is also needed to assess the uncertainties in LST data with its implications for quantifying the surface UHI.

Additional comparative research will be required to establish a set of indicators to quantify the surface UHI for findings in time series or across cities to be stable. This includes adding more years with varying climatic conditions such as humid or dry periods to identify the influence of these (both current and antecedent) climatic aspects onto the surface UHI. Furthermore, the surface UHI should be analysed for more than one month per summer/winter and additionally for spring and autumn, and basic topographical factors need to be controlled. Ideally, such a study would combine not only different remote sensing products but also meteorological measurements of air temperature differences from rural and urban weather stations.

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Appendix A. List of cities

Aalborg; Aarhus; Aberdeen; Ajaccio; Alicante/Alacant; Amiens; Amsterdam; Ancona; Antwerpen; Arnhem; Athina; Augsburg; Aveiro; Badajoz; Banska Bystrica; Barcelona; Bari; Belfast; Berlin; Besancon; Bialystok; Bielefeld; Bilbao; Birmingham; Bochum; Bologna; Bonn; Bordeaux; Bradford; Braga; Bratislava; Bremen; Bristol; Brno; Brugge; Bruxelles/Brussel; Bucuresti; Budapest; Bydgoszcz; Caen; Cagliari; Cambridge; Campobasso; Cardiff; Caserta; Catania; Catanzaro; Charleroi; Clermont-Ferrand; Coimbra; Cordoba; Cork; Cremona; Czestochowa; Darmstadt; Debrecen; Derry; Dijon; Dortmund; Dresden; Dublin; Duesseldorf; Edinburgh; Eindhoven; Enschede; Erfurt; Essen; Exeter; Faro; Firenze; Frankfurt (Oder); Frankfurt am Main; Freiburg im Breisgau; Galway; Gdansk; Genova; Gent; Gijon; Glasgow; Goeteborg; Goettingen; Gorzow Wielkopolski; Gozo; 's-Gravenhage; Gravesham; Graz; Grenoble; Groningen; Gyor; Halle an der Saale; Hamburg; Hannover; Heerlen; Helsinki; Ioannina; Irakleio; Jelenia Gora; Joenkoeping; Kalamata; Kalisz; Karlsruhe; Katowice; Kaunas; Kavala; Kecskemet; Kiel; Kielce; Kobenhavn; Koblenz; Koeln; Konin; Kosice; Koszalin; Krakow; L'Aquila; L'Hospitalet de Llobregat; Larisa; Le Havre; Leeds; Lefkosia; Leicester; Leipzig; Lens-Livin; Liege; Liepaja; Lille; Limerick; Limoges; Lincoln; Linkoeping; Linz; Lisboa; Liverpool; Ljubljana; Lodz; Logrono; London; Lublin; Luxembourg; Lyon; Madrid; Magdeburg; Mainz; Malaga; Malmo; Manchester; Maribor; Marseille; Metz; Milano; Miskolc; Moenchengladbach; Moers; Montpellier; Muelheim a.d. Ruhr; Muenchen; Murcia; Namur; Nancy; Nantes; Napoli; Newcastle upon Tyne; Nice; Nitra; Nowy Sacz; Nuernberg; Nyiregyhaza; Odense; Olsztyn; Opole; Oporto; Orebro; Orleans; Ostrava; Oulu; Oviedo; Palermo; Palma di Mallorca; Pamplona-Iruna; Panevezys; Paris; Patra; Pecs; Perugia; Pescara; Plock; Plzen; Poitiers; Portsmouth; Potenza; Potsdam; Poznan; Praha; Presov; Radom; Regensburg; Reggio di Calabria; Reims; Rennes; Riga; Roma; Rotterdam; Rouen; Rzeszow; Saint-Etienne; Santander; Santiago de Compostela; Sassari; Schwerin; Setubal; Sevilla; Sheffield; Stevenage; Stockholm; Strasbourg; Stuttgart; Suwalki; Szczecin; Szeged; Szekesfehervar; Tallinn; Tampere; Taranto; Tartu; Thessaloniki; Tilburg; Toledo; Torino; Torun; Toulon; Toulouse; Tours; Trencin; Trento; Trier; Trieste; Trnava; Turku; Umea; Uppsala; Usti nad Labem; Utrecht; Valencia; Valladolid; Valletta; Venezia; Verona; Vigo; Vilnius; Vitoria–Gasteiz; Volos; Warszawa; Weimar; Wien; Wiesbaden; Worcester; Wrexham; Wroclaw; Wuppertal; Zaragoza; Zielona Gora; Zilina; Zory

Appendix B. Technical description of indicators related to a Gaussian bell

The Gaussian area and Gaussian magnitude indicators were proposed by Streutker (2002, 2003), and the Gaussian magnitude empirical is a simplified version of the Gaussian magnitude. The overall idea is that the form of the LST over a city can be described by a Gaussian bell with an ellipse as its basis. The Gaussian bell is described with the following formula:

$$T(x,y) = T_0 + a_1x + a_2y + a_0 \times exp\left[-\frac{((x-x_0)\cos\phi + (y-y_0)\sin\phi)^2}{0.5{a_x}^2} - \frac{((y-y_0)\cos\phi-(x-x_0)\sin\phi)^2}{0.5{a_y}^2}\right]$$

$T(x,y)$	LST on pixel x, y
T_0	background LST
a_1, a_2	regression coefficients for planar surface of rural LST
a_0	Gaussian magnitude (height of the bell)
x_0, y_0	central location of UHI
ϕ	orientation of the UHI
a_x, a_y	spatial extent of UHI

Whereas *Gaussian magnitude* is directly included in the equation (a_0), the *Gaussian area* equals $\pi \times a_x \times a_y/4$. The parameters in the equation were estimated in a stepwise procedure following Streutker (2002, 2003). First, all water pixels were masked based on the landcover information. Second, the rural LST parameters (first three parts of the equation) were estimated for all the remaining pixels, except for urban surfaces, using linear regression. Third, this rural surface was subtracted from the overall LST. The resulting LST was then fitted to the *Gaussian bell*, the third part in the equation above. The fitting was done in R (R Development Core Team, 2010), using the nls function from the package stats. Estimation results were omitted from further analysis if (1) the fitting did not converge (1048 cases, 33%), or (2) parameter estimates for a_0 were not significant (1162 cases). The significance of the parameters was tested based on a bootstrap procedure from the package nlstools (Baty & Delignette-Muller, 2009). A total of 1958 cases (37%) were omitted from the analysis.

The first two steps of the calculation of the indicator *Gaussian magnitude empirical* are similar to the above-described procedure. However, instead of using a_0 from the fitted curve, the maximum residual temperature is used. Thereby, one might avoid errors during the curve fitting procedure.

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