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The Diversity of Modern Urbanism: An International Comparative Study of Urban Space

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The Diversity of Modern Urbanism:
An International Comparative Study of Urban Space

By
Fanhao Kong

A THESIS

Presented to the Faculty of
The Graduate College at the University of Nebraska
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The Diversity of Modern Urbanism:
An International Comparative Study of Urban Space

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While industrialization and globalization are continuing to bridge cultural and geographical gaps on the earth, differences still exist. Today, Developing countries are undergoing massive urban transition; and the transition appears to pursue the path of developed countries. However, the belief that global paths of urbanism will converge into one road is not convincing. Many studies on urbanism have been discussed in the past. However, these studies are mainly focused on urban areas in developed countries, mostly located in North America and Europe. In the last ten years, researchers have done more studies in developing areas, especially in East Asia. Though the study of urban issues in developing countries is still basic and rough, the uniqueness of the massive urban transition in developing regions is beginning to emerge. The differences of urban space in East Asian, Europe, and America is becoming much clearer; however, very few study have analyzed these dissimilarities with a global scope. The purpose of this paper is to explore the nature of these dissimilarities. Using ArcGIS data-sets for global population count and man-made impervious surface, the study makes an international comparison of urban landscapes. In this paper, several values will be calculated and compared. Multi-distance spatial statistics and zonal statistics are applied as the analytical tools. This study gives a statistic evidence that there is diversity not uniformity in modern urbanism: 1. The disperse and low density American urban; 2. the clustered and high density Chinese urban; and 3. the clustered and medium density European urban. The significant differences in global urbanism may indicates the need for new directions for developed theories in the future.

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Chapter 1. Introduction

Though more than half total population live in urban areas by 2016, and it's widely believed that more than 60% of total human will reside in cities in 2030 (UN, 2016), the future of cities are not clear. Concern about "Urban Sprawl" and "Land Consumption" are frequently discussed as the growth of cities occurs around the world. More concerns, however, is the lack of discussions about differences between global urban areas. In other words, it is not well-understood that the problems of American urbanism is not similar to Asian's nor European's. "Urban Sprawl" in North American context is not equal to urban expansion in East Asia. "Suburbanization", which seems to be a common phenomenon in the U.S. is not a global problem. Urban-rural dual structure in China also has not been observed in North America. Recent observations and records shows that more global comparative studies are necessary. This research bases on two of these observations.

1. The rapid urbanization in developing countries particularly in East Asia shows a new urban landscape different from western's (Schneider et al, 2015). Some studies have been done to analyze these differences. For example, T. G. McGee did research on Asiatic urbanization, and developed his theory for explaining the uniqueness of Asiatic urban landscape. Also, comparative studies were made recently to explore differences between Asian cities and other cities (e.g. Cao Shisong et al, 2018). These comparative studies, however, were narrow in their scope looking on few selected exceptional cases. This narrow view may not sufficient to reveal the universal and fundamental distinctions. According to Wen Tiejun's studies, there are three agriculture types correspond to three continental land: capitalized big farm in America; Rhine model of medium and small farm in Continental Europe; and Asiatic model of peasants' ecologic agriculture of Asian countries. Besides, research on comparative business systems also shows different models (Choi Chongju, 2006). Modern urbanization is a process of complex conversion

from rural to urban, and closely interrelating to finance and business. Therefore, we have hypothesis to divide today's urban landscape into several types. This comparative study is for showing these potential types.

2. Traditional theory equates the process of urbanization to the growth or expansion of certain settlements into cities, urban areas or metropolises. Urban studies usually focus on selected areas defined by population thresholds, density, jurisdiction, etc. and usually put urban spaces in the position opposite to non-urban spaces (Neil Brenner, 2013). However, today's urban spaces are combined in many places. Urban agglomerations as an evolving concept has a great impact on today's world (Fang Chuanglin et al, 2017). Also, those non-urban spaces (suburban, rural, exurban, or otherwise) are closely associated to urban spaces (Neil Brenner, 2013). The comparison of non-urban spaces between America, Europe, and Asia may reveal some important dissimilarities or similarities that not fully understand in preceding studies. For instance, the Asiatic phenomenon of "Desakota" (T. G. McGee, 2008) can be compared to western concept of suburban. This holistic study will analyze a wide sample of human built-up settlements.

Chapter 2. Study area

The feasibility of the research requires to narrow down the study area. Only cities in mainland America, mainland China, and Continental Europe; with a population of over three million are studied. According to the data from "Demographia World Urban Areas, 2018", totally 63 cities/area are selected. They are: Shanghai, New York, Beijing, Guangzhou-Foshan, Moscow, Los Angeles-Riverside, Tianjin, Shenzhen, Chengdu, Paris, Chicago, Chongqing, Dongguan, Shenyang-Fushun, Wuhan, Hong Kong, Boston-Providence, Hangzhou, Zhengzhou, Quanzhou, Essen-Dusseldorf, Dallas-Fort Worth, San Francisco-San Jose, Nanjing, Madrid, Houston, Miami, Suzhou, Qingdao, Xi'an, Philadelphia, Fuzhou, Atlanta, Milan, Washington DC, St. Petersburg, Harbin, Barcelona,

Dalian, Guiyang, Wenzhou, Phoenix, Xiamen, Berlin, Changsha, Rome, Jinan, Taiyuan, Kunming, Hefei, Seattle, Wuxi, Changzhou, Shijiazhuang, Ningbo, Detroit, Naples, Zhangjiaggang (Suzhou), Changchun, Urumqi, Zhongshan, Athens, San Diego (sort by population). Among these cities, 31 cities are combined in urban agglomerations that cannot be isolated from their merged cities. These study examples will be divided into two categories (Figure 1.3 & 1.4). 1. Urban agglomerations. Each of these study area will include several selected cities and their related surrounding settlements; and will cover a area of (350 km)². 2. Solo city with its surrounding settlements. These study area will cover respectively smaller land with a area of (200 km)². This category will include 41 study examples.

Because spatial cluster analysis in GIS is very sensitive to study area, each study area in one category has same size and same shape. The study boundary is not defined by jurisdictions, but is manually divided base on global man-made impervious surface (GMIS, 2010). The principle of defining the study boundary is to include selected cities and their related, merged settlements, in this way, the study will analyze the selected settlements regardless the traditional concept of urban or non-urban (Figure 2.1, 2.2 & 2.3). Because the study samples are from across the globe, the projection systems will dramatically influence the map output. The spatial statistics done in this way will be as accurate as possible based one the specific projection systems (Figure 1.3 & 1.4).

Chapter 3. Data-sets

Three data-sets are used in this study. All three data are from research that was funded and published by NASA Socioeconomic Data and Applications Center (SEDAC).

1. GMIS. Global Man-made Impervious Surface (GMIS) Dataset From Landsat, v1 (2010). 250m. This data-set covers all man-made impervious surface on the earth except some small islands. Therefore, this data is suitable for studying surfaces at conti-

mental scales to global scales. This data provides two kinds of resolution: 30m, and 250m. The 250m resolution is selected in this study for ensure the speed of computing.

2. GPW. UN-Adjusted Population Count, v4 (2010). 1km. This data contains the number of population per pixel with spatial information. The number is drawn from national census, but adjusted to match the 2015 Revision of the United Nation's World Population Prospects for the year 2010. The format of this data is helpful to integrate the population data to other sensing data. This UN-Adjusted data is useful for international comparative study. The data resolution is one kilometer.

3. HBASE. Global Human Built-up and Settlement Extent (HBASE) Dataset from Landsat, v1 (2010). 30m. This data masks out the human habitat surface from all impervious surface, that means the inter-state highway, airport and other none-habitat impervious surface will be excluded. By layering this data, this study get the most accurate distribution of human settlements. In this data, raster value 201 represents human habitat settlement. All raster cells that have values other than 201 will be excluded. The data resolution is 30m.

Chapter 4. Method

The method procedure is depicted in Figure 3.

1. GMIS shows the percentage of impervious surface in one cell (250m). It contains all impervious surface; however, the study only notes the impervious surface in settlements. To exclude the roads beyond the settlement areas, HBASE is used as a mask to clip out the settlement boundary in GMIS. Set the output as "I". "I" shows the impervious surface percentage of settlement areas, indicating the "footprint" of settlement. GPW (set as "P") adds the "thickness" on the "footprint". The products of "I" and "P" (set as "E", $E=I \times P$) will be recorded and compared. "E" is helpful in testing the density of urban development. The quotients of "P" and "I" (set as "D", $D=P \div I$) indicate the population

density on impervious surface. Both “E” and “I” show density (Figure 3.1).

The E-value maps will be reclassified into low density area (Desakota, suburban, rural), medium density area (peri-urban), and high density area (urban core). The threshold of reclassify is manually defined base on the hypothetical spatial configuration of an Asian mega-urban region (T. G. McGee, 2008). Because of the extreme range diverse of E-value in each study sample (eg, E-value range of Shnghai is much larger than Essen), the threshold is set to two low values (50 & 100). Some study samples may not have high density area (eg, Rome). “P”, “I”, “E” and “D” value will be tested in low density area, medium density area, and high density area respectively. (Figure 3.2).

Zonal Statistics and Multi-Distance Spatial Cluster Analysis are two GIS tools be applied in this study.

2. Zonal Statistics is used to do statistics for values in a specific area. Because the study boundary is defined manually rather than any available demographic criteria, demographic data is not qualified in this comparison. Zonal statistics for all study examples gives us the overall understanding of population count (P); man-made impervious surface coverage (I); population density on impervious surface (D); and urban space density (E). These four values also are tested in low density, medium density, and high density areas respectively (Graph 1, 2, 3 & 4). The study will figure out in what percentage the impervious surface, population, and urban space fall in low density area, medium density area, and high density area (Graph 5, 6, 7, & 8). It should be noticed that all of the values are not “real” number, which means the P-value will not show the real population; the D-value will not show the real population density per impervious surface, etc. These values are calculated for comparison and only useful in this study. (Figure 3.1 & 3.2).

3. Multi-Distance Spatial Cluster Analysis. In this analysis, “I” shows the location, and “E” will be calculated as “weights”. The output will show an important spatial character that cannot seen visually. The outputs are “Expected-K”, “Observed-K”, and

“Difference-K” (“Observed-K” minus “Expected-K”). The larger the “Difference-K”, the more clustered the space is. This analysis not only tests the degree of cluster, but also finds out in which distance the study area are most clustered (Graph 9 & 10). Before doing this analysis, E-value maps should be aggregated into new maps (E*-value) that have larger cells (Figure 3.3). Since the initial cell size is too small (250m), it will require too much computing times to process. The E*-value maps are extruded in ArcScene, from which outputs 3D views.

Chapter 5. Results

Totally five values are tested in this study, they are “E”, “D”, “I”, “P”, and “K”. The significant diversity of global urban space is found from the comparison of these values. The dissimilarity of China urbanism to US urbanism is obvious. It is widely understood that Asiatic urban and Europe urban areas are denser than US urban areas; and this study reinforces this understanding from a spatial statistics prospective. The concept of “density”, however, is not clearly defined in this understanding. This study defines “density” from several aspects: 1. The footprint of urban space (I-value, man-made impervious surface percentage); 2. The “thickness” of urban space (P-value, population count); 3. The “volume” of urban space (E-value, $E=I \times P$). 4. The degree of cluster (K-value) of the “volume”. 5. Also, the study calculates the population density on impervious surface (D-value, $D=P \div I$) to test “density”.

1. Zonal Statistics Results. (Graph 1, 2, 3 & 4)

The mean of E-value in China samples are higher than samples in USA or Europe. The European samples show two different ways, one of which has higher value, though still lower than China samples, than another (Graph 1.1 & 1.2). The Standard of deviation of E-value draws a same trend as the mean value (Graph 2.1 & 2.2). E-Value is significantly influenced by P-value. The mean of D-value and the standard of deviation of

D-value also show a same trend as E-value (Graph 3 & 4). These results shows that land occupation in China is more intensive.

2. Reclassified Zonal Statistics Results. (Graph 5 & 6)

This test does zonal statistics for population count (P-value) and population density on impervious surface (D-value) by using reclassified zones. These zones are reclassified from E-value map (Figure 3.2). P-value percentage results (Graph 5) show in which percentage population fall in low density area, medium density area, and high density area. The results indicate that most percentage of population in USA samples occupy the low density and medium density areas; while obviously higher percentage of population in China samples occupy the high density area. “Graph 6” shows the mean of D-value in low density area, medium density area, and high density area respectively. The results show that in USA and Europe samples, D-Mean of High density area is not much different from D-Mean of medium density area or low density area. However, in China samples, D-Mean of High density area is much higher than D-Mean of medium density area and low density area. This indicates the huge gaps between urban core and urban margin of China.

3. Multi-Distance Spatial Statistics Results. (Graph 7 & 8)

This test shows the degree of cluster of urban space, also figures out in which distance the urban space is most clustered. “Graph 7” shows the degree of cluster in different distance bands (Expected-K) for each study sample. The higher the “Different-K” is, the more cluster. “Graph 8” shows in which distance the study area is most clustered. The line trend indicates that China samples most cluster in a shorter distance than Europe samples; and Europe samples most cluster in a shorter distance than USA samples. It should be noticed that some exceptional samples in China are coastal cities whose urban footprint are strictly restricted by geography. Therefore, these samples typically have higher “Distance”.

4. 3-D View. (Map 1 & 2)

D View is aggregated from E-value map and extruded in ArcScene. These results helps to show the significant diversity of urban space visually. From these maps, we can see that China samples typically have several very “tall” cells; and the cells are much cluster. However, In USA samples and some Europe samples, the cells are much spread and the “height” is shorter.

Chapter 6. Discussions

This study reveals the universal and fundamental distinctions of urban space between the Europe, USA, and China. Generally, urban space in America tends to cluster in larger distances than those in China or in Europe. In other words, American Cities are more dispersed. China cities, though observed as the highly urbanized and populated districts, are clustered in relatively smaller distances than European cities. In addition, generally all settlement space in China have higher density than in America and Europe; and the density difference from urban core to urban margin in China is much larger. This study supports observations of the differences between urbanization in China and USA from a statistical perspective. Suburbanization is a urban phenomenon that is frequently talked in USA. Urban-rural dual structure is another urban phenomenon that being reported and debated in China in these years. This study also shows the diverse urban space in Europe.

1. Suburbanization in USA.

Suburbanization, currently regarded as a negative phenomenon, is a main problem of American cities. However, at least at the beginning of the suburbanization movement in early 20 century, “go to suburban” was thought to be a positive concept. This study will not give a value judgement for any space character or urban phenomenon, but reveal the nature of these urban phenomenon from a spatial statistics way. Suburban is opposite

to downtown. According to the density classify method (E- value) in this study, downtown area, which is high density, occupy minor percentage of the total urban land. Suburban in America, on the contrary, not only cover a large low density area, also consist of a continuous and homogeneous space. The space character of “homogeneity”, but not just “low density”, is the core nature of the space of suburban as understood in this study.

2. Urban-Rural Dual Structure in China.

The huge gap of development between urban and rural is being discussed in China in recent few decades. China’s urbanization has speed up during the last decade. Meanwhile, the urban-rural dual structure has gotten more attentions. The nation financed rural development with a large allocation funds in last two decades (e.g. New Rural Reconstruction Movement). Though the rural area is being reconstructed and modernized, the imbalance between urban and rural development has not solved. In last decade, the speed of rural development has been slower than the speed of urban development. Rural areas, though not regarded as “urban” in Chinese context, has higher density than suburban in USA. Urban areas in China are not only high density, but also highly compact. This phenomenon maybe result from strict urban planning. In China, the state owns the urban land, but the rural land is collectively owned by village. Rural land transactions are controlled, supervised by law and executive order. In this situation, land acquisition is completely under the control of local governments, who become the only land provider for real estate companies. Thus, rural land that are not requisitioned by municipal government, will not be planned as part of an “urban” area. In this government-led urbanization, rural is put in a weak position.

3. Medium and small cities in Europe.

This study shows the diverse urban space in Europe. For example, Paris, Moscow, and St.Petersburg have space characters much like urban in China. They all have high density in urban core, and cluster in a short distance. However, other European study

areas show different features. Essen*, for example, cluster in a short distance, and has low density in urban cores. Cities like Rome, Berlin, Madrid, etc, all have medium and low density in urban cores, and cluster in a short distance. These medium and small cities are not common in either USA or China. In USA, though density is low, these low density urban space cover a large area. In China, urban space is highly compact, and the density is really high. Not like the uniform urban space in USA or in China, European urban spaces are diverse.

4. The lack of modern urban theories.

Urban theories in USA, Europe, and China are different. Their goals, preferences, and the standpoints are built in their own context. Here are some examples. 1. The concept of “suburbanization” is hardly being comprehended in China, since the “suburban” in China is totally another kind of space (Desakota). 2. The space of urban core is much denser in China than in USA or Europe, so transport systems cannot be copied from each other. This can in some way explain why massive transit is more successful in China and Europe. 3. Detached houses are popular residential model of American cities, apartments are common in European cities, but tower buildings which have more than ten stories become the main urban residential model in China. In this situation, community plan problems and theories differ greatly in US and China. 4. The massive number of small villages that dotted scatter on east China and central Europe compose a settlement landscape that not exist in USA. This indicates the the severe conflicts between rural and urban that exist in China or used to exist in Europe are not ever become a national problem in USA. 5. The degree of disperse as well as the size and homogeneity of American urban area distinguish American cities from others’. “urban sprawl” or “suburbanization”, a precondition of many urban studies, is not a global phenomenon. Previous urban studies mainly focus on urban phenomenon in western context, given the differences noted in this study, these western theories for the urbanization may be inappropriate for none-western con-

text. For instance, Schneider's study on urban landscape in East-Southeast Asia found out that majority of urban area are increasing in density (Schneider et al, 2015). This result challenges the previous urban predictions that urban density are globally decline. Schneider's research indicates that a new urban landscape occur in Asia. Inspired by this observation, this study attempts to compare various urban landscapes and reveal the nature of their spacial characters. Because of the fast changes of urban landscape in developed countries, and the variety of urban spaces, global urban study should widen their focus.

Chapter 7. Limitations

Limitations come from both data-sets and method. 1. GMIS and HBASE have errors or omit some features. Because the data is derived from remote sensing, clouds cover and scan failure decline the reliability of data-sets. 2. GPW is calculated from global national census, whose standards vary; therefore, the accuracy of the whole data are not continuous. 3. Spatial Statistics test is the most important part of this study, and the test is very sensitive to study size and shape. However, because of the massive land of study area, their shapes and size are significantly influenced by project coordination systems. The degree of influences are not certain. 4. This study tries to reveal the diversity of modern urban space around the world. The availability of data-sets narrows down the study focus to China, USA, and part of Europe. South Asia, South America, Africa, the Middle East, and Oceania should be studied in the future.

Chapter 8. Conclusions

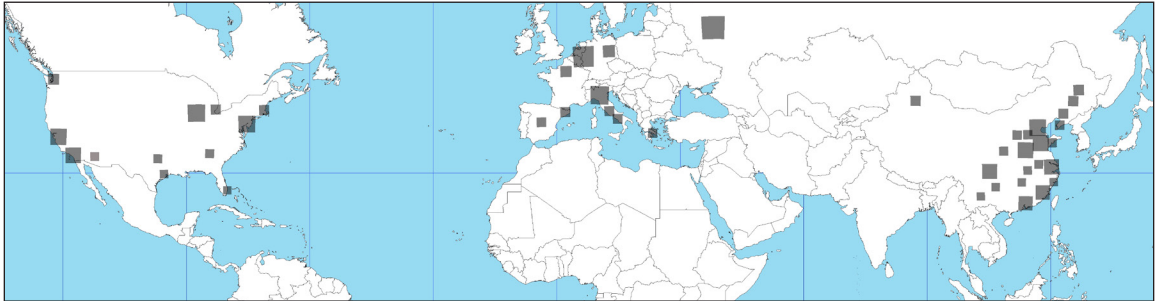
This study gives a statistic evidence that there is diversity not uniformity in modern urbanism: 1. The disperse and low density American urban; 2. the clustered and high density Chinese urban; and 3. the clustered and medium density European urban. These kind of diversity need to be continuously recorded and further studied in the future to determine the lessons to be learned or ignored between the different urban forms. The results questions today's urban theories, which focus on global identity but neglect the complexity of differences. This study also challenges the myth that global urban will able to be understood and even to be planned by one hypothesis. The different part of the world should develop their own theories appropriate to their own context.

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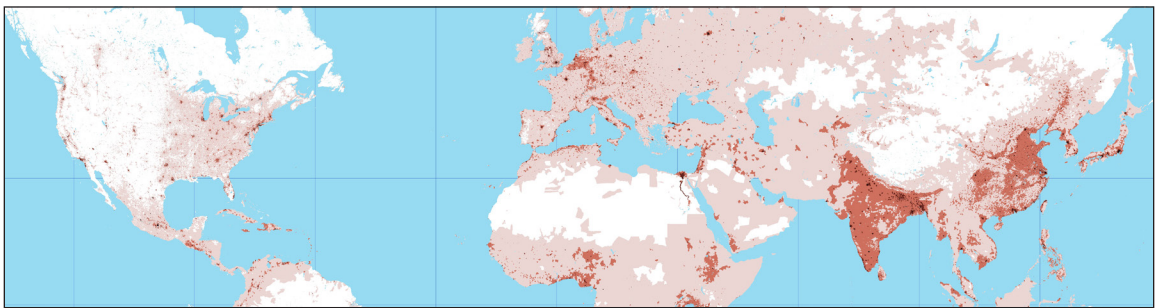
Figure 1. Study Location

Figure 1.1. Study Location



Projected Coordinate Systems: WGS_1984_World_Mercator

Figure 1.2. World Population Density map



Projected Coordinate Systems: WGS_1984_World_Mercator

Population Count (1 km)

0 100 1000 5000 >5000



Figure 1. Study Location

15

Cities in Study Area:

Sort by Population

(Population > 5 Millions)

1. Shanghai
2. New York
3. Beijing
4. Guangzhou-Foshan
5. Moscow
6. Los Angeles-Riverside
7. Tianjing
8. Shenzhen
9. Chengdu
10. Paris
11. Chicago
12. Chongqing
13. Dongguan
14. Shenyang-Fushun
15. Wuhan
16. Hong Kong
17. Boston
18. Hangzhou
19. Zhengzhou
20. Quanzhou
21. Essen-Dusseldorf
22. Dallas-Fort Worth
23. San Francisco-San Jose
24. Nanjing
25. Madrid
26. Houston
27. Miami
28. Suzhou
29. Qingdao
30. Xi'an
31. Philadelphia
32. Fuzhou
33. Atlanta
34. Milan
35. Washington, D.C.
36. St, Petersburg
37. Harbin

(Population > 3 Millions)

38. Barcelona
39. Dalian
40. Guiyang
41. Wenzhou
42. Phoenix
43. Xiamen
44. Berlin
45. Changsha
46. Rome
47. Jinan
48. Taiyuan
49. Kunming
50. Hefei
51. Seattle
52. Wuxi
53. Changzhou
54. Shijiazhuang
55. Ningbo
56. Detroit
57. Naples
58. Zhangjiagang
59. Changchun
60. Urumqi
61. Zhongshan
62. Athens
63. San Diego

According to "Demographia World Urban Areas 14th Annual Edition: 201804"

Figure 1. Study Location

Figure 1.3. Study Location, Urban Agglomerations

		Projection	Area Extent		Description
			Top	Left	
US	New York*	WGS_1984_UTM_Zone_18N	4575000	300000	Include New York, Philadelphia, Washington, DC, and Baltimore
	Los Angeles*	WGS_1984_UTM_Zone_11N	3900000	280000	Include Los Angeles and San Diego
	Chicago*	WGS_1984_UTM_Zone_16N	4800000	280000	Include Chicago, Grand Rapids, and Milwaukee
	San Francisco*	WGS_1984_UTM_Zone_10N	4310000	495000	Include San Francisco, San Jose, and Sacramento
EU	Moscow*	WGS_1984_UTM_Zone_37N	6314000	260000	Moscow
	Essen*	WGS_1984_UTM_Zone_32N	5850000	150000	Include Essen, Dusseldorf, Cologne, Bonn, Frankfurt, Brussels, Antwerp, Rotterdam, Amsterdam, and etc.
	Milan*	WGS_1984_UTM_Zone_32N	5150000	436000	Include Milan, Venice, Bologna, Florence, and etc.
CH	Shanghai*	WGS_1984_UTM_Zone_51N	3640000	60000	Include Shanghai, Hangzhou, Nanjing, Suzhou, Changzhou, Wuxi, Zhangjiagang, Nantong, Ningbo, and etc.
	Beijing*	WGS_1984_UTM_Zone_50N	4500000	310000	Include Beijing, Tianjing, Tangshan, Langfang, Baoding, Cangzhou, Dezhou, and etc.
	Guangzhou*	WGS_1984_UTM_Zone_49N	2770000	620000	Include Guangzhou, Foshan, Zhongshan, Macau, Dongguan, Shenzhen, Hong Kong, Zhuhai, and etc.
	Chengdu*	WGS_1984_UTM_Zone_48N	3530000	340000	Include Chengdu, Chongqing, Nanchong, and etc.
	Zhengzhou*	WGS_1984_UTM_Zone_49N	4018000	590000	Include Zhengzhou, Kaifeng, Luoyang, Shangqiu, Xuchang, and etc.
	Fuzhou*	WGS_1984_UTM_Zone_50N	3030000	430000	Include Fuzhou, Quanzhou, Xiamen, Putian, and etc.
	Jinan*	WGS_1984_UTM_Zone_50N	4170000	375000	Include Jinan, Jining, Xuzhou, Linyi, Tai'an, Weifang, and etc.

*Urban Agglomerations
Study Area Size: (350 km)²*

Figure 1. Study Location

17

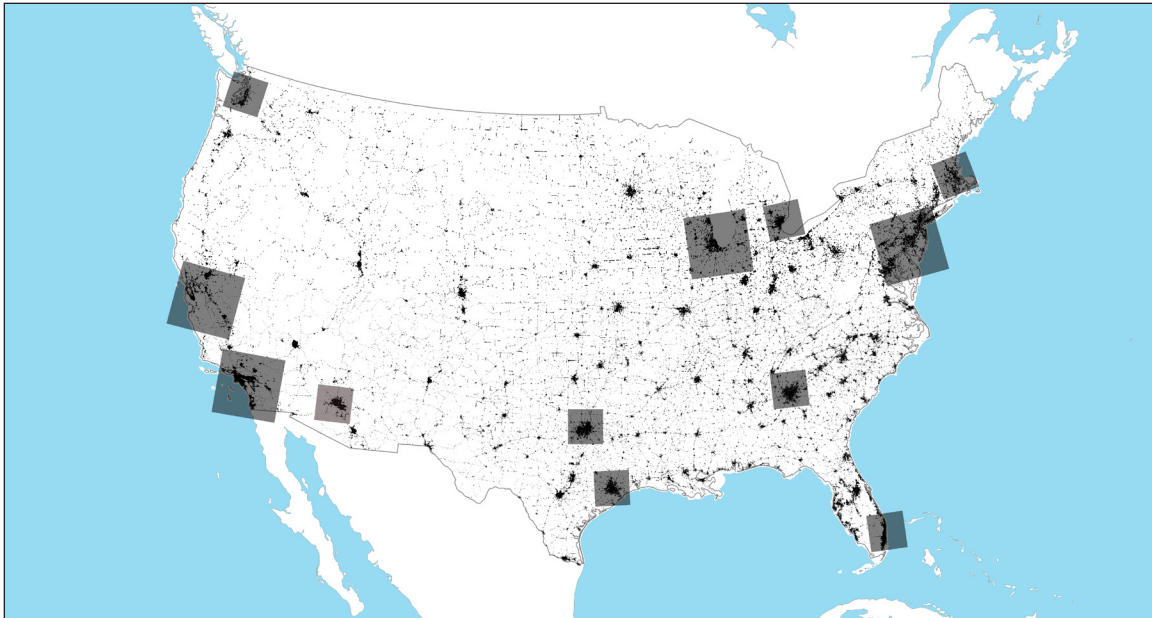
Figure 1.4. Study Location, Cities

		Projection	Area Extent	
			Top	Left
US	Boston	WGS_1984_UTM_Zone_19N	4790000	225000
	Dallas	WGS_1984_UTM_Zone_14N	3750000	595000
	Houston	WGS_1984_UTM_Zone_15N	3397000	166000
	Miami	WGS_1984_UTM_Zone_17N	3010000	496000
	Atlanta	WGS_1984_UTM_Zone_16N	3867000	646000
	Phoenix	WGS_1984_UTM_Zone_12N	3800000	281000
	Seattle	WGS_1984_UTM_Zone_10N	5376000	455000
	Detroit	WGS_1984_UTM_Zone_17N	4800000	245000
EU	Paris	WGS_1984_UTM_Zone_31N	5511000	345000
	Madrid	WGS_1984_UTM_Zone_30N	4540000	338000
	St,petersburg	WGS_1984_UTM_Zone_36N	6740000	273000
	Barcelona	WGS_1984_UTM_Zone_31N	4745000	324000
	Berlin	WGS_1984_UTM_Zone_33N	5866000	240000
	Rome	WGS_1984_UTM_Zone_33N	4768000	214500
	Naples	WGS_1984_UTM_Zone_33N	4610000	381000
	Athens	WGS_1984_UTM_Zone_34N	4315000	600000
CH	Shenyang	WGS_1984_UTM_Zone_51N	4716000	406000
	Wuhan	WGS_1984_UTM_Zone_50N	3483000	150000
	Qingdao	WGS_1984_UTM_Zone_51N	4105000	166000
	Xi'an	WGS_1984_UTM_Zone_49N	3923000	178000
	Harbin	WGS_1984_UTM_Zone_52N	5178000	229000
	Dalian	WGS_1984_UTM_Zone_51N	4480000	329000
	Guiyang	WGS_1984_UTM_Zone_48N	3087000	562000
	Wenzhou	WGS_1984_UTM_Zone_51N	3208000	176000
	Changsha	WGS_1984_UTM_Zone_49N	3198000	593000
	Taiyuan	WGS_1984_UTM_Zone_49N	4270000	476000
	Kunming	WGS_1984_UTM_Zone_48N	2860000	200000
	Hefei	WGS_1984_UTM_Zone_50N	3620000	410000
	Shijiazhuang	WGS_1984_UTM_Zone_50N	4280000	175000
	Changchun	WGS_1984_UTM_Zone_51N	4967000	600000
Urumqi	WGS_1984_UTM_Zone_45N	4970000	413000	

Cities
Study Area Size: (200 km)²

Figure 2. Study Location & Impervious Surface

Figure 2.1. Study Location & Impervious Surface, USA.



Projected Coordinate Systems: WGS_1984_UTM_Zone_14N

Cities in Study Area: USA. Sort by Population

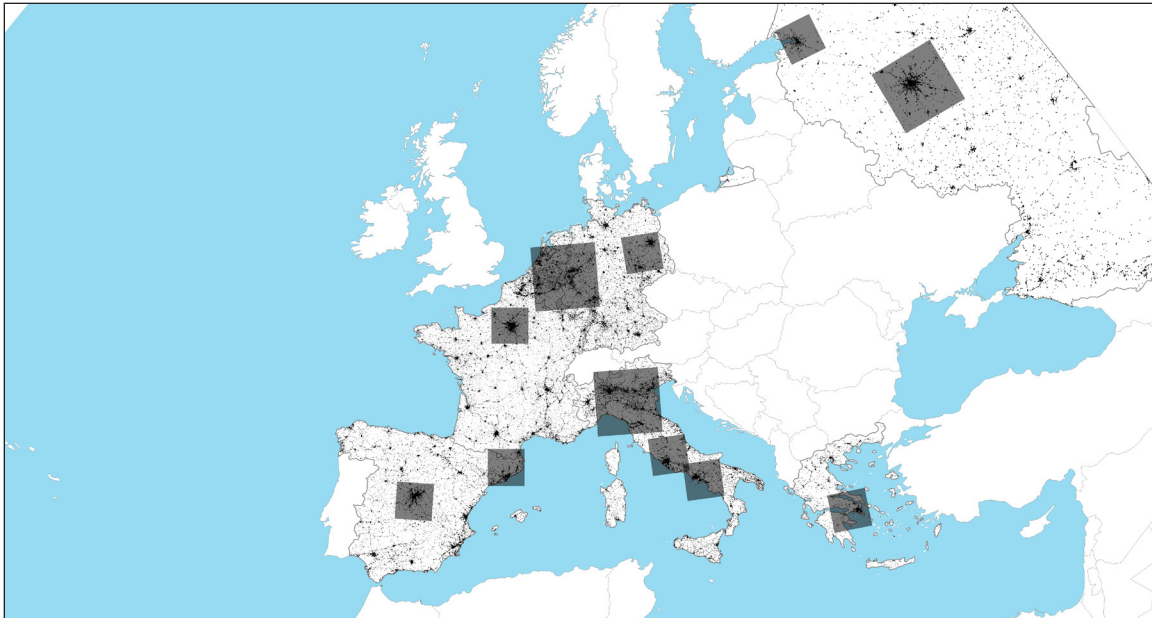
(Population > 5 Millions)

2. New York
6. Los Angeles-Riverside
11. Chicago
17. Boston
22. Dallas-Fort Worth
23. San Francisco-San Jose
26. Houston
27. Miami
31. Philadelphia
33. Atlanta
35. Washington, D.C.

(Population > 3 Millions)

42. Phoenix
56. Detroit
63. San Diego

Figure 2.2. Study Location & Impervious Surface, Europe



Projected Coordinate Systems: WGS_1984_UTM_Zone_31N

Cities in Study Area: Europe
Sort by Population

(Population > 5 Millions)

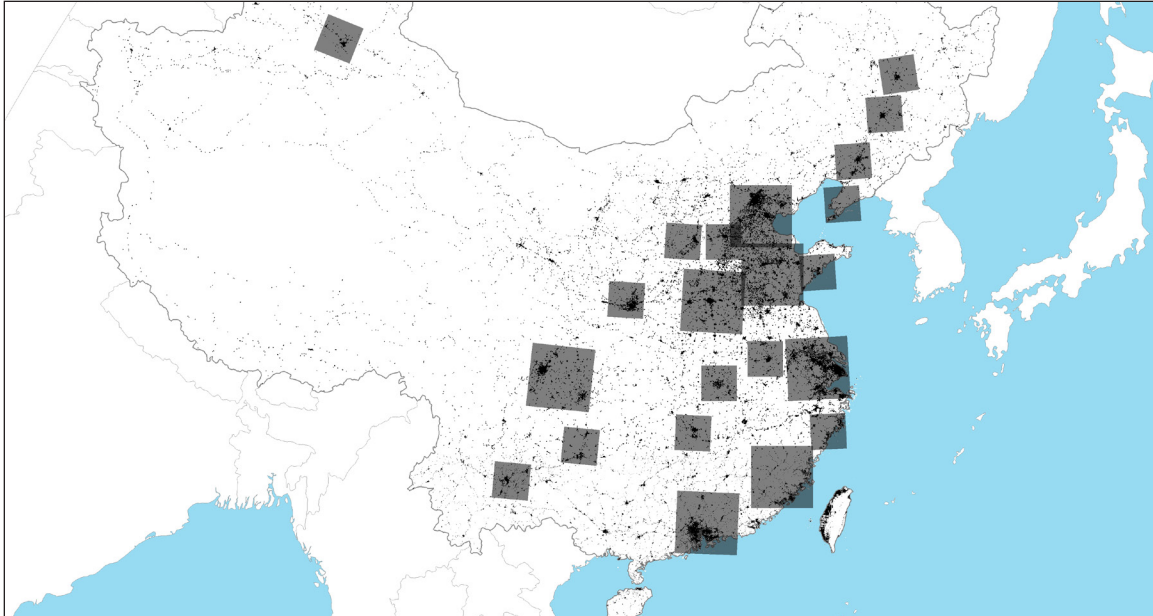
- 5. Moscow
- 10. Paris
- 21. Essen-Dusseldorf
- 25. Madrid
- 34. Milan
- 36. St, Petersburg

(Population > 3 Millions)

- 38. Barcelona
- 44. Berlin
- 46. Rome
- 57. Naples
- 62. Athens

Figure 2. Study Location & Impervious Surface

Figure 2.3. Study Location & Impervious Surface, China



Projected Coordinate Systems: WGS_1984_UTM_Zone_50N

Cities in Study Area: China

Sort by Population

(Population > 5 Millions)

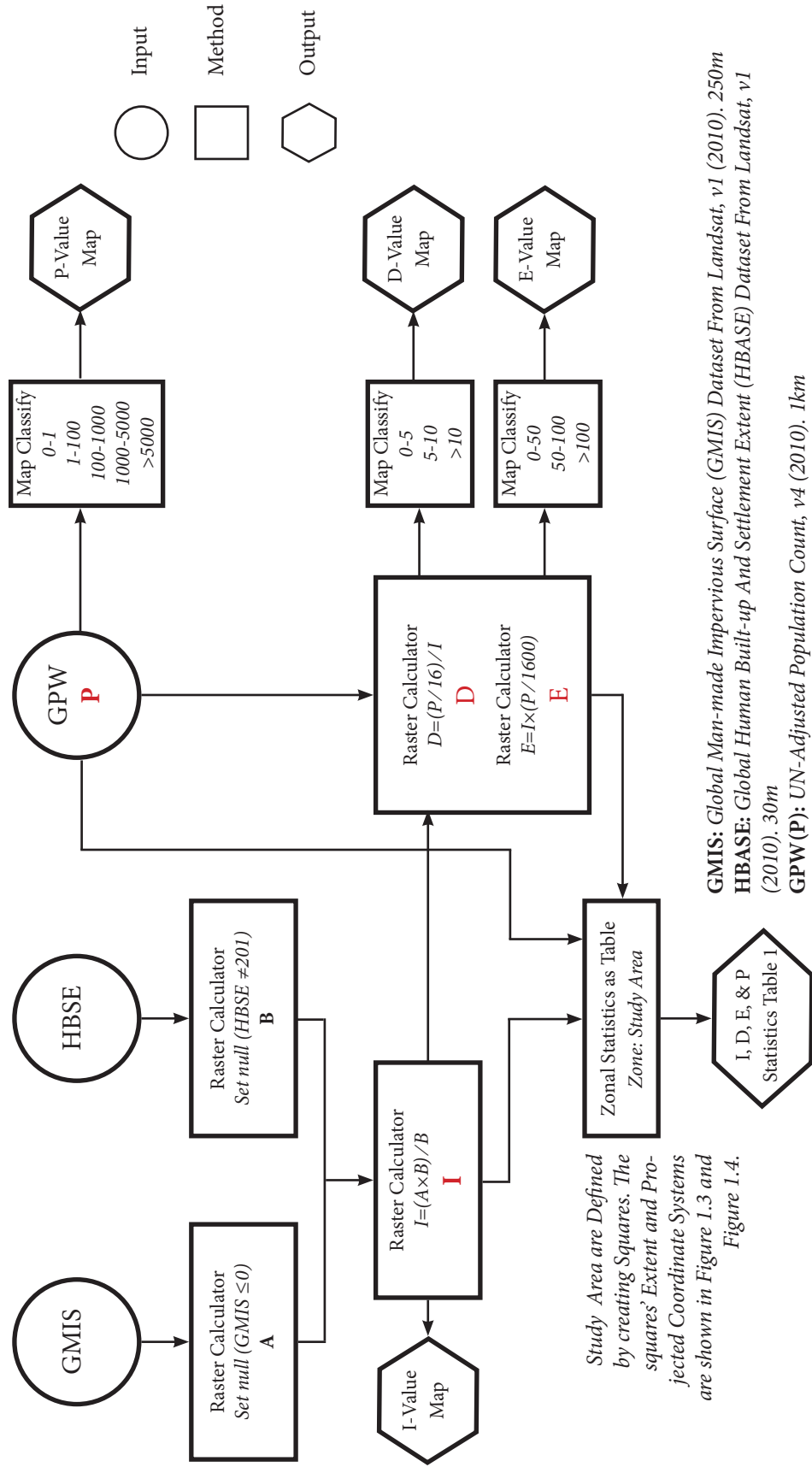
1. Shanghai
3. Beijing
4. Guangzhou-Foshan
7. Tianjing
8. Shenzhen
9. Chengdu
12. Chongqing
13. Dongguan
14. Shenyang-Fushun
15. Wuhan
16. Hong Kong
18. Hangzhou
19. Zhengzhou
20. Quanzhou
24. Nanjing
28. Suzhou
29. Qingdao
30. Xi'an
32. Fuzhou
37. Harbin

(Population > 3 Millions)

39. Dalian
40. Guiyang
41. Wenzhou
43. Xiamen
45. Changsha
47. Jinan
48. Taiyuan
49. Kunming
50. Hefei
52. Wuxi
53. Changzhou
54. Shijiazhuang
55. Ningbo
58. Zhangjiagang
59. Changchun
60. Urumqi
61. Zhongshan

Figure 3. Method

Figure 3.1.



GMIS: Global Man-made Impervious Surface (GMIS) Dataset From Landsat, v1 (2010). 250m
HBASE: Global Human Built-up And Settlement Extent (HBASE) Dataset From Landsat, v1 (2010). 30m

GPW (P): UN-Adjusted Population Count, v4 (2010). 1km

I: Impervious Surface Percentage (250m) **E:** The products of value-P and value-I (250m)

D: The quotients of value -P and value-I (250m) **E*:** Aggregate from value-E

K: A value that indicates the degree of cluster.

Figure 3. Method

Figure 3.2.

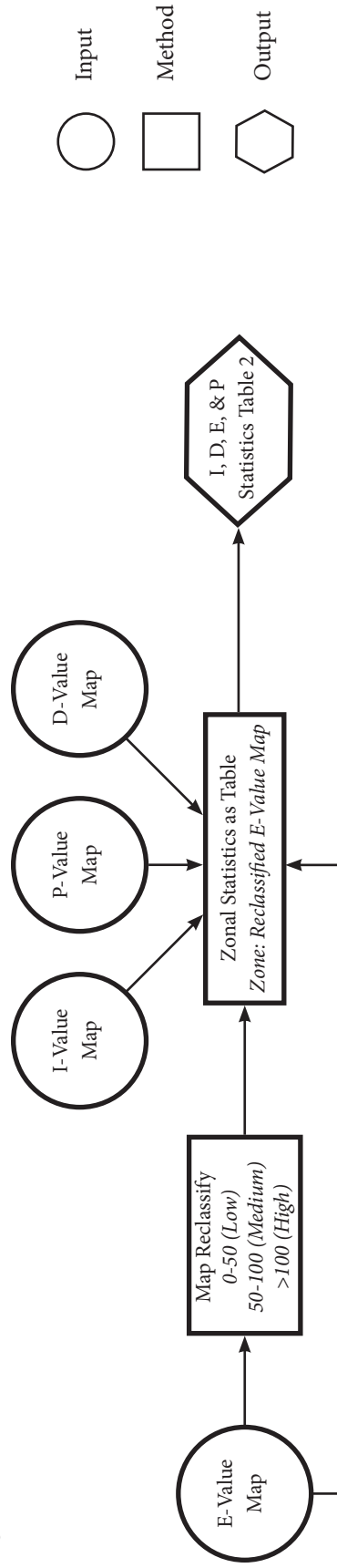
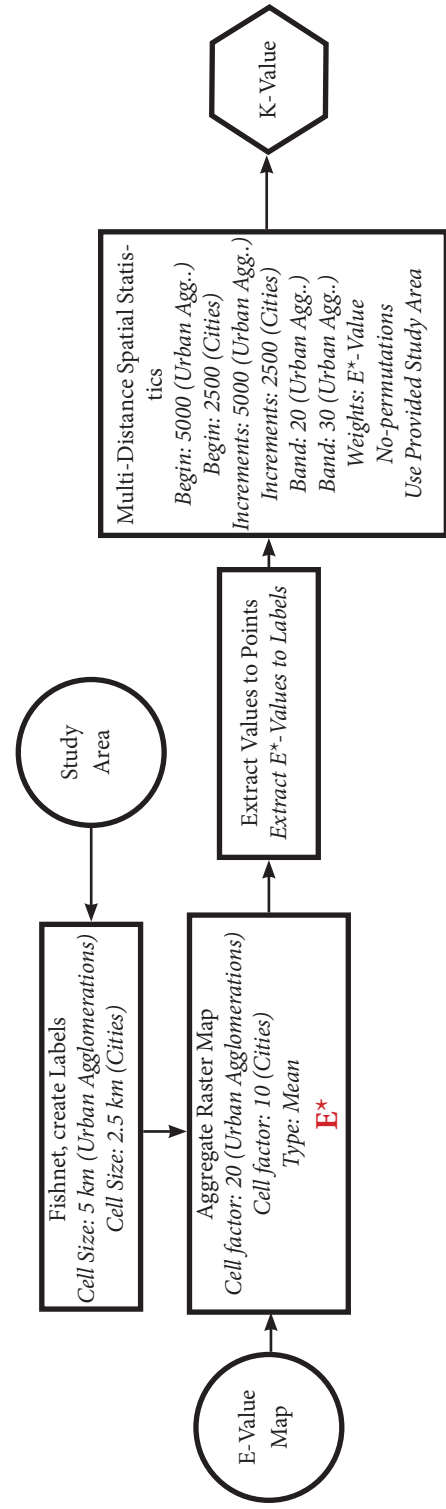
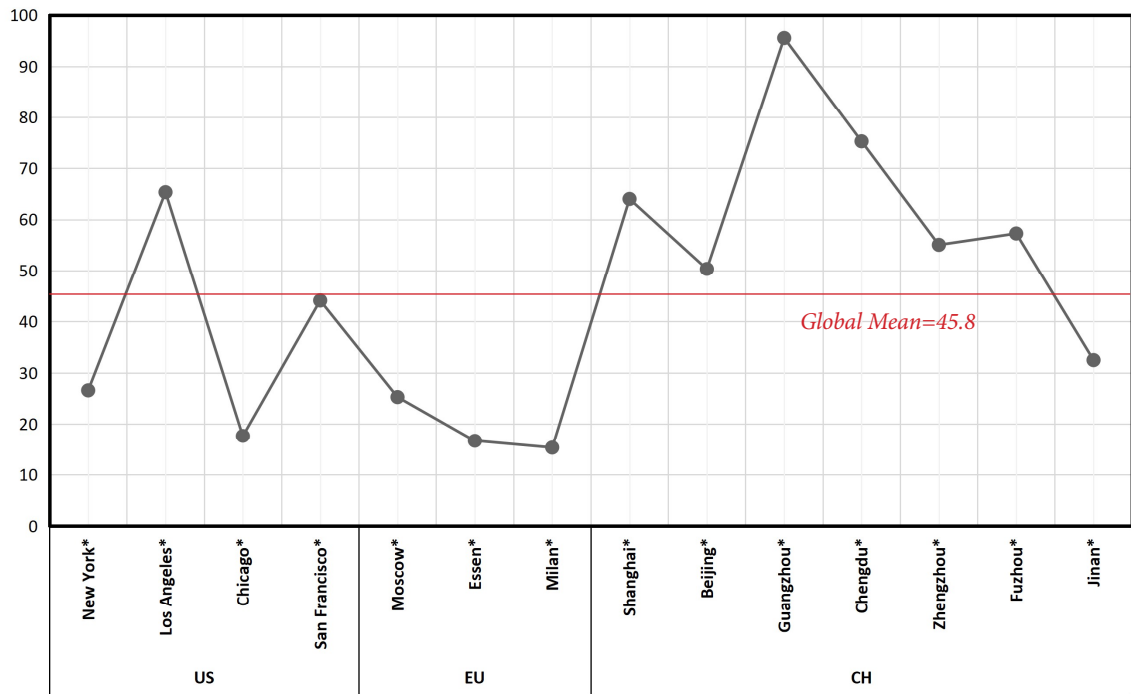


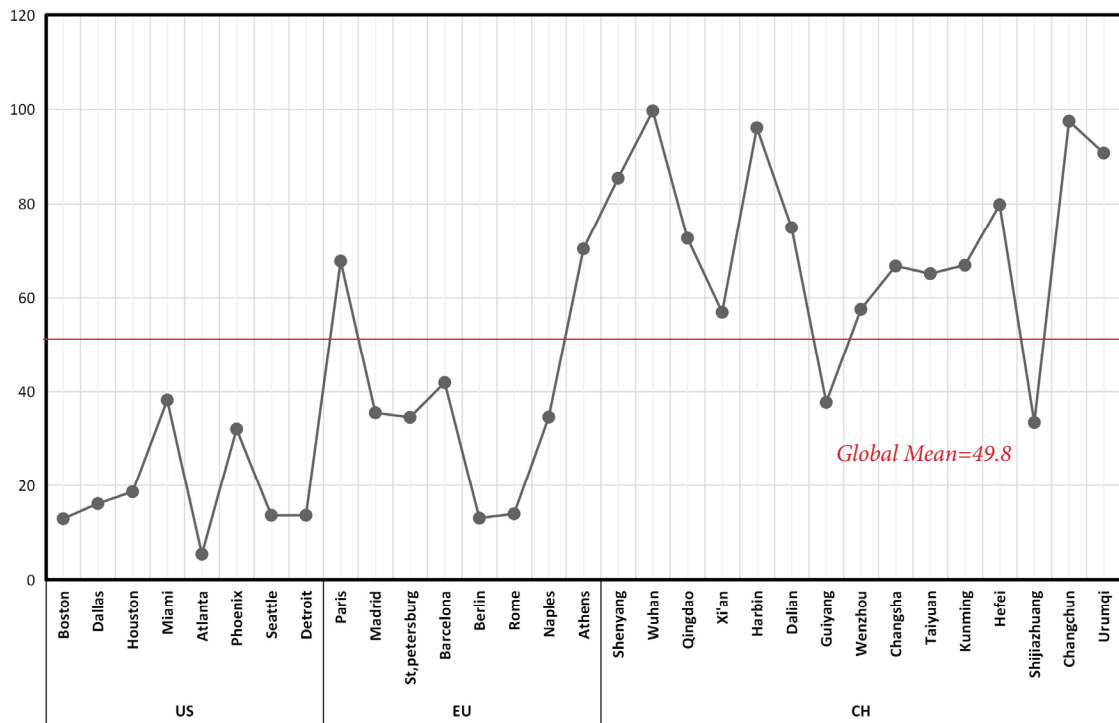
Figure 3.3.



Graph 1.1. Urban Agglomerations, Value-E Mean

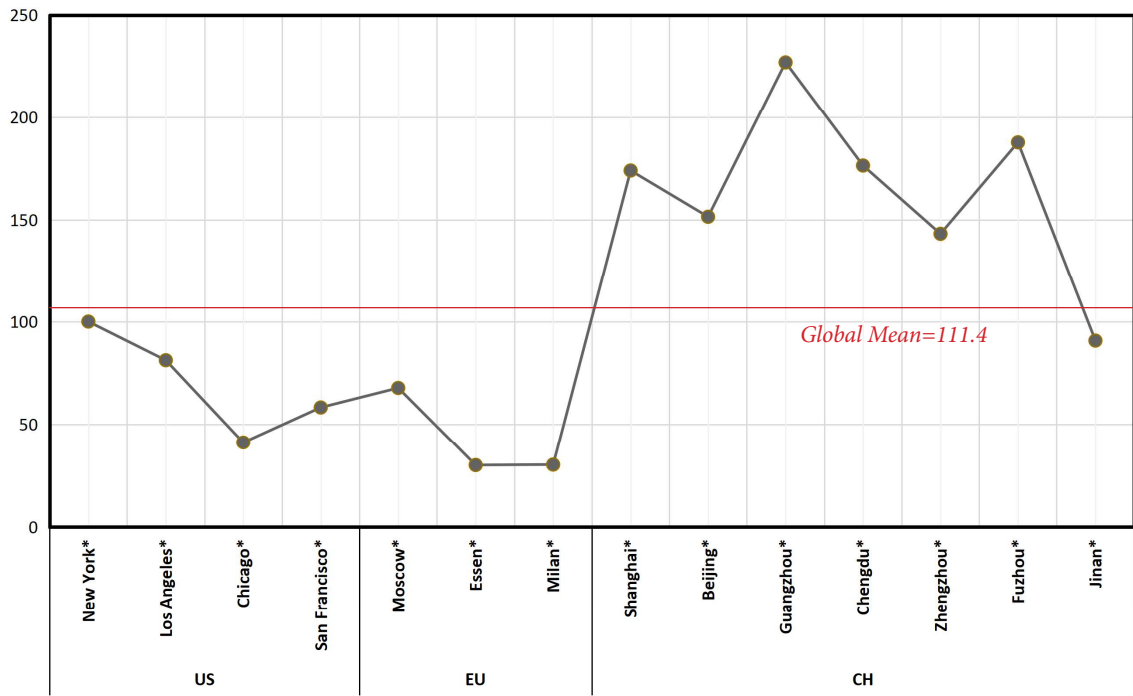


Graph 1.2. Cities, Value-E Mean

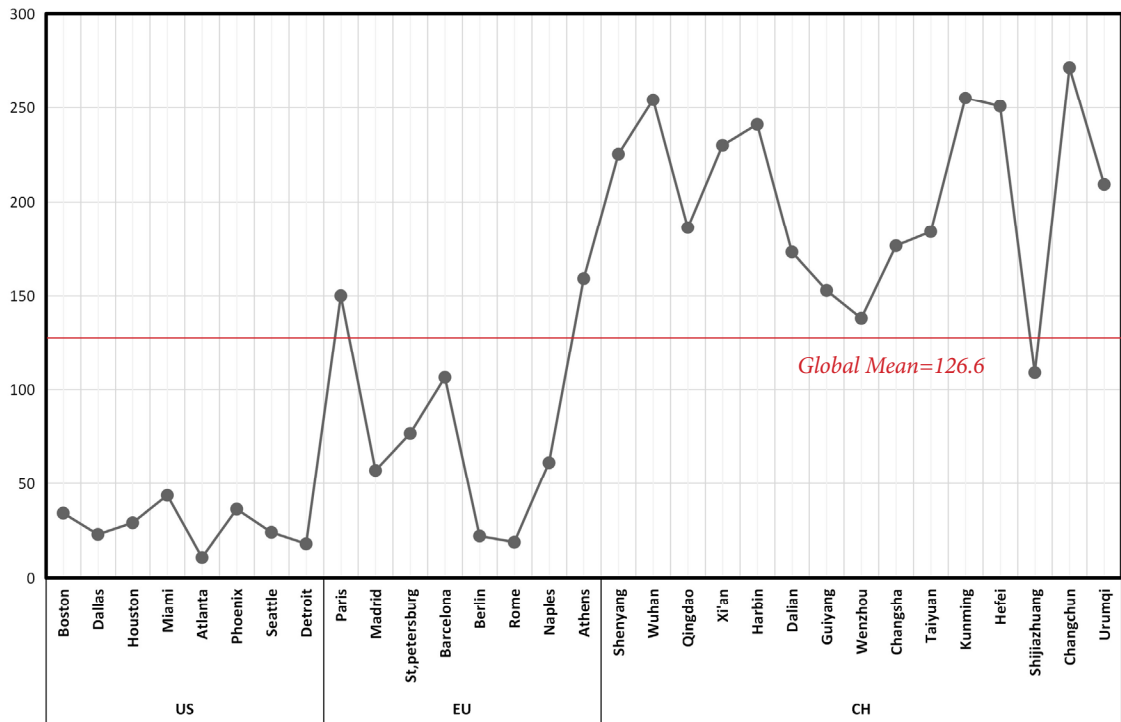


Graph 2. Value-E STD

Graph 2.1. Urban Agglomerations, Value-E STD

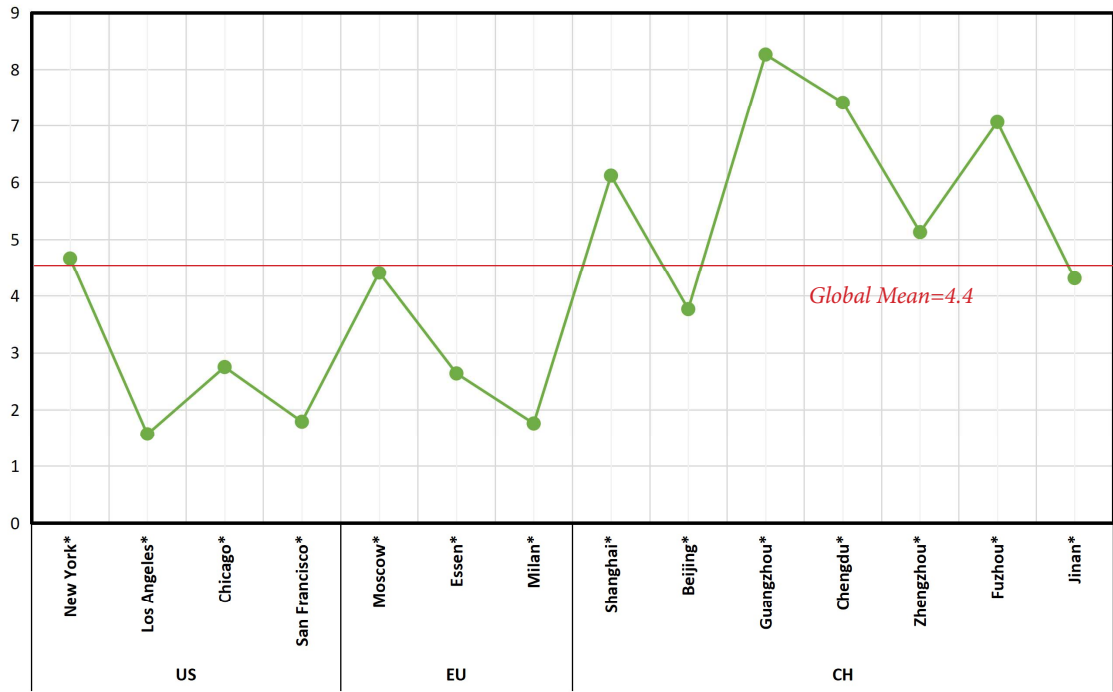


Graph 2.2. Cities, Value-E STD

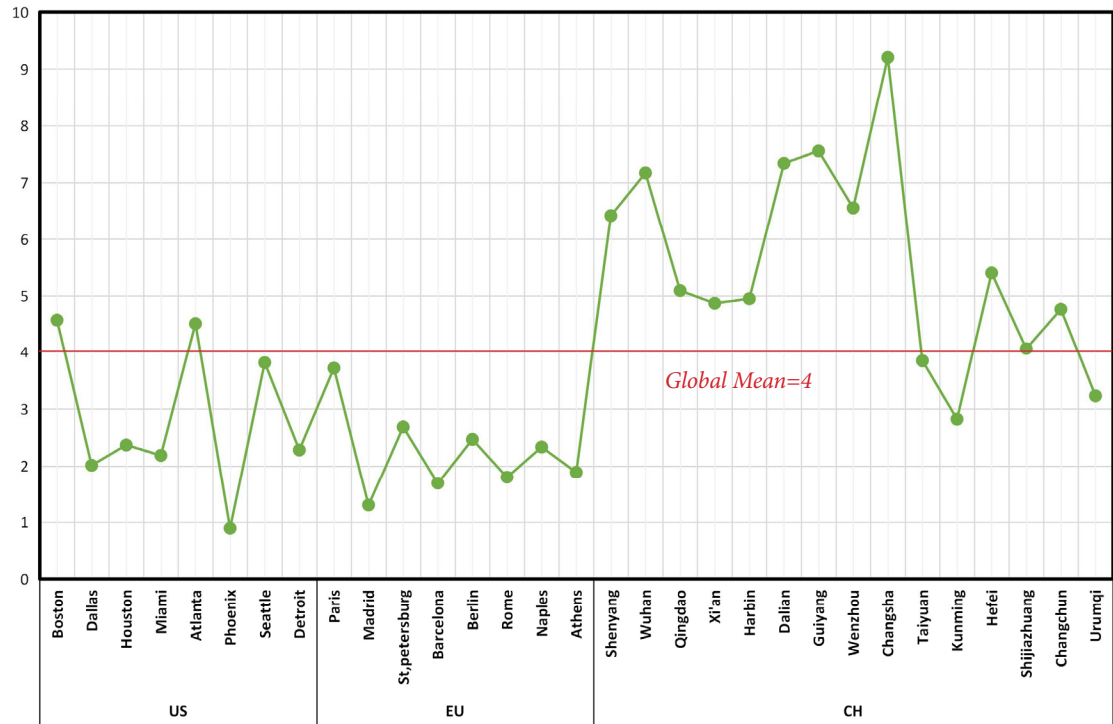


Graph 3. Value-D Mean

Graph 3.1. Urban Agglomerations, Value-D Mean

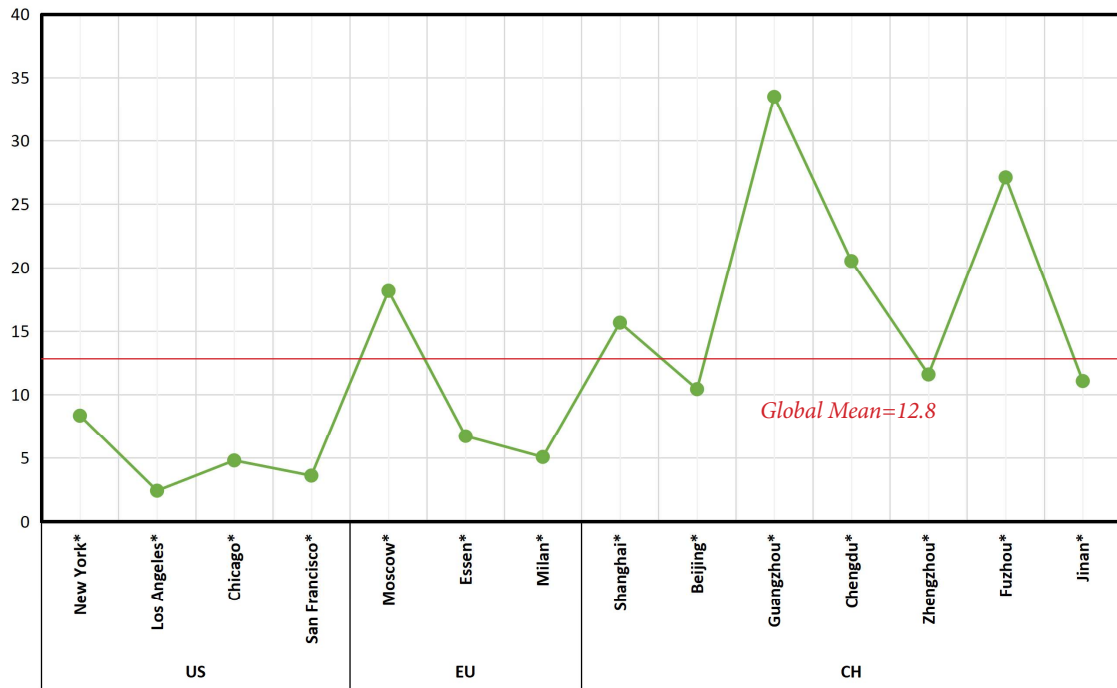


Graph 3.2. Cities, Value-D Mean

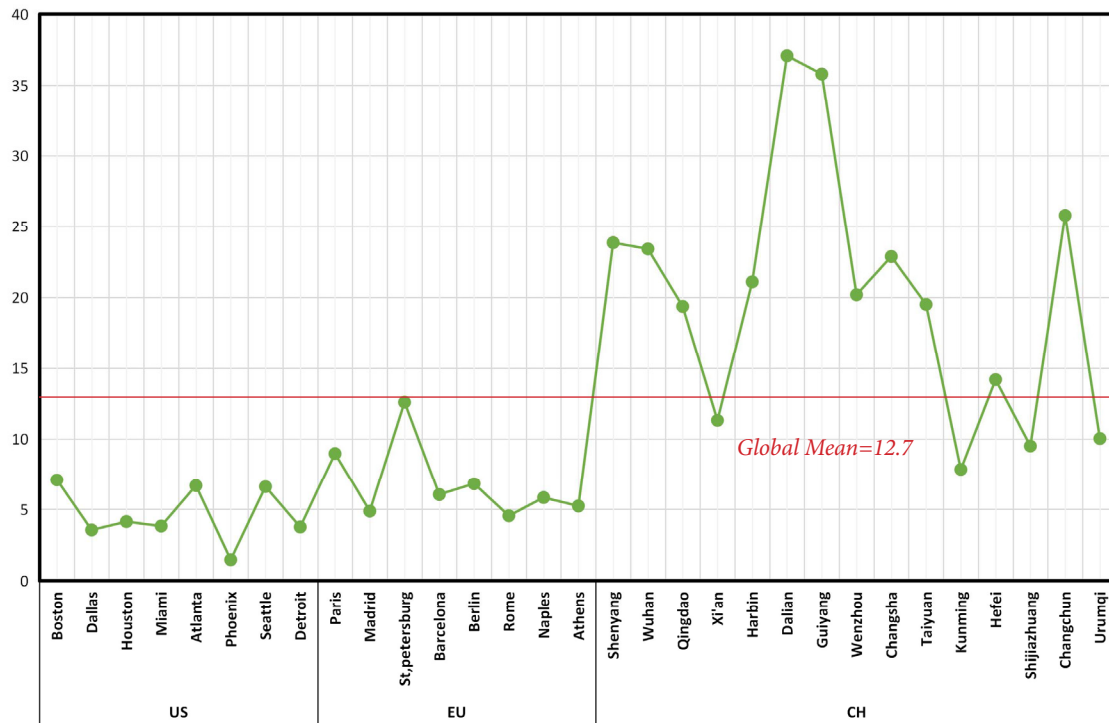


Graph 4. Value-D STD

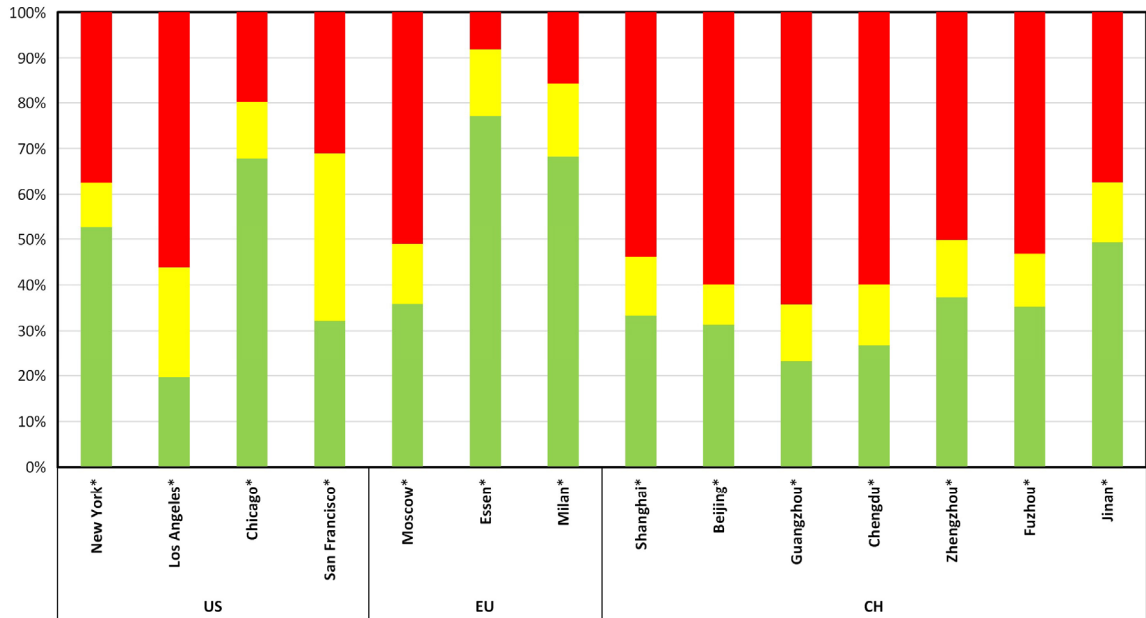
Graph 4.1. Urban Agglomerations, Value-D STD



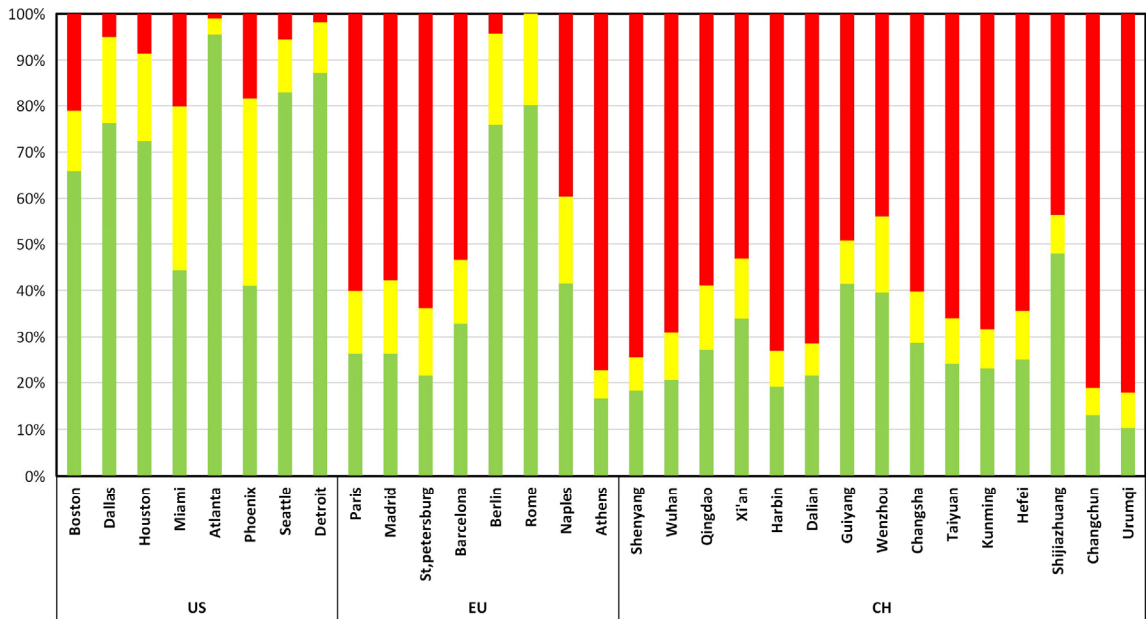
Graph 4.2. Cities, Value-D STD



Graph 5.1. Urban Agglomerations, Value-P Percentage

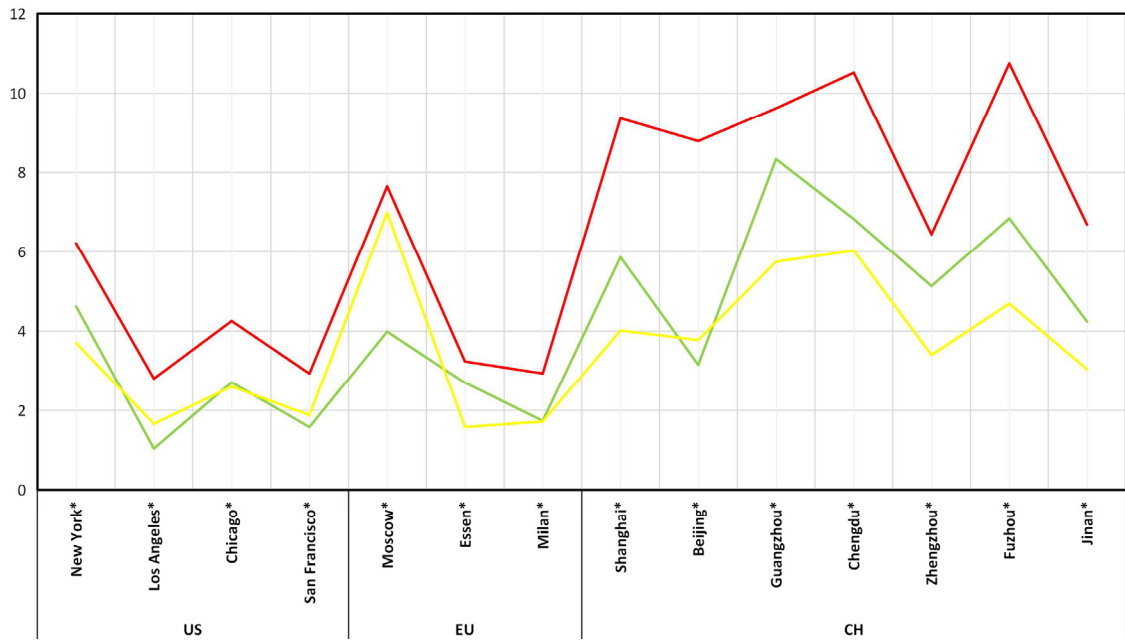


Graph 5.2. Cities, Value-P Percentage

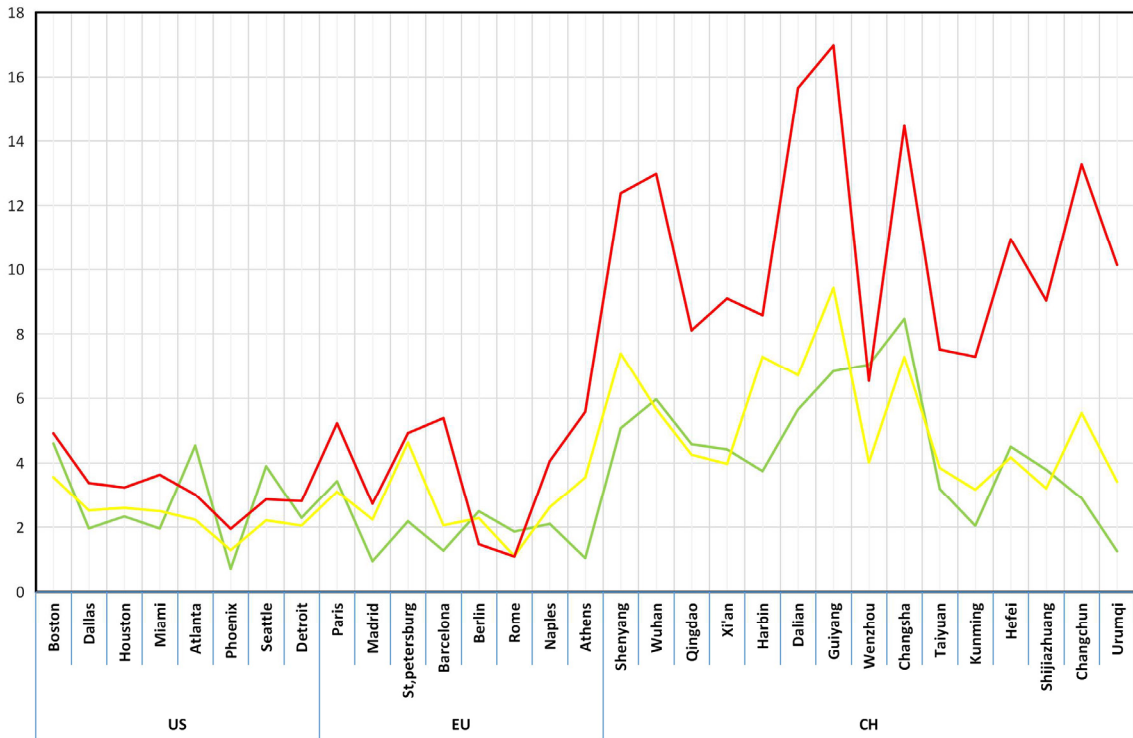


Graph 6. Value-D Mean (Reclassify)

Graph 6.1. Urban Agglomerations, Value-D Mean (Reclassify)



Graph 6.2. Cities, Value-D Mean (Reclassify)

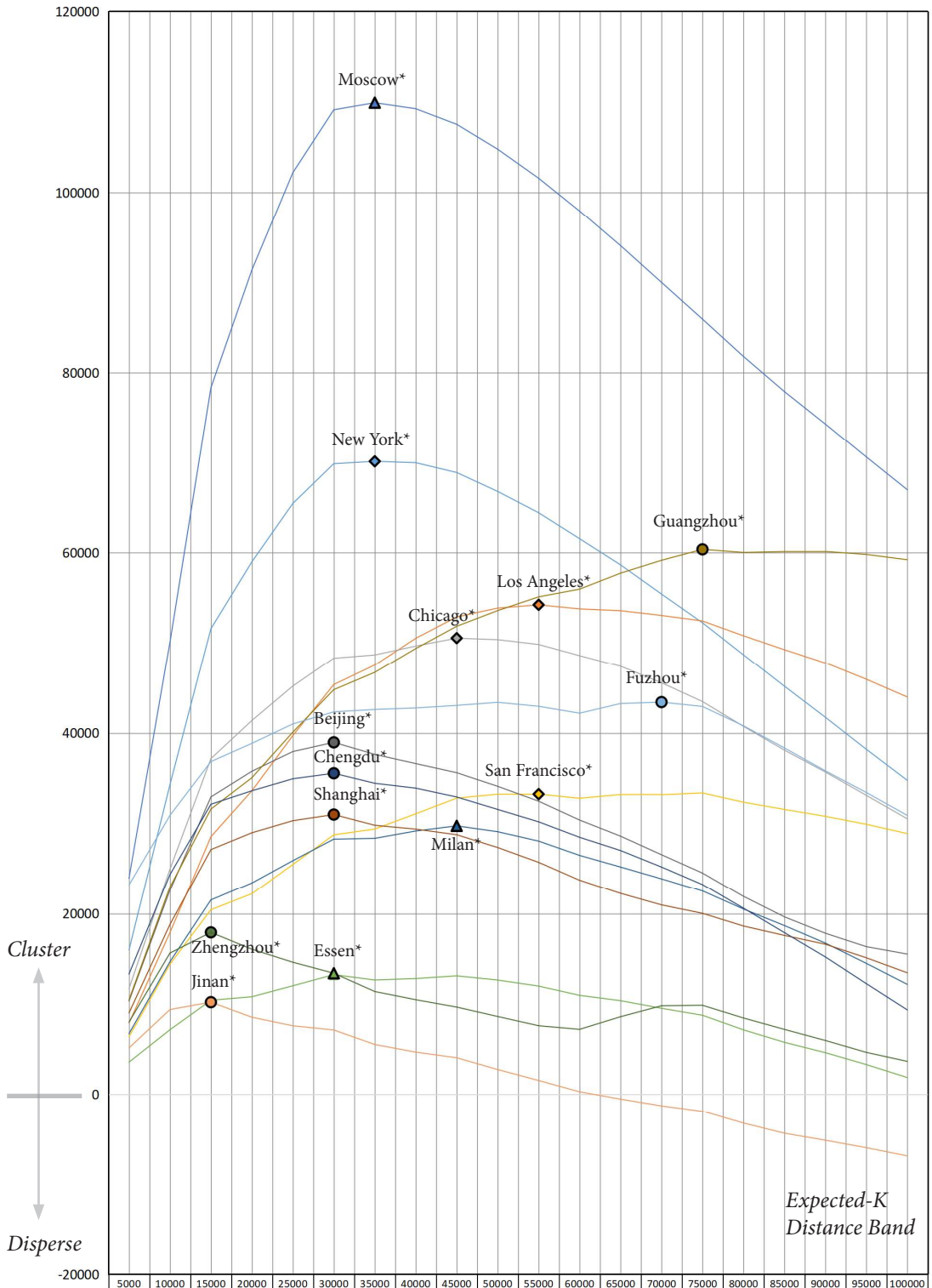


Graph 7. Value-K

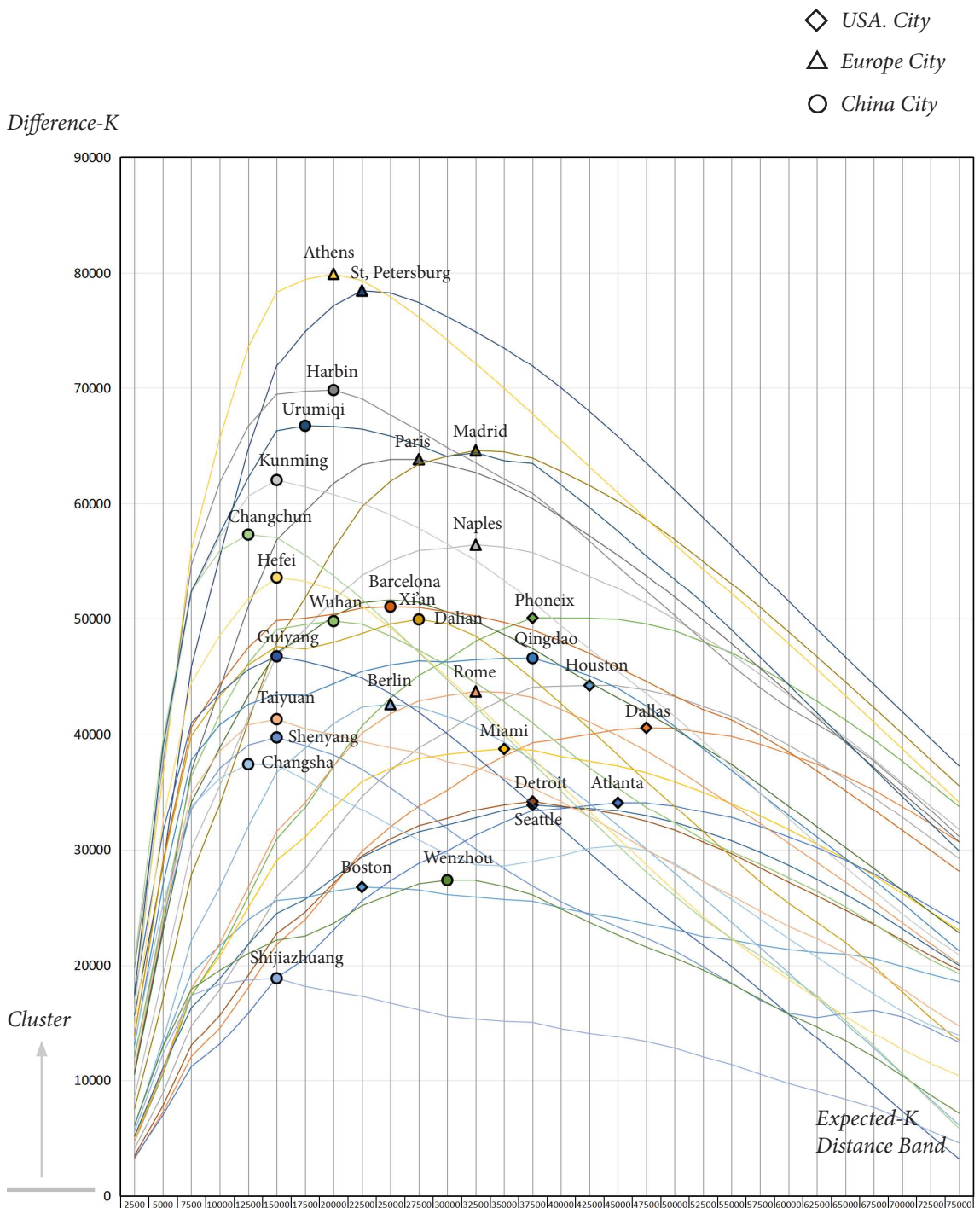
Graph 7.1. Urban Agglomerations, Value-K

- ◇ USA. Urban
- △ Europe Urban
- China Urban

Difference-K

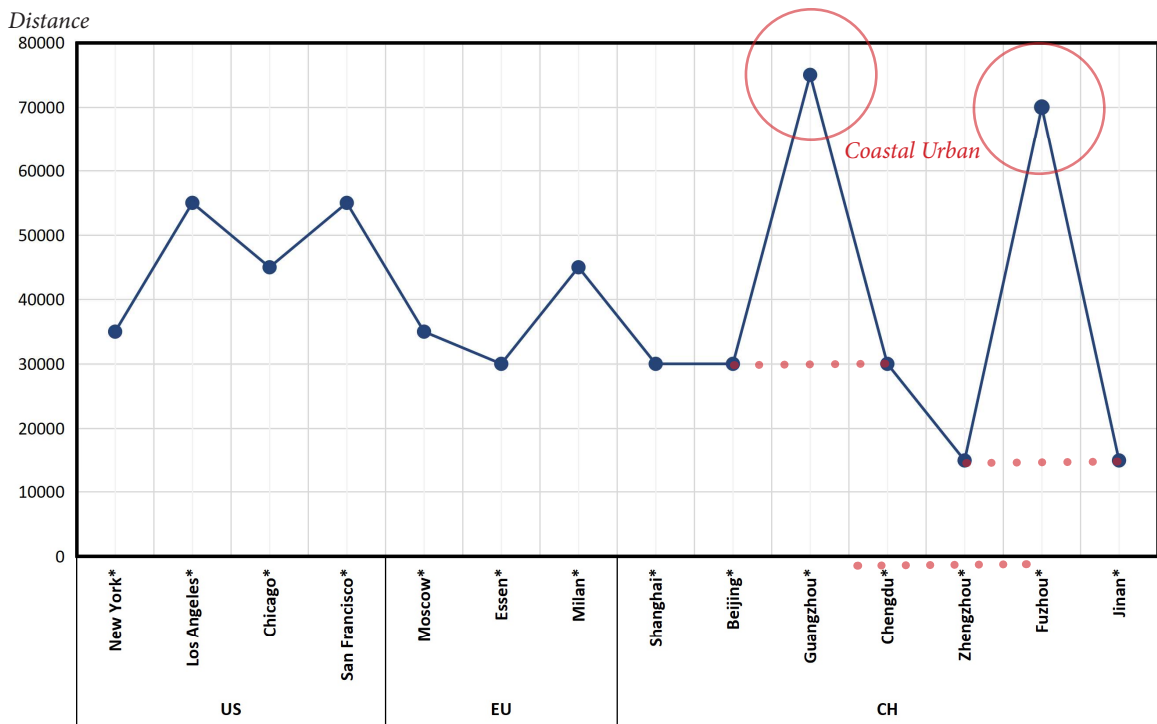
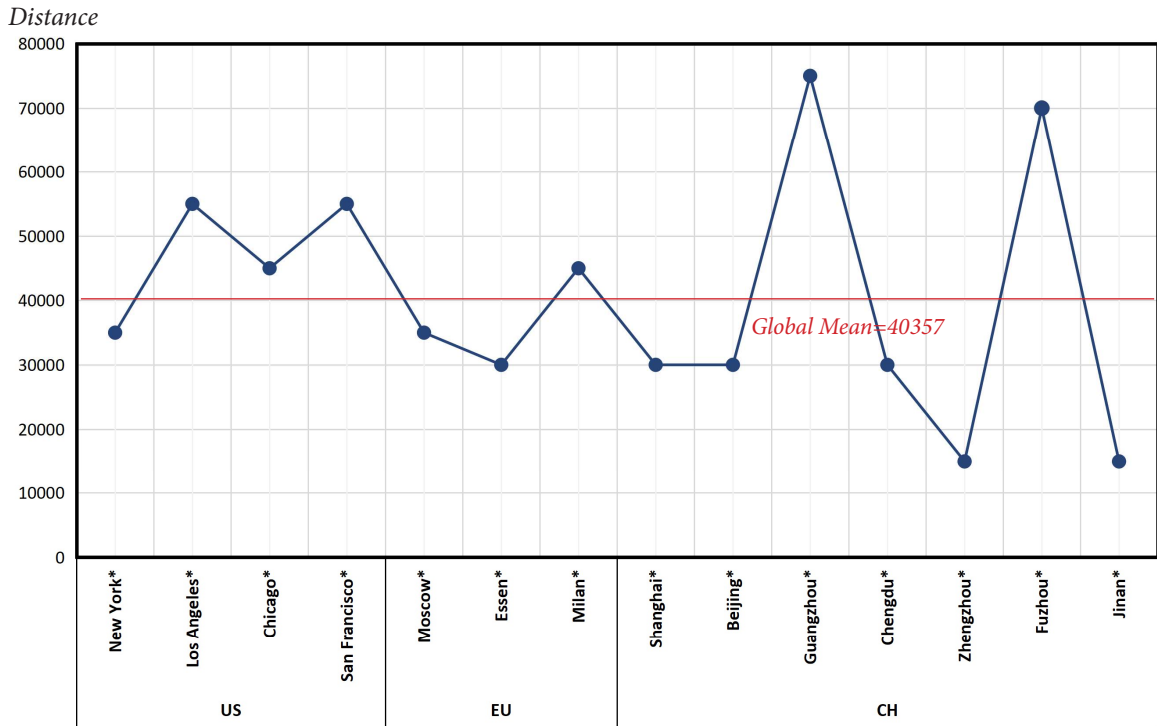


Graph 7.2. Cities, Value-K



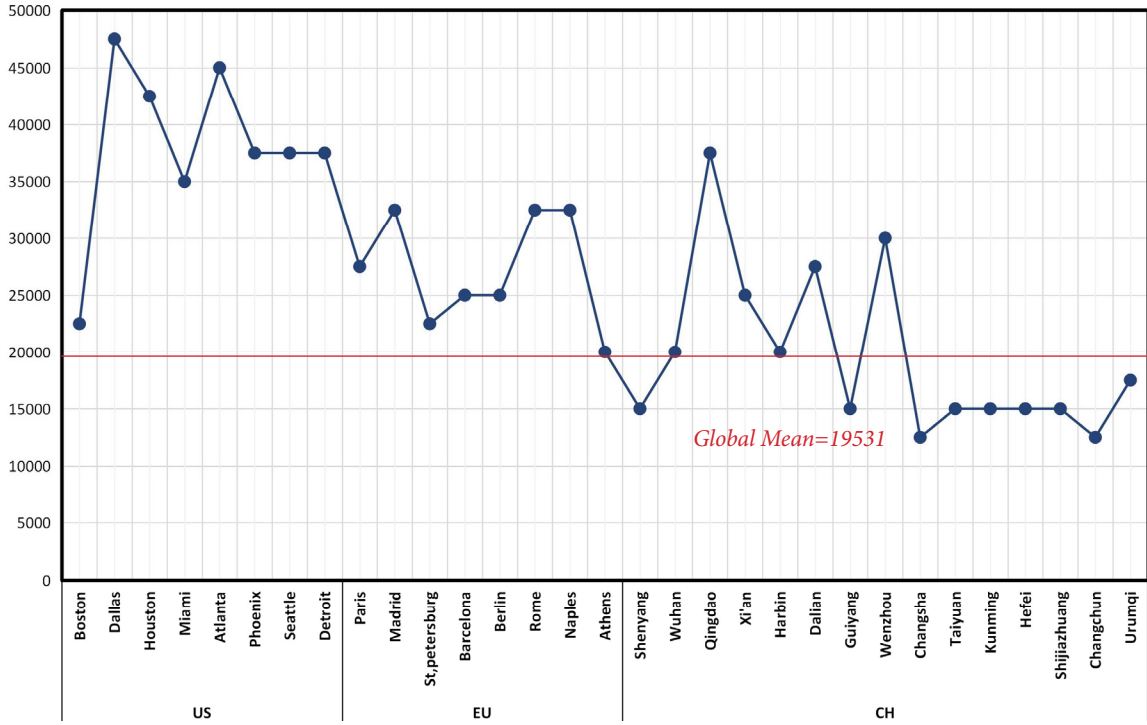
Graph 8. “Expected-K” When “Difference-K” is Highest

Graph 8.1. Urban Agglomerations, “Expected-K” When “Difference-K” is Highest

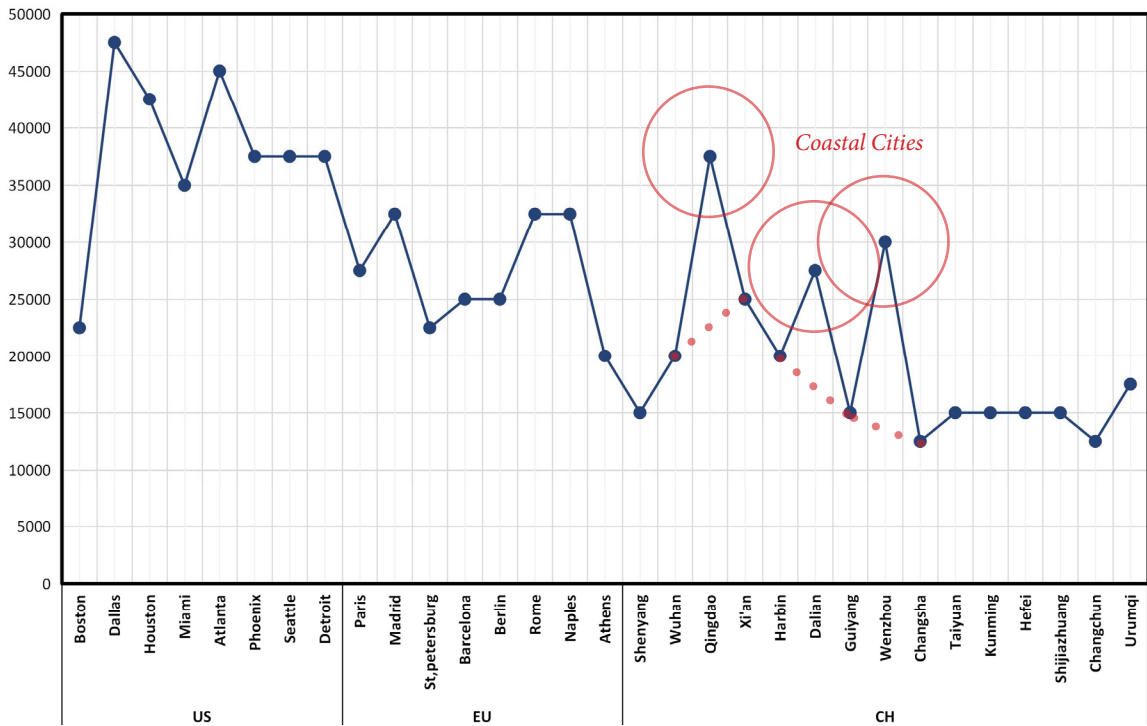


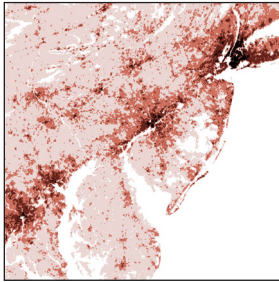
Graph 8.2. Urban Agglomerations, “Expected-K” When “Difference-K” is Highest

Distance

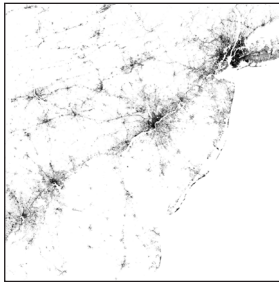


Distance

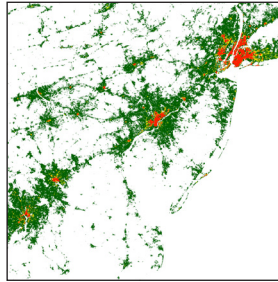




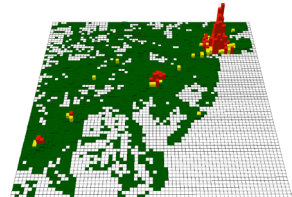
New York*
Population Count (1 km)
P Range: 42178
P Mean: 276
P STD: 1053



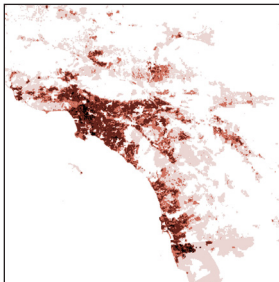
New York*
Impervious Percentage (250m)
I Sum: 7257330
I Mean: 22 *I STD:* 23



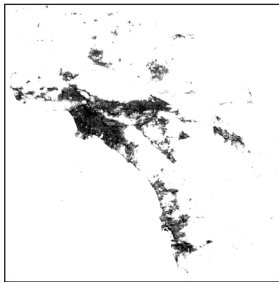
New York*
E Value Map (250m)
E Range: 2504
E Mean: 27
E STD: 100



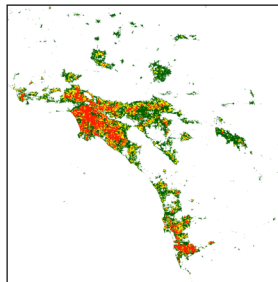
New York*
E* Value 3D View (5 km)
E Highest:* 778



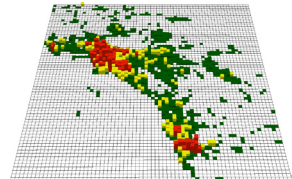
Los Angeles*
Population Count (1 km)
P range: 16689
P Mean: 195
P STD: 717



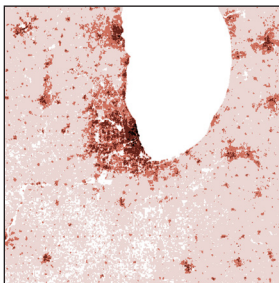
Los Angeles*
Impervious Percentage (250m)
I Sum: 10091595
I Mean: 61 *I STD:* 25



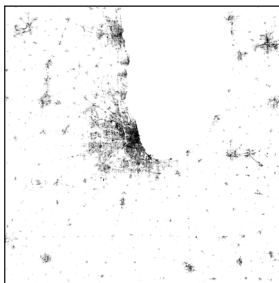
Los Angeles*
E Value Map (250m)
E Range: 1022
E Mean: 65
E STD: 81



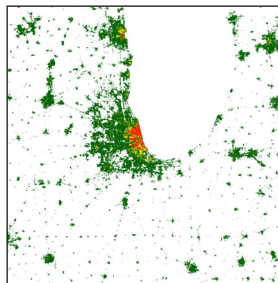
Los Angeles*
E* Value 3D View (5 km)
E Highest:* 359



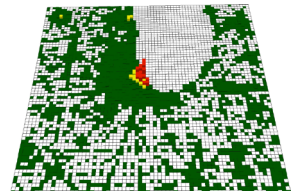
Chicago*
Population Count (1 km)
P range: 17894
P Mean: 104
P STD: 397



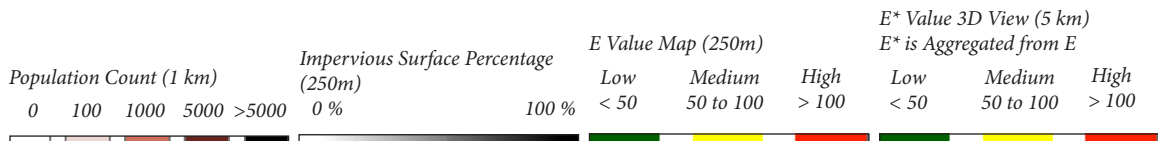
Chicago*
Impervious Percentage (250m)
I Sum: 4754086
I Mean: 28 *I STD:* 23



Chicago*
E Value Map (250m)
E Range: 1018
E Mean: 18
E STD: 41

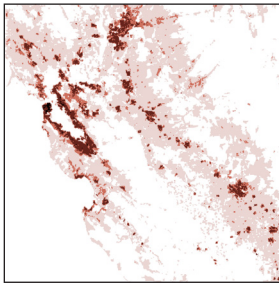


Chicago*
E* Value 3D View (5 km)
E Highest:* 292

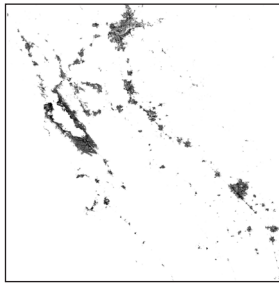


Map 1. Urban Agglomerations

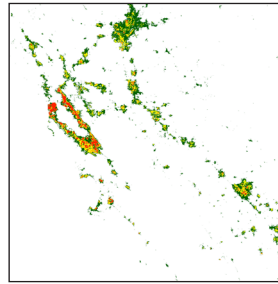
Study Area Size: (350 km)²



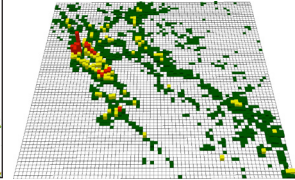
San Francisco*
Population Count (1 km)
P Range: 25337
P Mean: 90
P STD: 421



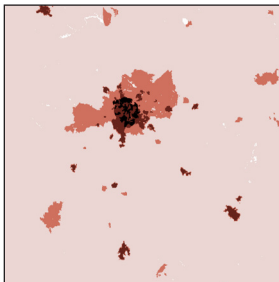
San Francisco*
Impervious Percentage (250m)
I Sum: 5123980
I Mean: 51 *I STD:* 25



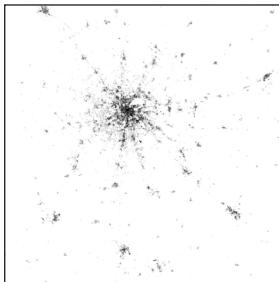
San Francisco*
E Value Map (250m)
E Range: 1552
E Mean: 44
E STD: 58



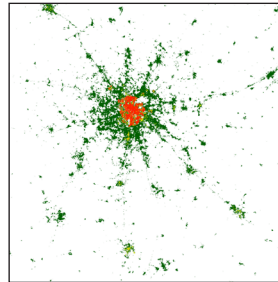
San Francisco*
E* Value 3D View (5 km)
E Highest:* 425



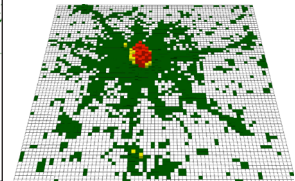
Moscow*
Population Count (1 km)
P Range: 14459
P Mean: 92
P STD: 546



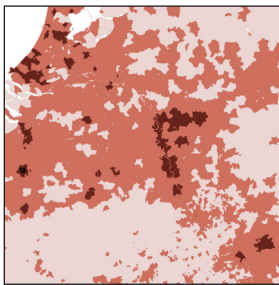
Moscow*
Impervious Percentage (250m)
I Sum: 2840315
I Mean: 24 *I STD:* 23



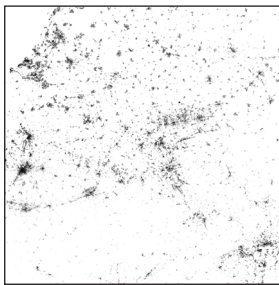
Moscow*
E Value Map (250m)
E Range: 718
E Mean: 25
E STD: 68



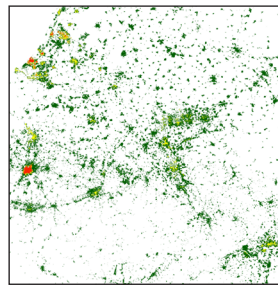
Moscow*
E* Value 3D View (5 km)
E Highest:* 272



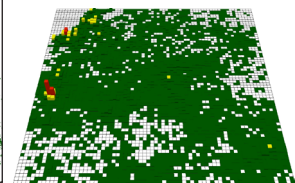
Essen*
Population Count (1 km)
P Range: 11842
P Mean: 222
P STD: 338



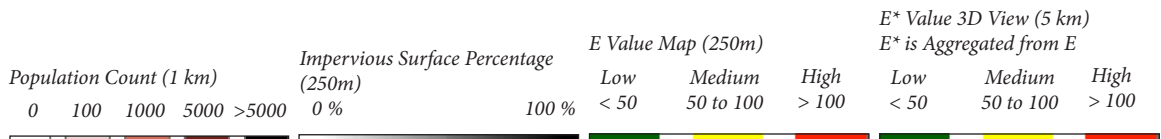
Essen*
Impervious Percentage (250m)
I Sum: 6742720
I Mean: 35 *I STD:* 24

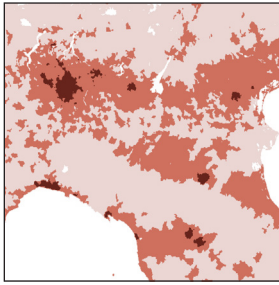


Essen*
E Value Map (250m)
E Range: 740
E Mean: 17
E STD: 30

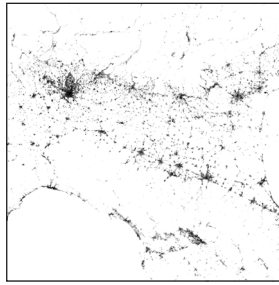


Essen*
E* Value 3D View (5 km)
E Highest:* 336

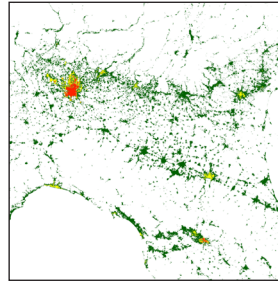




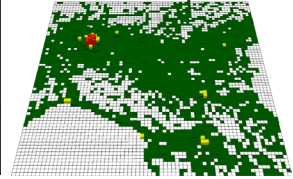
Milan*
Population Count (1 km)
P Range: 4464
P Mean: 152
P STD: 298



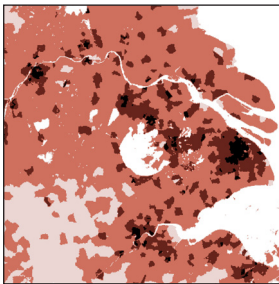
Milan*
Impervious Percentage (250m)
I Sum: 6288014
I Mean: 39 I STD: 26



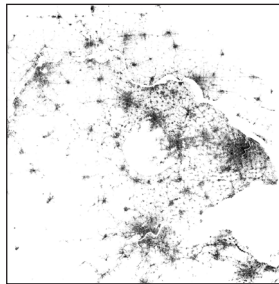
Milan*
E Value Map (250m)
E Range: 269
E Mean: 15
E STD: 30



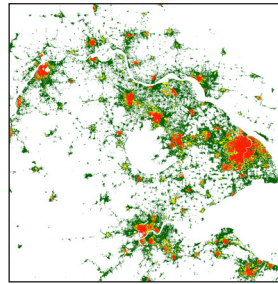
Milan*
E* Value 3D View (5 km)
E Highest: 221*



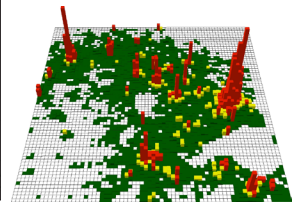
Shanghai*
Population Count (1 km)
P Range: 110446
P Mean: 748
P STD: 2061



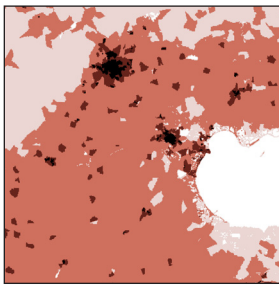
Shanghai*
Impervious Percentage (250m)
I Sum: 11874749
I Mean: 35 I STD: 24



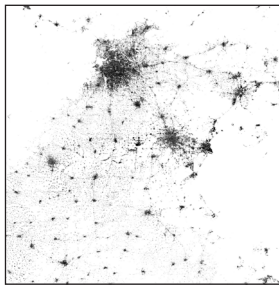
Shanghai*
E Value Map (250m)
E Range: 4594
E Mean: 64
E STD: 174



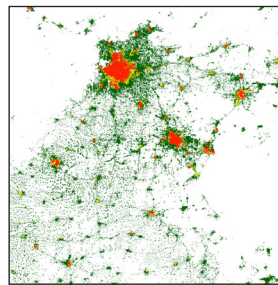
Shanghai*
E* Value 3D View (5 km)
E Highest: 1406*



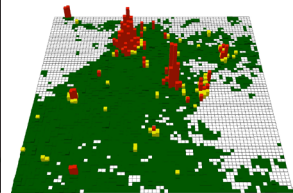
Beijing*
Population Count (1 km)
P Range: 97140
P Mean: 446
P STD: 1401



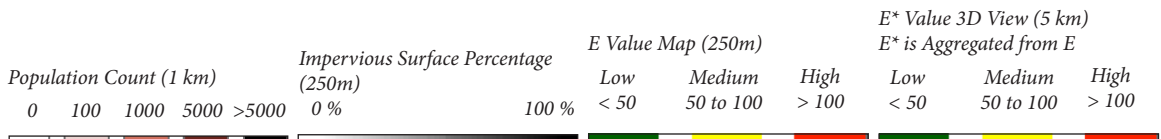
Beijing*
Impervious Percentage (250m)
I Sum: 9259057
I Mean: 37 I STD: 25

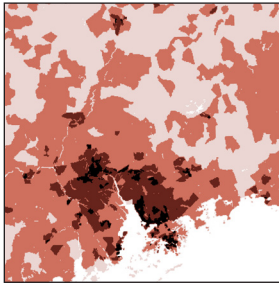


Beijing*
E Value Map (250m)
E Range: 5100
E Mean: 50
E STD: 152

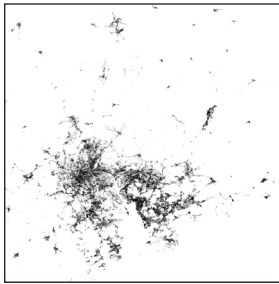


Beijing*
E* Value 3D View (5 km)
E Highest: 869*

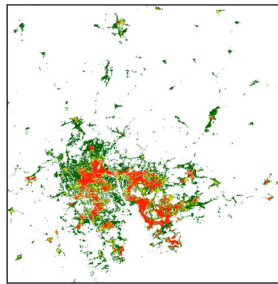




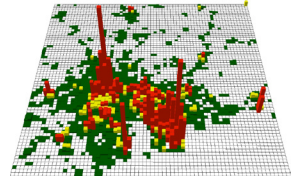
Guangzhou*
Population Count (1 km)
P Range: 100576
P Mean: 558
P STD: 2165



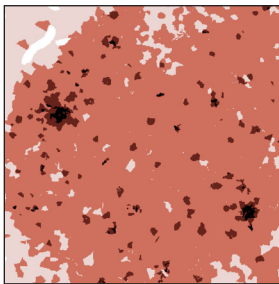
Guangzhou*
Impervious Percentage (250m)
I Sum: 8001910
I Mean: 42 *I STD:* 28



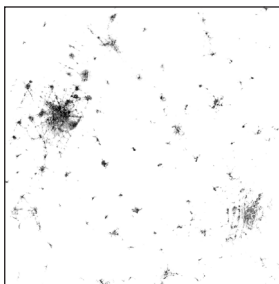
Guangzhou*
E Value Map (250m)
E Range: 6160
E Mean: 96
E STD: 227



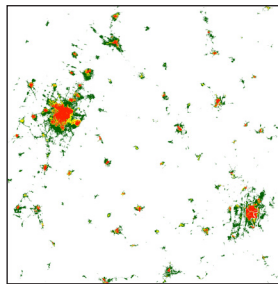
Guangzhou*
E* Value 3D View (5 km)
E Highest:* 1562



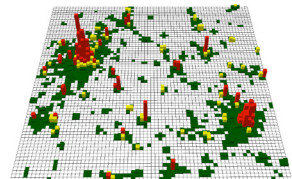
Chengdu*
Population Count (1 km)
P Range: 88804
P Mean: 435
P STD: 1192



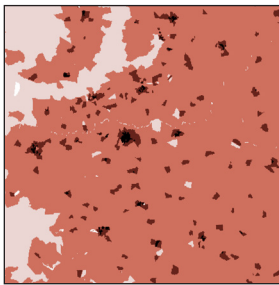
Chengdu*
Impervious Percentage (250m)
I Sum: 3537395
I Mean: 36 *I STD:* 24



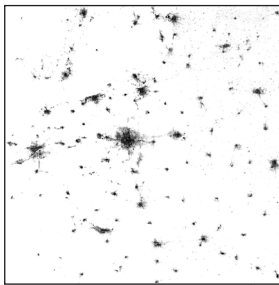
Chengdu*
E Value Map (250m)
E Range: 4804
E Mean: 75
E STD: 176



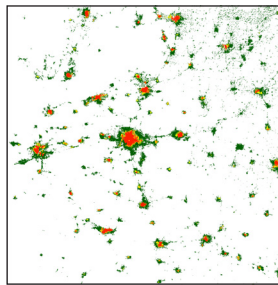
Chengdu*
E* Value 3D View (5 km)
E Highest:* 885



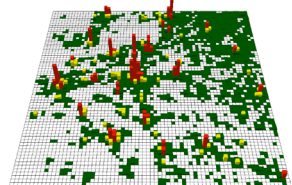
Zhengzhou*
Population Count (1 km)
P Range: 59541
P Mean: 475
P STD: 879



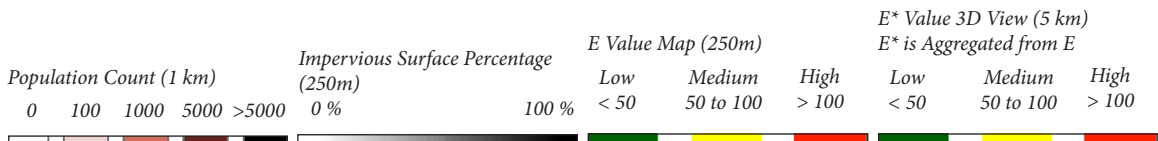
Zhengzhou*
Impervious Percentage (250m)
I Sum: 4696833
I Mean: 36 *I STD:* 26

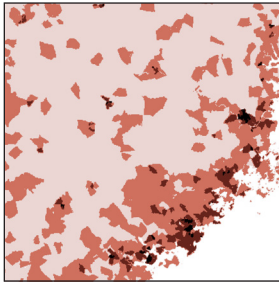


Zhengzhou*
E Value Map (250m)
E Range: 22880
E Mean: 55
E STD: 143

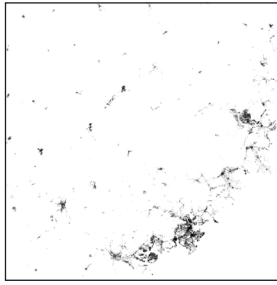


Zhengzhou*
E* Value 3D View (5 km)
E Highest:* 880

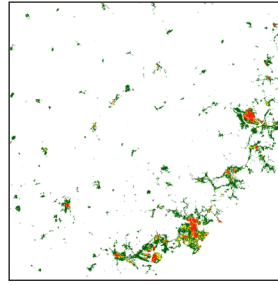




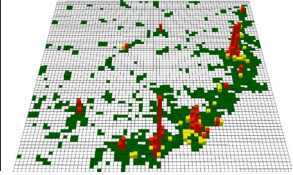
Fuzhou*
Population Count (1 km)
P Range: 141715
P Mean: 242
P STD: 1144



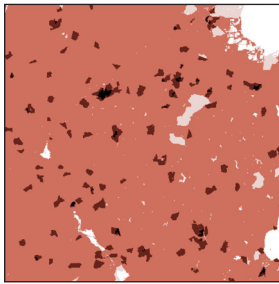
Fuzhou*
Impervious Percentage (250m)
I Sum: 2894778
I Mean: 34 I STD: 26



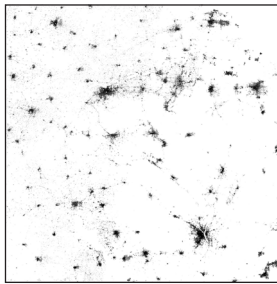
Fuzhou*
E Value Map (250m)
E Range: 6997
E Mean: 57
E STD: 188



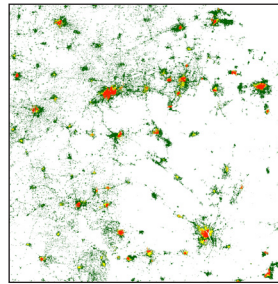
Fuzhou*
E* Value 3D View (5 km)
E Highest: 1129*



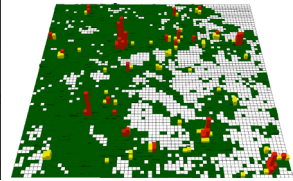
Jinan*
Population Count (1 km)
P Range: 52388
P Mean: 451
P STD: 761



Jinan*
Impervious Percentage (250m)
I Sum: 6158942
I Mean: 33 I STD: 25



Jinan*
E Value Map (250m)
E Range: 2881
E Mean: 32
E STD: 91



Jinan*
E* Value 3D View (5 km)
E Highest: 609*

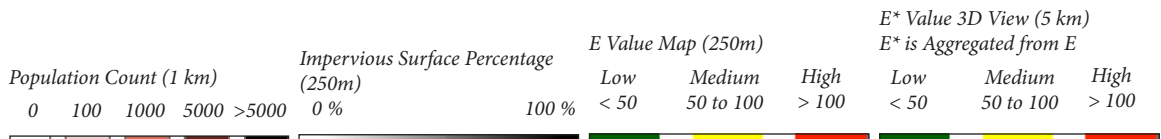
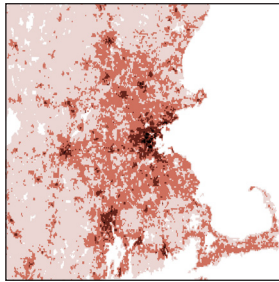
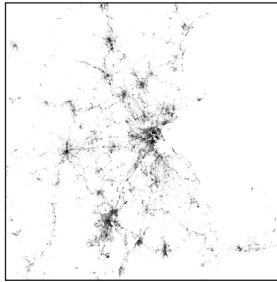


Figure 4. Urban Agglomerations. P, I, E, E* Value.

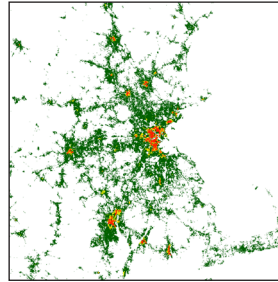
	P				I				E				E*
	Range	Mean	STD	Sum	Mean	STD	Range	Mean	STD	Range	Mean	STD	
US	New York*	42178	276	1053	7257330	22	23	2504	27	100	778		
	Los Angeles*	16689	195	717	10091595	61	25	1022	65	81	359		
	Chicago*	17894	104	397	4754086	28	23	1018	18	41	292		
	San Francisco*	25337	90	421	5123980	51	25	1552	44	58	425		
	Moscow*	14459	92	546	2840315	24	23	718	25	68	272		
EU	Essen*	11842	222	338	6742720	35	24	740	17	30	336		
	Milan*	4464	152	298	6288014	39	26	269	15	30	221		
	Shanghai*	110446	748	2061	11874749	35	24	4594	64	174	1406		
CH	Beijing*	97140	446	1401	9259057	37	25	5100	50	152	869		
	Guangzhou*	100576	558	2165	8001910	42	28	6160	96	227	1562		
	Chengdu*	88804	435	1192	3537395	36	24	4804	75	176	885		
	Zhengzhou*	59541	475	879	4696833	36	26	2880	55	143	880		
	Fuzhou*	141715	242	1144	2894778	34	26	6997	57	188	1129		
	Jinan*	52388	451	761	6158942	33	25	2881	32	91	609		



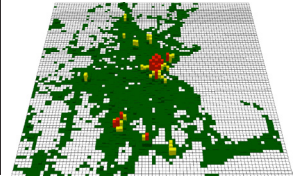
Boston
Population Count (1 km)
P Range: 12657
P Mean: 186
P STD: 488



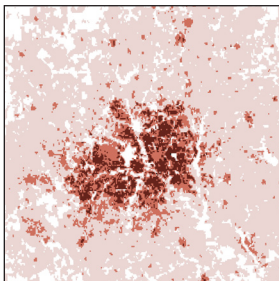
Boston
Impervious Percentage (250m)
I Sum: 1470649
I Mean: 18 *I STD:* 20



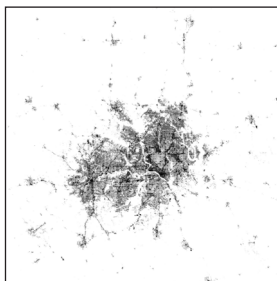
Boston
E Value Map (250m)
E Range: 649
E Mean: 13
E STD: 34



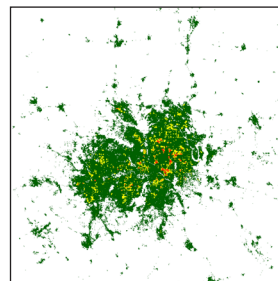
Boston
E* Value 3D View (2.5 km)
E Highest:* 223



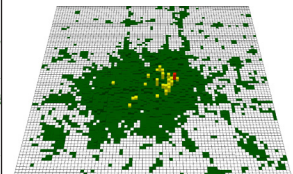
Dallas
Population Count (1 km)
P Range: 8742
P Mean: 123
P STD: 370



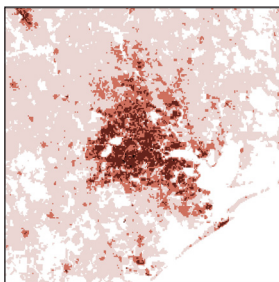
Dallas
Impervious Percentage (250m)
I Sum: 2799812
I Mean: 30 *I STD:* 20



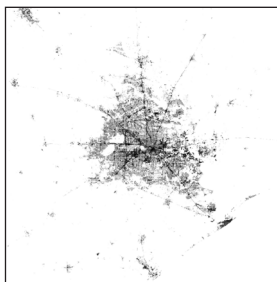
Dallas
E Value Map (250m)
E Range: 410
E Mean: 16
E STD: 23



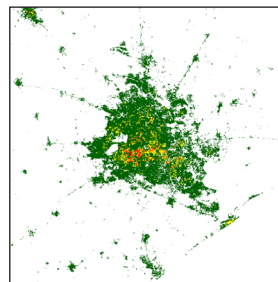
Dallas
E* Value 3D View (2.5 km)
E Highest:* 105



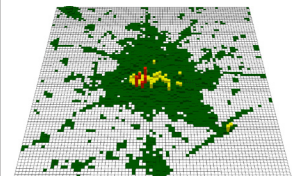
Houston
Population Count (1 km)
P Range: 10615
P Mean: 133
P STD: 409



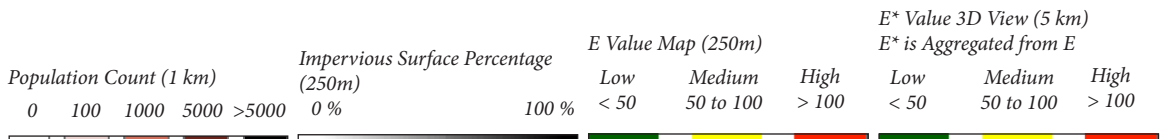
Houston
Impervious Percentage (250m)
I Sum: 2412918
I Mean: 31 *I STD:* 22

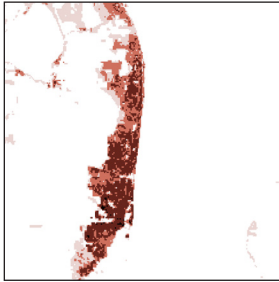


Houston
E Value Map (250m)
E Range: 650
E Mean: 19
E STD: 29



Houston
E* Value 3D View (2.5 km)
E Highest:* 191

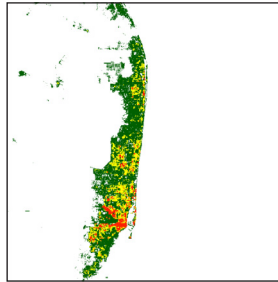




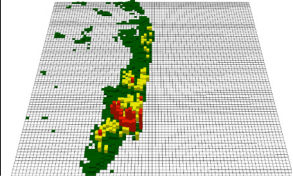
Miami
Population Count (1 km)
P Range: 9104
P Mean: 259
P STD: 688



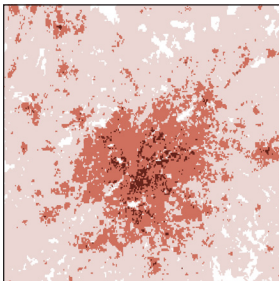
Miami
Impervious Percentage (250m)
I Sum: 2254330
I Mean: 43 *I STD:* 21



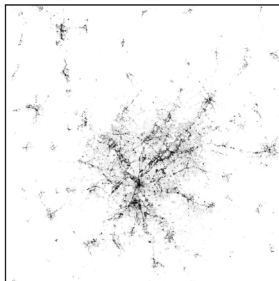
Miami
E Value Map (250m)
E Range: 529
E Mean: 38
E STD: 44



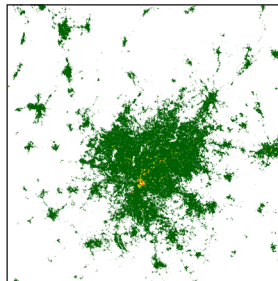
Miami
E* Value 3D View (2.5 km)
E Highest:* 247



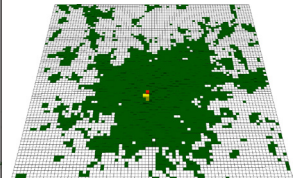
Atlanta
Population Count (1 km)
P Range: 4883
P Mean: 114
P STD: 245



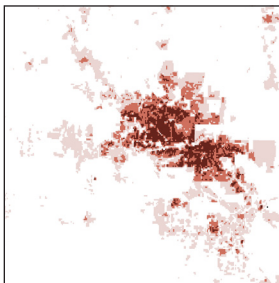
Atlanta
Impervious Percentage (250m)
I Sum: 1819952
I Mean: 17 *I STD:* 18



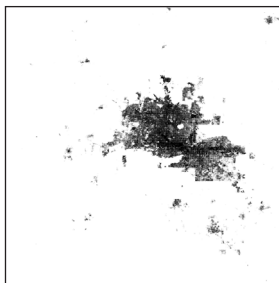
Atlanta
E Value Map (250m)
E Range: 294
E Mean: 5
E STD: 11



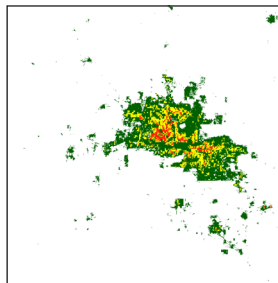
Atlanta
E* Value 3D View (2.5 km)
E Highest:* 102



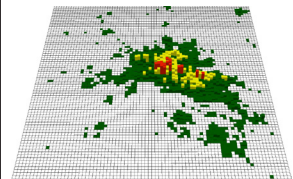
Phoenix
Population Count (1 km)
P Range: 7345
P Mean: 75
P STD: 314



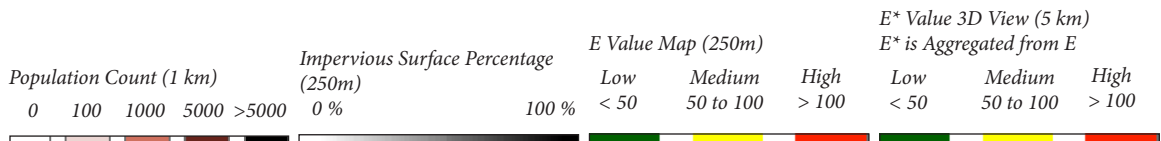
Phoenix
Impervious Percentage (250m)
I Sum: 3393894
I Mean: 57 *I STD:* 25

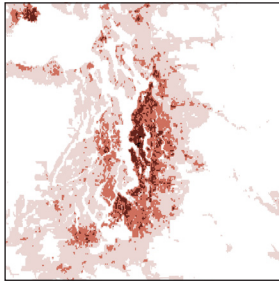


Phoenix
E Value Map (250m)
E Range: 427
E Mean: 32
E STD: 36

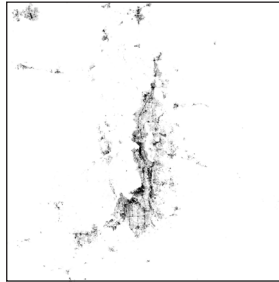


Phoenix
E* Value 3D View (2.5 km)
E Highest:* 130

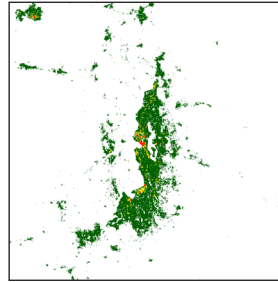




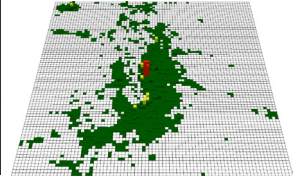
Seattle
Population Count (1 km)
P Range: 6915
P Mean: 75
P STD: 272



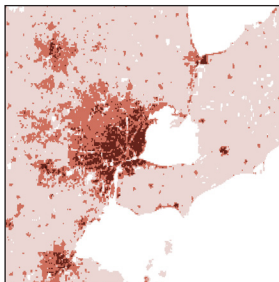
Seattle
Impervious Percentage (250m)
I Sum: 1220509
I Mean: 27 *I STD:* 24



Seattle
E Value Map (250m)
E Range: 407
E Mean: 14
E STD: 24



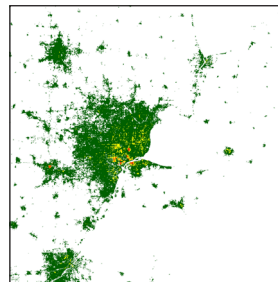
Seattle
E* Value 3D View (2.5 km)
E Highest:* 181



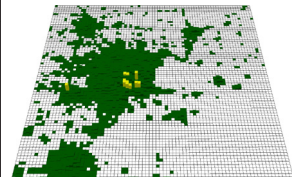
Detroit
Population Count (1 km)
P Range: 6767
P Mean: 143
P STD: 338



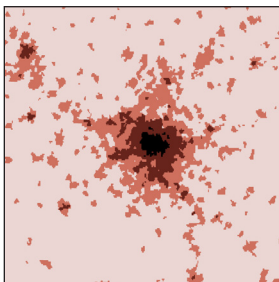
Detroit
Impervious Percentage (250m)
I Sum: 2228410
I Mean: 30 *I STD:* 21



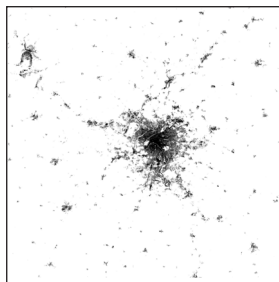
Detroit
E Value Map (250m)
E Range: 266
E Mean: 14
E STD: 18



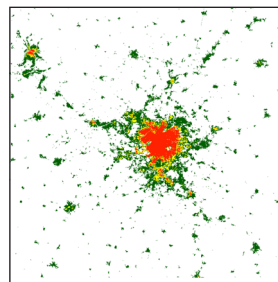
Detroit
E* Value 3D View (2.5 km)
E Highest:* 98



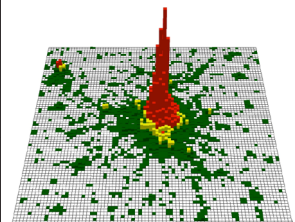
Paris
Population Count (1 km)
P Range: 26213
P Mean: 209
P STD: 933



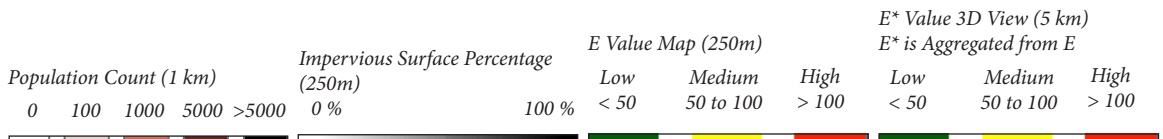
Paris
Impervious Percentage (250m)
I Sum: 2063164
I Mean: 40 *I STD:* 26

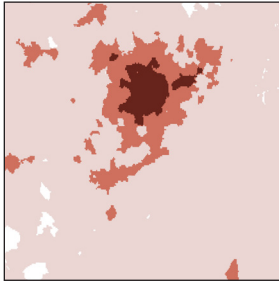


Paris
E Value Map (250m)
E Range: 1638
E Mean: 68
E STD: 150

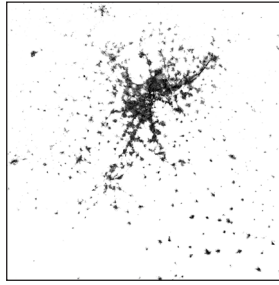


Paris
E* Value 3D View (2.5 km)
E Highest:* 1141

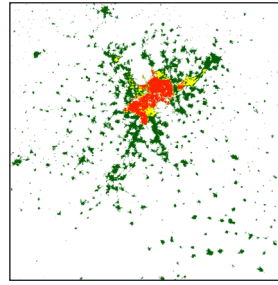




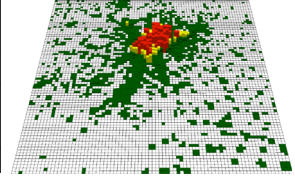
Madrid
Population Count (1 km)
P Range: 4811
P Mean: 125
P STD: 492



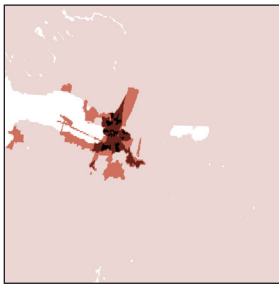
Madrid
Impervious Percentage (250m)
I Sum: 2673792
I Mean: 53 *I STD:* 26



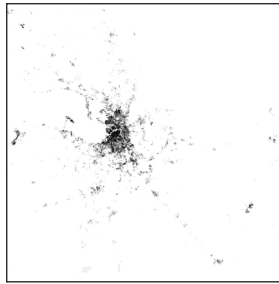
Madrid
E Value Map (250m)
E Range: 301
E Mean: 35
E STD: 57



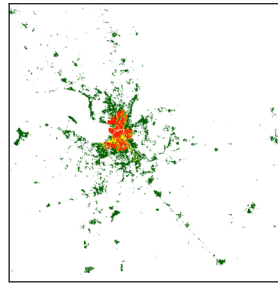
Madrid
E* Value 3D View (2.5 km)
E Highest:* 201



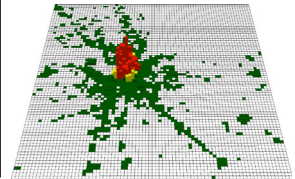
St,Petersburg
Population Count (1 km)
P Range: 13178
P Mean: 69
P STD: 464



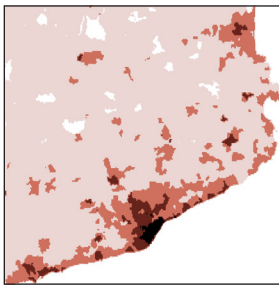
St,Petersburg
Impervious Percentage (250m)
I Sum: 3393894
I Mean: 32 *I STD:* 27



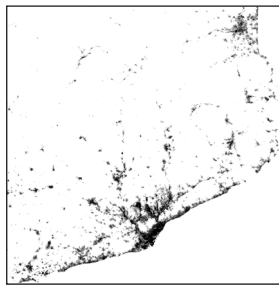
St,Petersburg
E Value Map (250m)
E Range: 815
E Mean: 35
E STD: 77



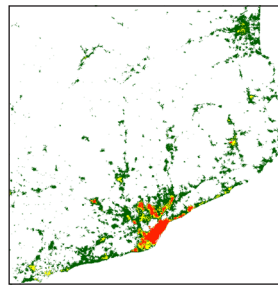
St,Petersburg
E* Value 3D View (2.5 km)
E Highest:* 389



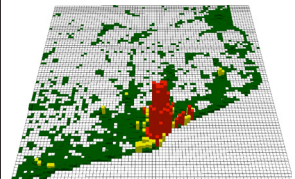
Barcelona
Population Count (1 km)
P Range: 12100
P Mean: 155
P STD: 745



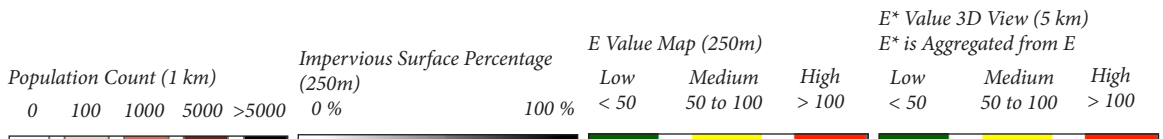
Barcelona
Impervious Percentage (250m)
I Sum: 2248819
I Mean: 46 *I STD:* 26



Barcelona
E Value Map (250m)
E Range: 756
E Mean: 42
E STD: 106

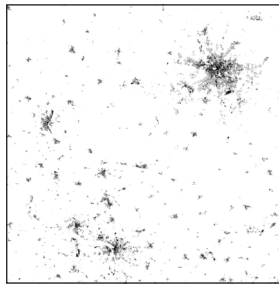


Barcelona
E* Value 3D View (2.5 km)
E Highest:* 647

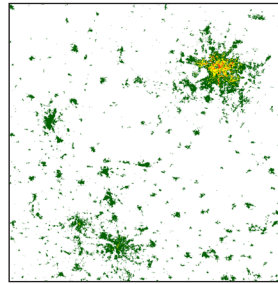




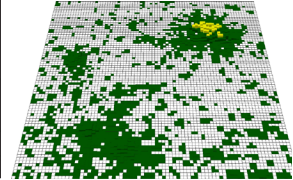
Berlin
Population Count (1 km)
P Range: 2042
P Mean: 110
P STD: 304



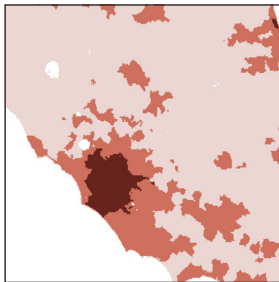
Berlin
Impervious Percentage (250m)
I Sum: 1384493
I Mean: 30 I STD: 22



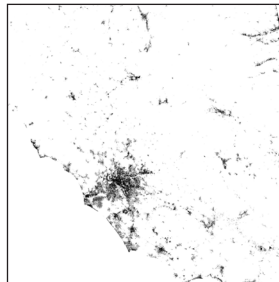
Berlin
E Value Map (250m)
E Range: 127
E Mean: 13
E STD: 22



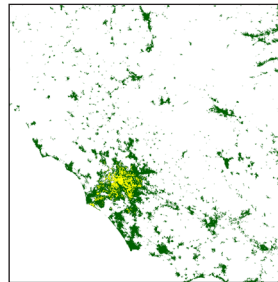
Berlin
E* Value 3D View (2.5 km)
E Highest: 99*



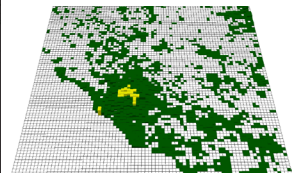
Rome
Population Count (1 km)
P Range: 1782
P Mean: 133
P STD: 266



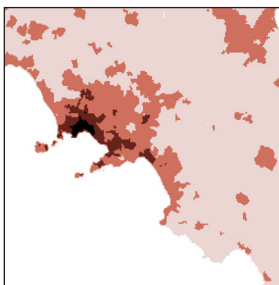
Rome
Impervious Percentage (250m)
I Sum: 1599091
I Mean: 35 I STD: 24



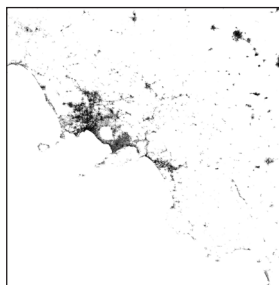
Rome
E Value Map (250m)
E Range: 108
E Mean: 14
E STD: 19



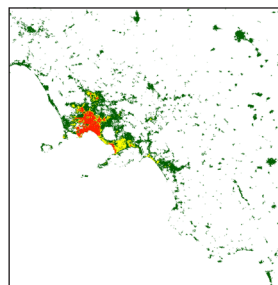
Rome
E* Value 3D View (2.5 km)
E Highest: 71*



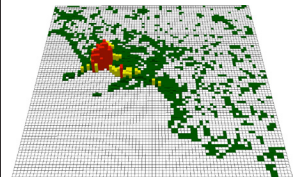
Naples
Population Count (1 km)
P Range: 7735
P Mean: 176
P STD: 513



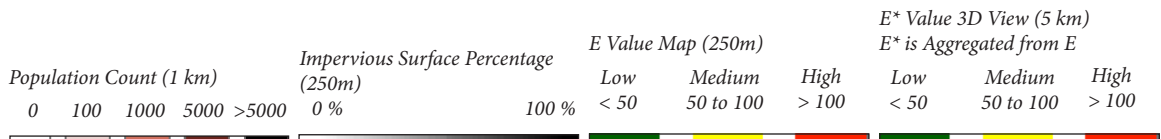
Naples
Impervious Percentage (250m)
I Sum: 1452514
I Mean: 42 I STD: 26

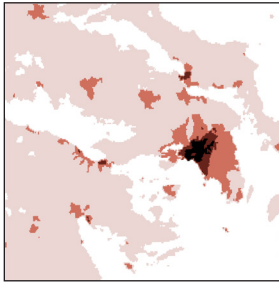


Naples
E Value Map (250m)
E Range: 474
E Mean: 35
E STD: 61

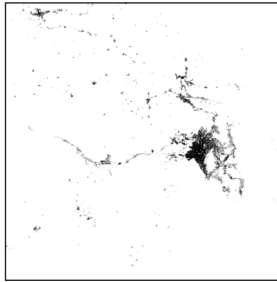


Naples
E* Value 3D View (2.5 km)
E Highest: 310*

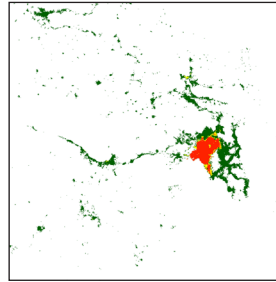




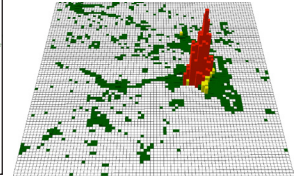
Athens
Population Count (1 km)
P Range: 14604
P Mean: 135
P STD: 833



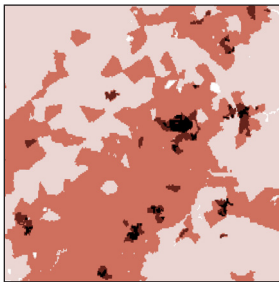
Athens
Impervious Percentage (250m)
I Sum: 1086477
I Mean: 45 I STD: 27



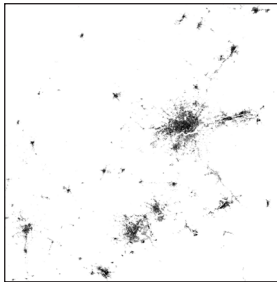
Athens
E Value Map (250m)
E Range: 885
E Mean: 70
E STD: 159



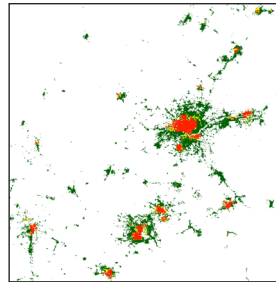
Athens
E* Value 3D View (2.5 km)
E Highest: 780*



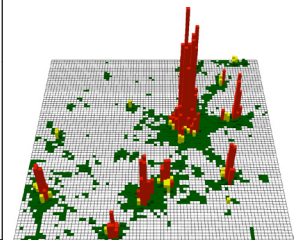
Shenyang
Population Count (1 km)
P Range: 58443
P Mean: 318
P STD: 1460



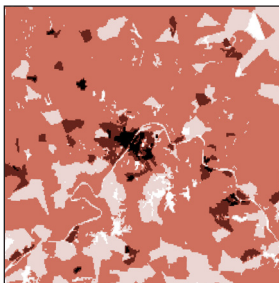
Shenyang
Impervious Percentage (250m)
I Sum: 1339275
I Mean: 36 I STD: 26



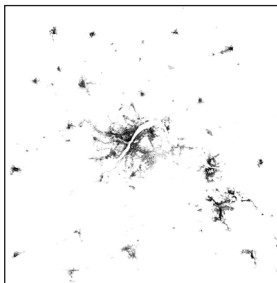
Shenyang
E Value Map (250m)
E Range: 3284
E Mean: 85
E STD: 225



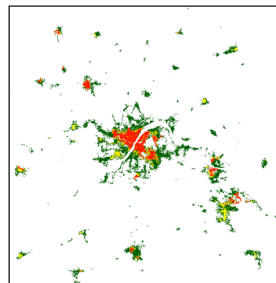
Shenyang
E* Value 3D View (2.5 km)
E Highest: 1207*



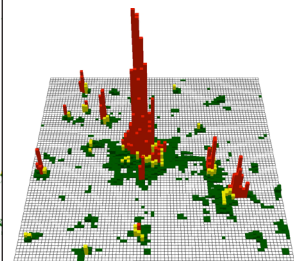
Wuhan
Population Count (1 km)
P Range: 64624
P Mean: 453
P STD: 1539



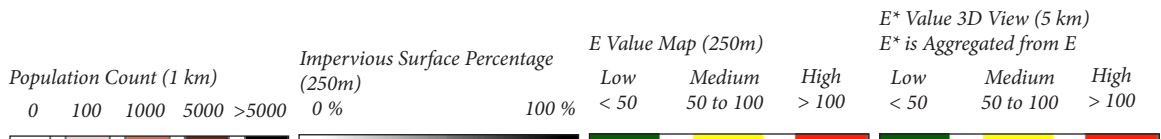
Wuhan
Impervious Percentage (250m)
I Sum: 1318867
I Mean: 39 I STD: 27

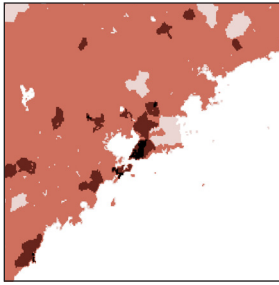


Wuhan
E Value Map (250m)
E Range: 3756
E Mean: 100
E STD: 254

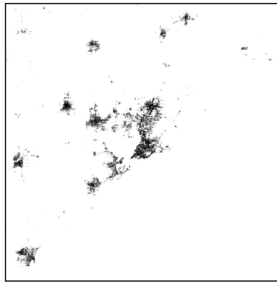


Wuhan
E* Value 3D View (2.5 km)
E Highest: 1421*

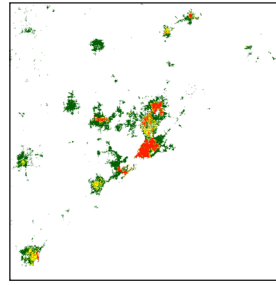




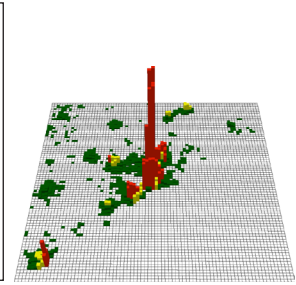
Qingdao
Population Count (1 km)
P Range: 47292
P Mean: 453
P STD: 1237



Qingdao
Impervious Percentage (250m)
I Sum: 1129309
I Mean: 45 *I STD:* 27



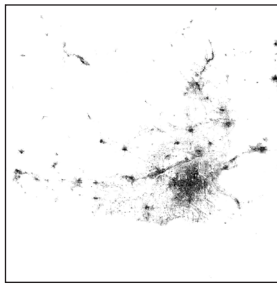
Qingdao
E Value Map (250m)
E Range: 2365
E Mean: 73
E STD: 186



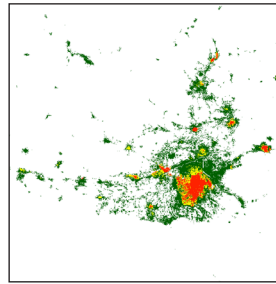
Qingdao
E* Value 3D View (2.5 km)
E Highest:* 1143



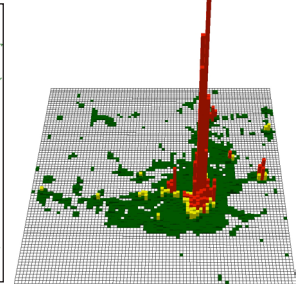
Xi'an
Population Count (1 km)
P Range: 109076
P Mean: 332
P STD: 1498



Xi'an
Impervious Percentage (250m)
I Sum: 1555863
I Mean: 32 *I STD:* 23



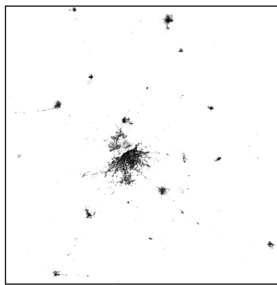
Xi'an
E Value Map (250m)
E Range: 6136
E Mean: 57
E STD: 230



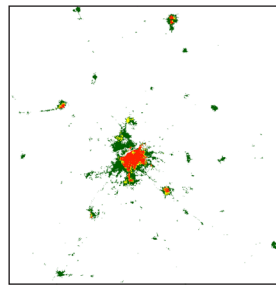
Xi'an
E* Value 3D View (2.5 km)
E Highest:* 2070



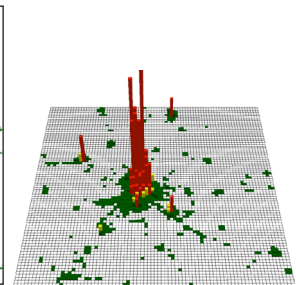
Harbin
Population Count (1 km)
P Range: 60750
P Mean: 180
P STD: 941



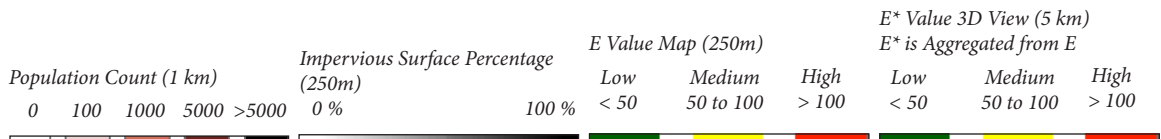
Harbin
Impervious Percentage (250m)
I Sum: 758948
I Mean: 44 *I STD:* 29

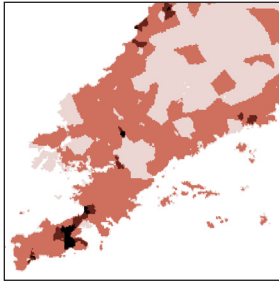


Harbin
E Value Map (250m)
E Range: 2810
E Mean: 96
E STD: 241

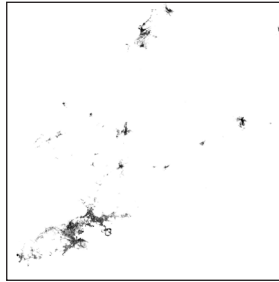


Harbin
E* Value 3D View (2.5 km)
E Highest:* 1200

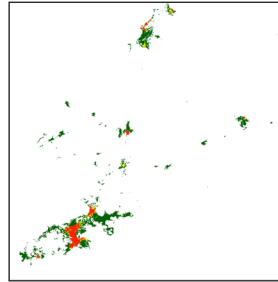




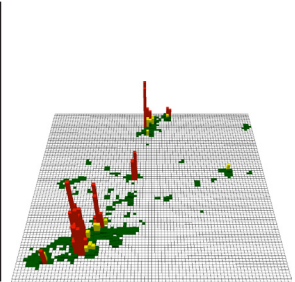
Dalian
Population Count (1 km)
P Range: 56055
P Mean: 293
P STD: 1303



Dalian
Impervious Percentage (250m)
I Sum: 558993
I Mean: 40 *I STD:* 25



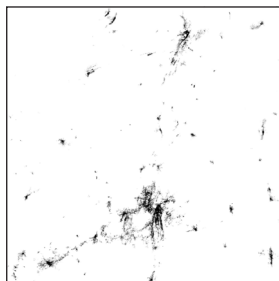
Dalian
E Value Map (250m)
E Range: 2102
E Mean: 75
E STD: 173



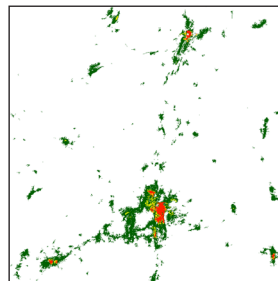
Dalian
E* Value 3D View (2.5 km)
E Highest:* 741



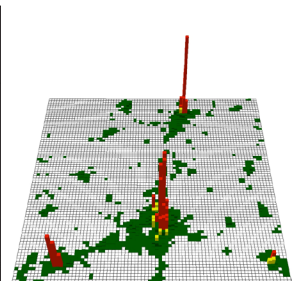
Guiyang
Population Count (1 km)
P Range: 46900
P Mean: 243
P STD: 962



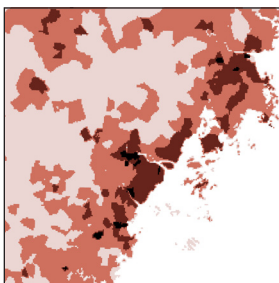
Guiyang
Impervious Percentage (250m)
I Sum: 755632
I Mean: 24 *I STD:* 20



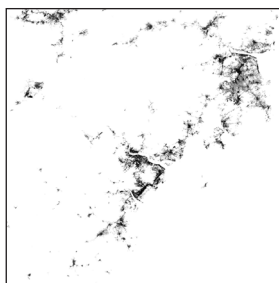
Guiyang
E Value Map (250m)
E Range: 2697
E Mean: 38
E STD: 153



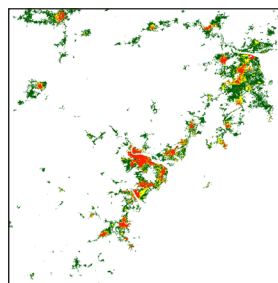
Guiyang
E* Value 3D View (2.5 km)
E Highest:* 858



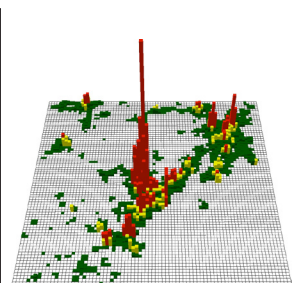
Wenzhou
Population Count (1 km)
P Range: 65538
P Mean: 448
P STD: 1311



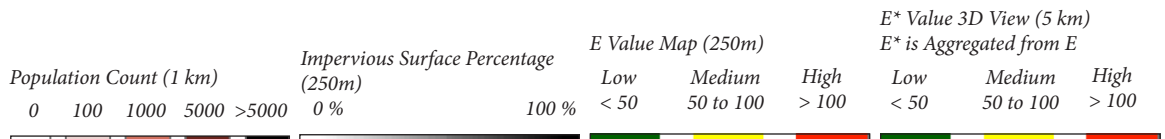
Wenzhou
Impervious Percentage (250m)
I Sum: 1798661
I Mean: 38 *I STD:* 26

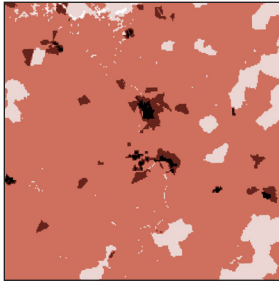


Wenzhou
E Value Map (250m)
E Range: 3630
E Mean: 58
E STD: 138

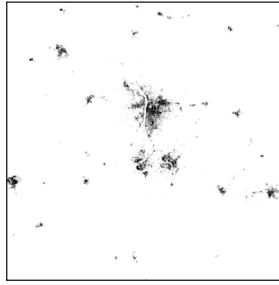


Wenzhou
E* Value 3D View (2.5 km)
E Highest:* 1426

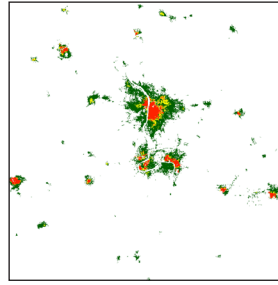




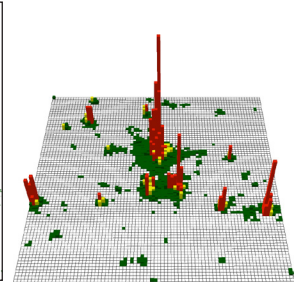
Changsha
Population Count (1 km)
P Range: 65554
P Mean: 398
P STD: 1192



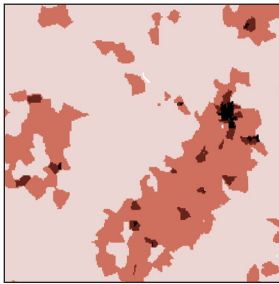
Changsha
Impervious Percentage (250m)
I Sum: 771299
I Mean: 28 *I STD:* 23



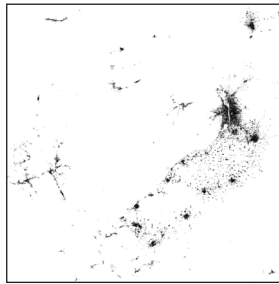
Changsha
E Value Map (250m)
E Range: 3769
E Mean: 67
E STD: 176



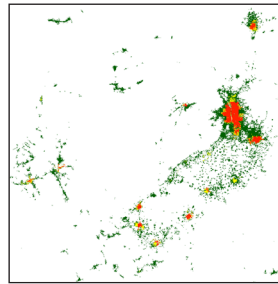
Changsha
E* Value 3D View (2.5 km)
E Highest:* 1237



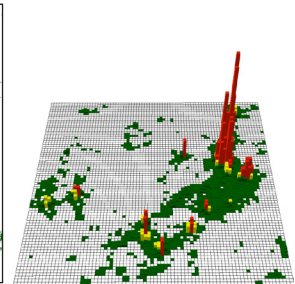
Taiyuan
Population Count (1 km)
P Range: 70296
P Mean: 191
P STD: 931



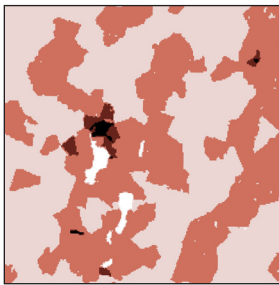
Taiyuan
Impervious Percentage (250m)
I Sum: 1252070
I Mean: 43 *I STD:* 27



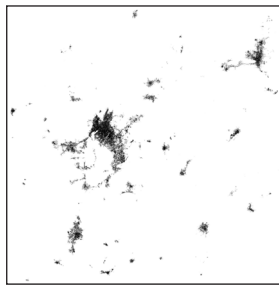
Taiyuan
E Value Map (250m)
E Range: 3954
E Mean: 65
E STD: 184



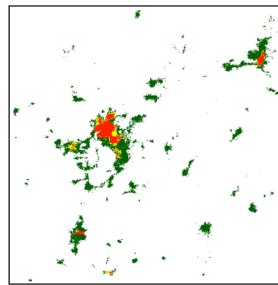
Taiyuan
E* Value 3D View (2.5 km)
E Highest:* 1104



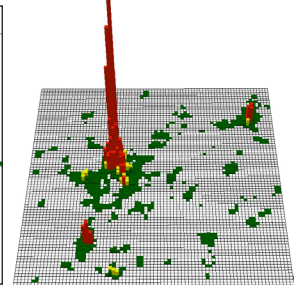
Kunming
Population Count (1 km)
P Range: 94989
P Mean: 217
P STD: 1145



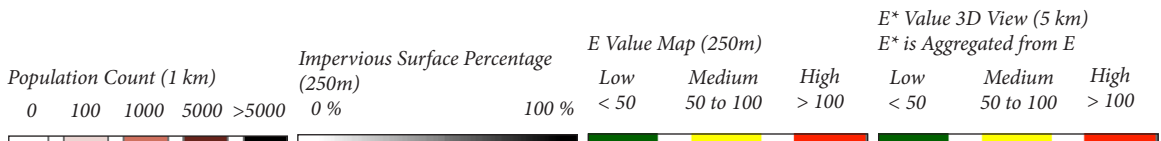
Kunming
Impervious Percentage (250m)
I Sum: 1237118
I Mean: 42 *I STD:* 25

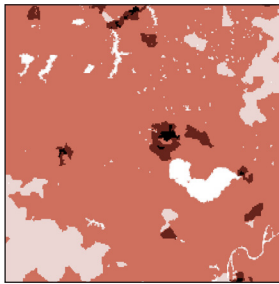


Kunming
E Value Map (250m)
E Range: 5581
E Mean: 67
E STD: 255

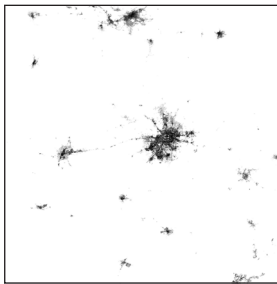


Kunming
E* Value 3D View (2.5 km)
E Highest:* 2012

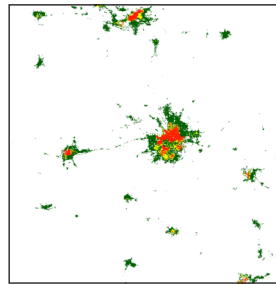




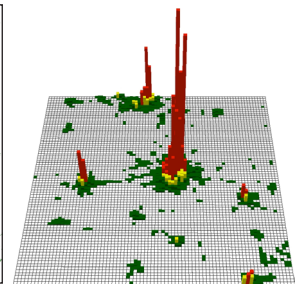
Hefei
Population Count (1 km)
P Range: 78549
P Mean: 345
P STD: 1224



Hefei
Impervious Percentage (250m)
I Sum: 971352
I Mean: 38 *I STD:* 26



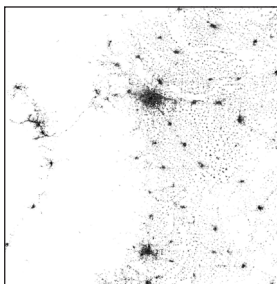
Hefei
E Value Map (250m)
E Range: 4320
E Mean: 80
E STD: 251



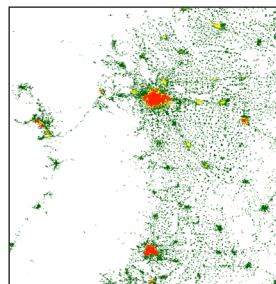
Hefei
E* Value 3D View (2.5 km)
E Highest:* 1595



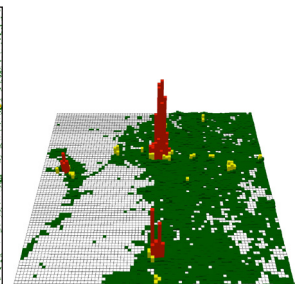
Shijiazhuang
Population Count (1 km)
P Range: 37257
P Mean: 380
P STD: 887



Shijiazhuang
Impervious Percentage (250m)
I Sum: 1929321
I Mean: 32 *I STD:* 22



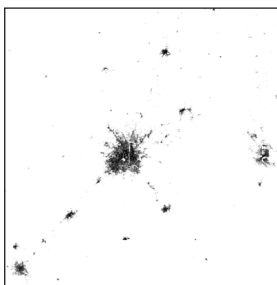
Shijiazhuang
E Value Map (250m)
E Range: 2040
E Mean: 33
E STD: 109



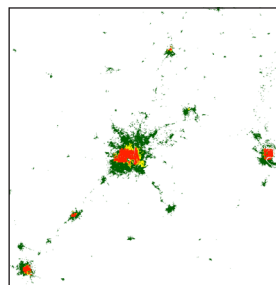
Shijiazhuang
E* Value 3D View (2.5 km)
E Highest:* 825



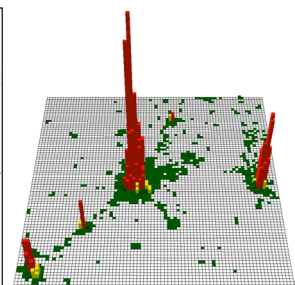
Changchun
Population Count (1 km)
P Range: 48317
P Mean: 200
P STD: 1194



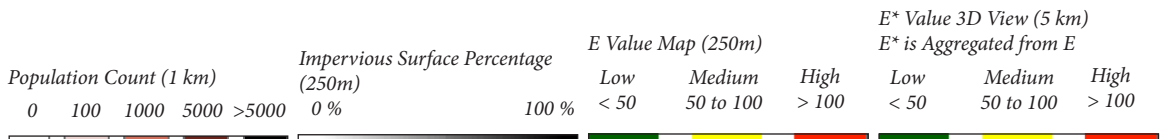
Changchun
Impervious Percentage (250m)
I Sum: 911190
I Mean: 43 *I STD:* 28

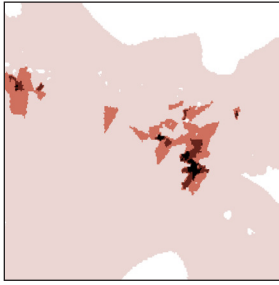


Changchun
E Value Map (250m)
E Range: 2902
E Mean: 97
E STD: 271

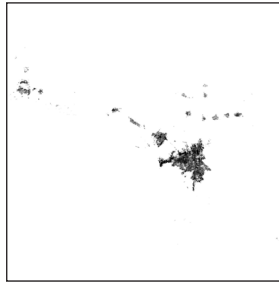


Changchun
E* Value 3D View (2.5 km)
E Highest:* 1672

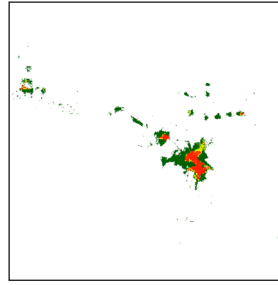




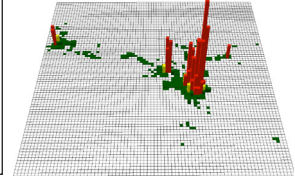
Urumqi
Population Count (1 km)
P Range: 55450
P Mean: 73
P STD: 794



Urumqi
Impervious Percentage (250m)
I Sum: 686280
I Mean: 53 I STD: 25



Urumqi
E Value Map (250m)
E Range: 2599
E Mean: 91
E STD: 209



Urumqi
E* Value 3D View (2.5 km)
E Highest: 938*

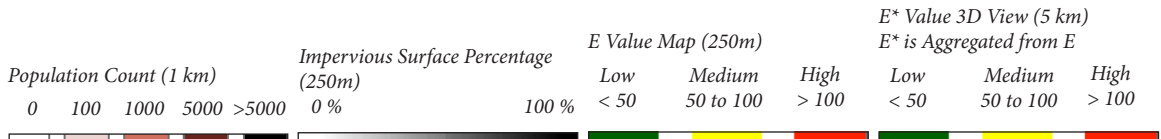


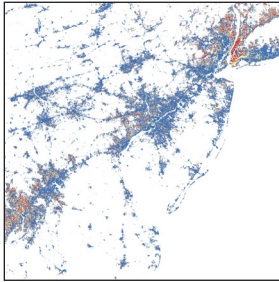
Figure 5. Cities. P, I, E, E* Value.

	P				I			E			E*
	Range	Mean	STD	Sum	Mean	STD	Range	Mean	STD	Highest	
US	Boston	12657	186	488	1470649	18	20	649	13	34	223
	Dallas	8742	123	370	2799812	30	20	410	16	23	105
	Houston	10615	133	409	2412918	31	22	650	19	29	191
	Miami	9104	259	688	2254330	43	21	529	38	44	247
	Atlanta	4883	114	245	1819952	17	18	294	5	11	102
	Phoenix	7345	75	314	3393894	57	25	427	32	36	130
	Seattle	6915	75	272	1220509	27	24	407	14	24	181
	Detroit	6767	143	338	2228410	30	21	266	14	18	98
	Paris	26213	209	933	2063164	40	26	1638	68	150	1141
	Madrid	4811	125	492	2673792	53	26	301	35	57	201
EU	St,petersburg	13178	69	464	877089	32	27	815	35	77	389
	Barcelona	12100	155	745	2248819	46	26	756	42	106	647
	Berlin	2042	110	304	1384493	30	22	127	13	22	99
	Rome	1782	133	266	1599091	35	24	108	14	19	71
	Naples	7735	176	513	1452514	42	26	474	35	61	310
	Athens	14604	135	833	1086477	45	27	885	70	159	780

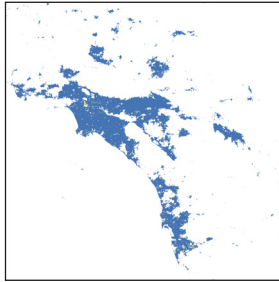
Figure5. Cities. P, I, E, E* Value.

	P				I				E				E*
	Range	Mean	STD	Sum	Mean	STD	Range	Mean	STD	Range	Mean	STD	Highest
Shenyang	58443	318	1460	1339275	36	26	3284	85	225	1207			
Wuhan	64624	453	1539	1318867	39	27	3756	100	254	1421			
Qingdao	47292	453	1237	1129309	45	27	2365	73	186	1143			
Xian	109076	332	1498	1555863	32	23	6136	57	230	2070			
Harbin	60750	180	941	758948	44	29	2810	96	241	1200			
Dalian	56055	293	1303	558993	40	25	2102	75	173	741			
Guiyang	46900	243	962	755632	24	20	2697	38	153	858			
Wenzhou	65538	448	1311	1798661	38	26	3630	58	138	1426			
Changsha	65554	398	1192	771299	28	23	3769	67	176	1237			
Taiyuan	70296	191	931	1252070	43	27	3954	65	184	1104			
Kunming	94989	217	1145	1237118	42	25	5581	67	255	2012			
Hefei	78549	345	1224	971352	38	26	4320	80	251	1595			
Shijiazhuang	37257	380	887	1929321	32	22	2040	33	109	825			
Changchun	48317	200	1194	911190	43	28	2902	97	271	1672			
Urumqi	55450	73	794	686280	53	25	2599	91	209	938			

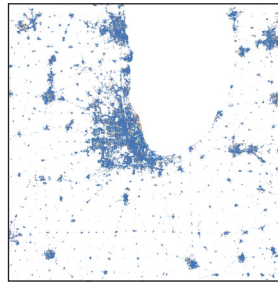
HO



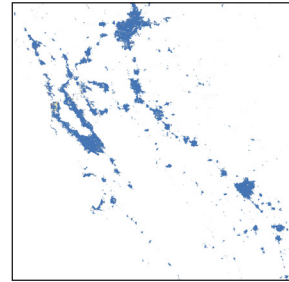
New York*
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 8



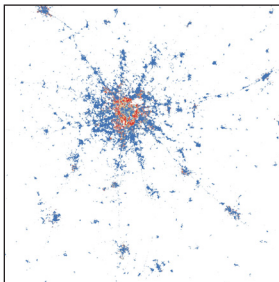
Los Angeles*
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 2



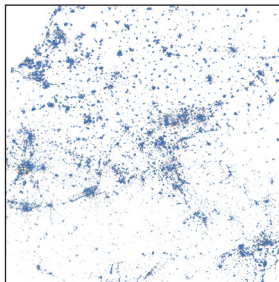
Chicago*
Population Density on
Impervious Surface
(250m)
D Mean: 3 D STD: 5



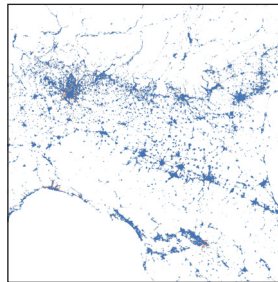
San Francisco*
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 4



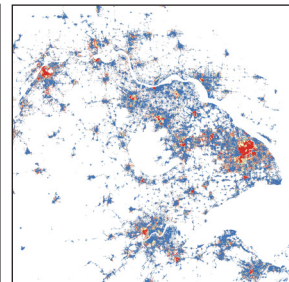
Moscow*
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 18



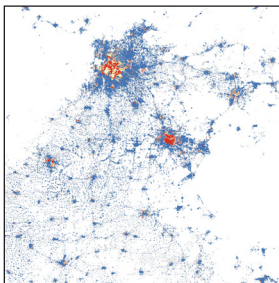
Essen*
Population Density on
Impervious Surface
(250m)
D Mean: 3 D STD: 7



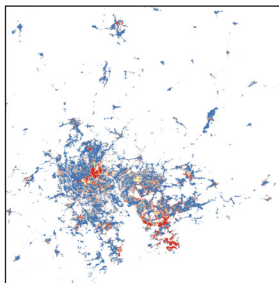
Milan*
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 5



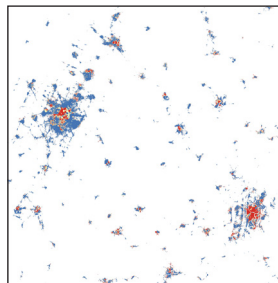
Shanghai*
Population Density on
Impervious Surface
(250m)
D Mean: 6 D STD: 16



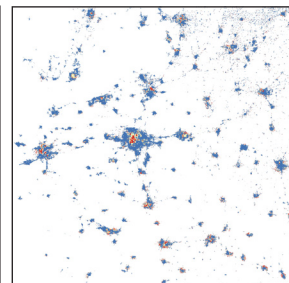
Beijing*
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 10



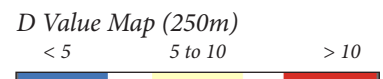
Guangzhou*
Population Density on
Impervious Surface
(250m)
D Mean: 8 D STD: 33

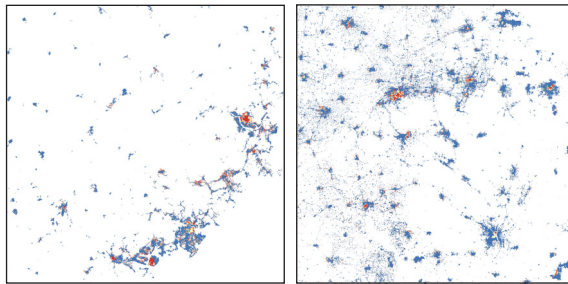


Chengdu*
Population Density on
Impervious Surface
(250m)
D Mean: 7 D STD: 21



Zhengzhou*
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 12





Fuzhou*
Population Density on
Impervious Surface
(250m)

D Mean: 7 D STD: 27

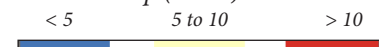
Jinan*
Population Density on
Impervious Surface
(250m)

D Mean: 4 D STD: 11

Figure6. Urban Agglomerations. D Value.

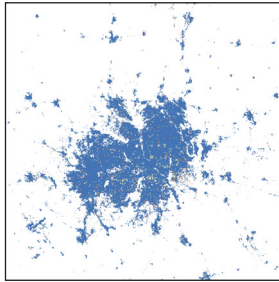
		D	
		Mean	STD
US	New York*	5	8
	Los Angeles*	2	2
	Chicago*	3	5
	San Francisco*	2	4
EU	Moscow*	4	18
	Essen*	3	7
	Milan*	2	5
CH	Shanghai*	6	16
	Beijing*	4	10
	Guangzhou*	8	33
	Chengdu*	7	21
	Zhengzhou*	5	12
	Fuzhou*	7	27
	Jinan*	4	11

D Value Map (250m)

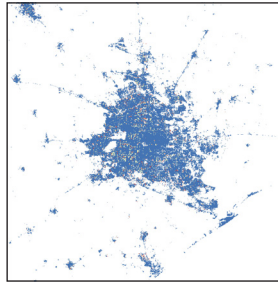




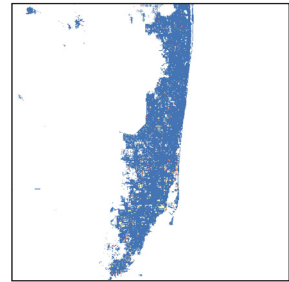
Boston
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 7



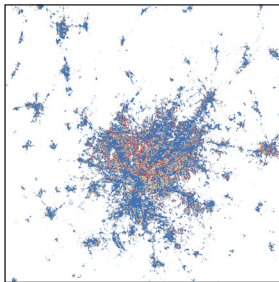
Dallas
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 4



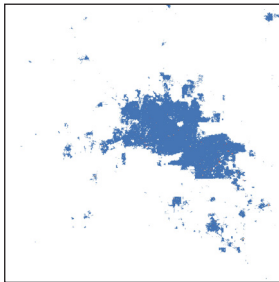
Houston
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 4



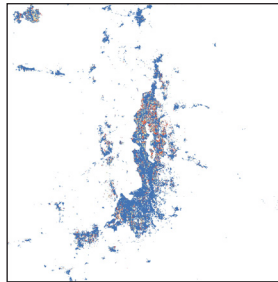
Miami
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 4



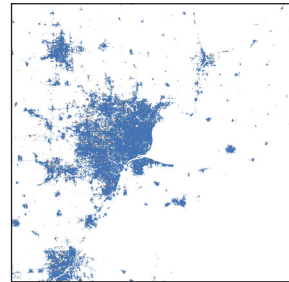
Atlanta
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 7



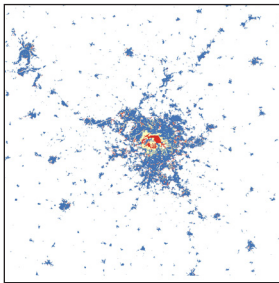
Phoenix
Population Density on
Impervious Surface
(250m)
D Mean: 1 D STD: 1



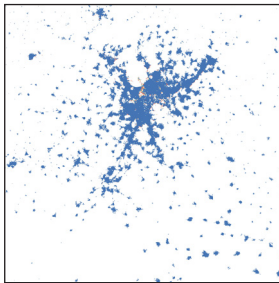
Seattle
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 7



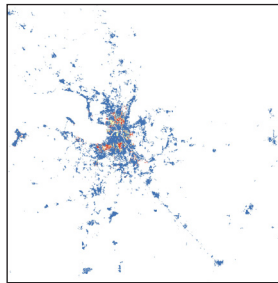
Detroit
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 4



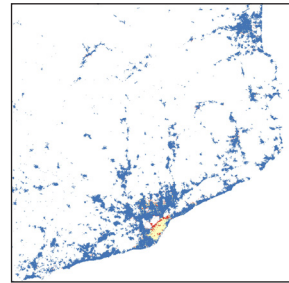
Paris
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 9



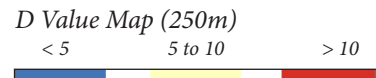
Madrid
Population Density on
Impervious Surface
(250m)
D Mean: 1 D STD: 5

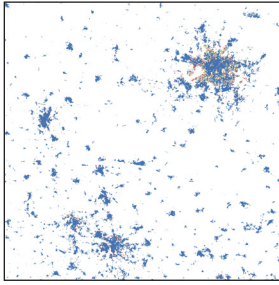


St, petersburg
Population Density on
Impervious Surface
(250m)
D Mean: 3 D STD: 13

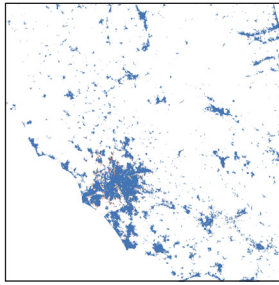


Barcelona
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 6

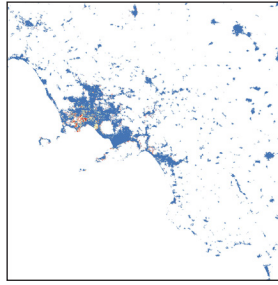




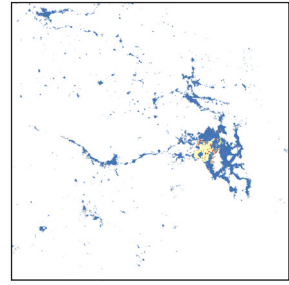
Berlin
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 7



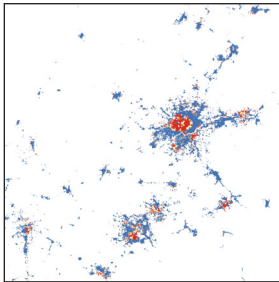
Rome
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 5



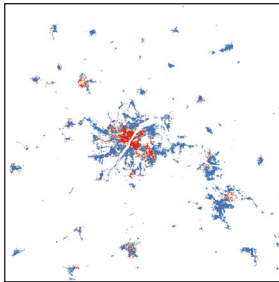
Naples
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 6



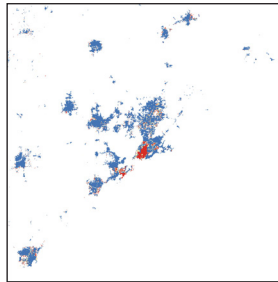
Athens
Population Density on
Impervious Surface
(250m)
D Mean: 2 D STD: 5



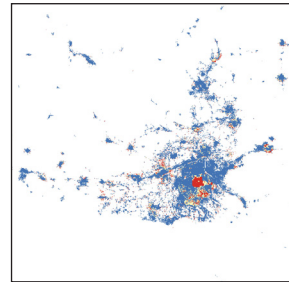
Shenyang
Population Density on
Impervious Surface
(250m)
D Mean: 6 D STD: 24



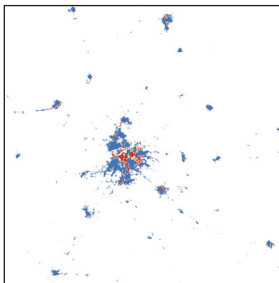
Whuan
Population Density on
Impervious Surface
(250m)
D Mean: 7 D STD: 23



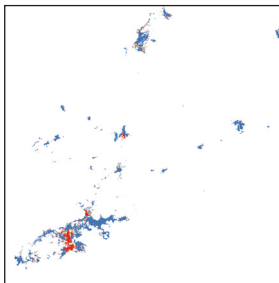
Qingdao
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 19



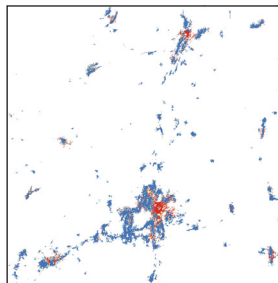
Xi'an
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 11



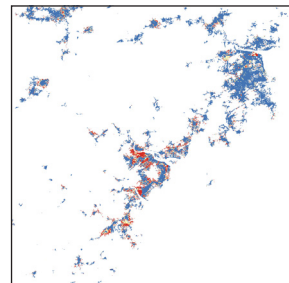
Harbin
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 21



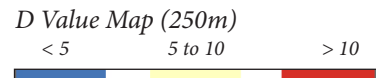
Dalian
Population Density on
Impervious Surface
(250m)
D Mean: 7 D STD: 37

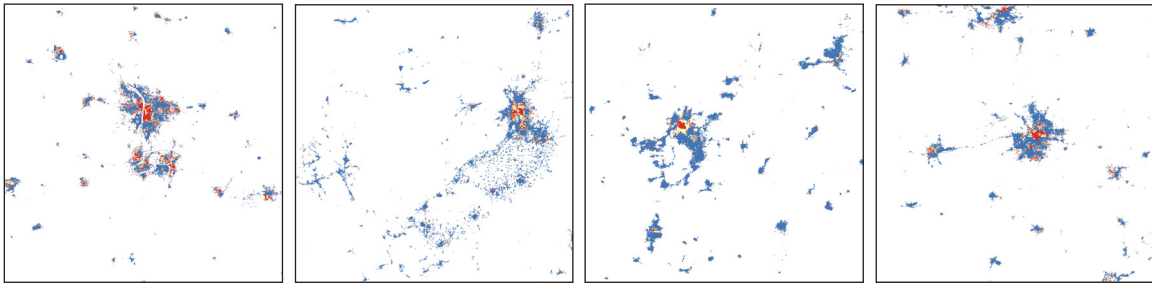


Guiyang
Population Density on
Impervious Surface
(250m)
D Mean: 8 D STD: 36



Wenzhou
Population Density on
Impervious Surface
(250m)
D Mean: 7 D STD: 20



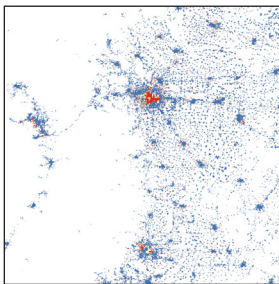


Changsha
Population Density on
Impervious Surface
(250m)
D Mean: 9 D STD: 23

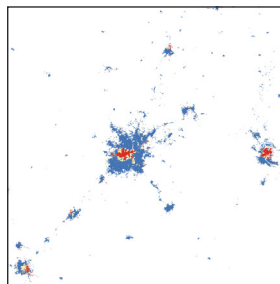
Taiyuan
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 20

Kunming
Population Density on
Impervious Surface
(250m)
D Mean: 3 D STD: 8

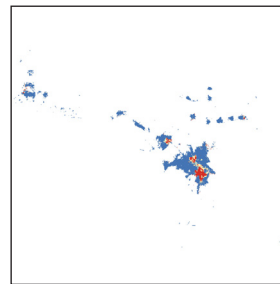
Hefei
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 14



Shijiazhuang
Population Density on
Impervious Surface
(250m)
D Mean: 4 D STD: 9



Changchun
Population Density on
Impervious Surface
(250m)
D Mean: 5 D STD: 26



Urumqi
Population Density on
Impervious Surface
(250m)
D Mean: 3 D STD: 10

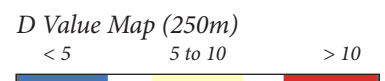


Figure7. Cities. D Value.

		D	
		Mean	STD
US	Boston	5	7
	Dallas	2	4
	Houston	2	4
	Miami	2	4
	Atlanta	5	7
	Phoenix	1	1
	Seattle	4	7
	Detroit	2	4
EU	Paris	4	9
	Madrid	1	5
	St,petersburg	3	13
	Barcelona	2	6
	Berlin	2	7
	Rome	2	5
	Naples	2	6
	Athens	2	5
CH	Shenyang	6	24
	Wuhan	7	23
	Qingdao	5	19
	Xi'an	5	11
	Harbin	5	21
	Dalian	7	37
	Guiyang	8	36
	Wenzhou	7	20
	Changsha	9	23
	Taiyuan	4	20
	Kunming	3	8
	Hefei	5	14
	Shijiazhuang	4	9
	Changchun	5	26
Urumqi	3	10	