The Nature of Human Settlement: Building an understanding of high performance city design (a.k.a. Block Typologies)

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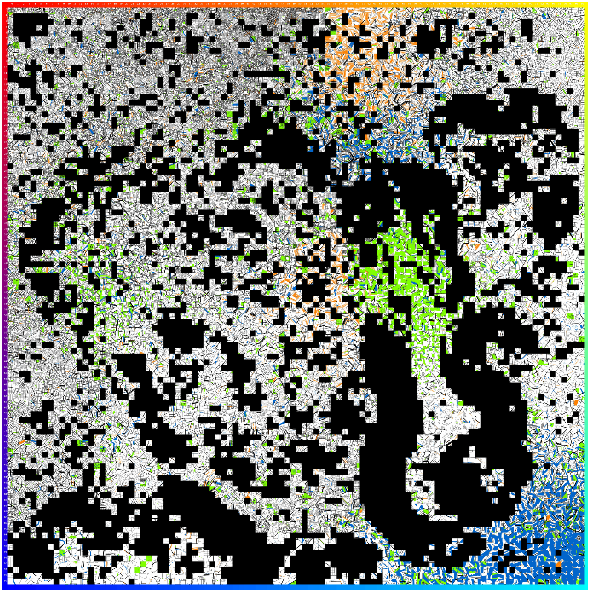
Research questions

- Can you perform inter- and intra-city comparisons?
- Or are cities unique?
- How do you characterise different types of neighbourhoods?
- How do you determine the impact of urban form on health?
- How do you assess cities that perform well?
- Can you transfer lessons from one city to another?
- Can you predict health outcomes based on urban form?

Block typologies - Self organizing map (SOM)



A visualisation of the 2-dimensional 100x100 SOM trained with 1.7 million map images from 1667 cities. Each x,y point shows a representative map section associated with each node while nodes without associated maps are shown in black.

Previous work in city analysis - Network analysis

Work to characterize cities based on road networks, using closeness, betweenness, centrality.

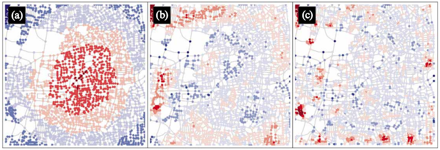


Figure 3. The primal approach. Closeness centrality (C^C) spatial flow in Ahmedabad: scores are calculated on the nodes of the primal weighted graph, where weights are the metric lengths of edges. (a) Global closeness: C^C is calculated on the whole network; (b) local closeness: C^C is calculated on the subnetwork of nodes at distance $d < 400$ meters from each node; (c) local closeness: $C^C$is calculated on the subnetwork of nodes at distance $d < 200$ meters from each node. Here color nodes are attributed to the centrality of *nodes*, though in other cases it may be preferable to code the centrality of *edges*, as in figure 4(a).

S. Porta et al. / Physica A 369 (2006) 853–866

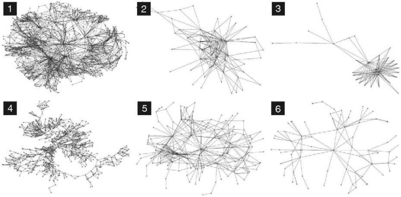


Fig. 3. The dual graphs of the six cities, shown in the same order of Fig. 2.

Porta et al. (2006a,b)

Previous work in city analysis - Land cell shapes

Work to characterize cities based on distribution of land cell shapes.

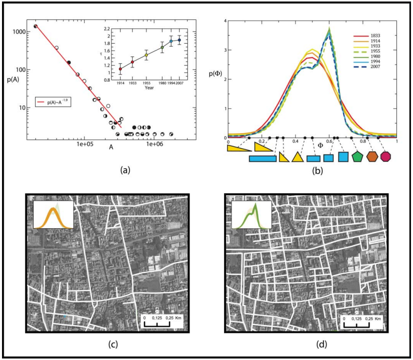


Figure 3 | (a) The size distribution of cell areas at $t = 2007$ can be fitted with a power-law $p(A) \sim A^{-\tau}$, with an exponent $\tau \simeq 1.9$. The inset shows the value of τ at different times. (b) Distribution of cell shapes at different times, as quantified by the shape factor Φ. The shape factor of different polygons is reported at the bottom axis for comparison. (c) and (d) Maps showing the cell shapes (white lines) for the network as it is before 1955 (left panel) and as it is after 1955 (right panel). We see on the left panel that we have predominantly triangles and rectangles, while on the right panel we can observe a predominance of rectangles with sides of almost the same length.

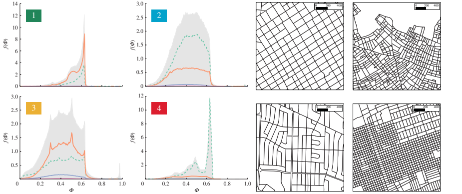


Figure 5. The four groups. (Left) Average distribution of the shape factor Φ for each group found by the clustering algorithm (each area bin is represented by a different colour from small areas in dashed green, medium size in orange, and large cells in blue). (Right) Typical street patterns for each group (plotted at the same scale in order to observe differences both in shape and areas). Group 1: Buenos Aires; Group 2: Athens; Group 3: New Orleans; Group 4: Mogadishu. (Online version in colour.)

Strano et al. (2012); Louf and Barthelemy (2014)

Previous work with self organizing maps

A neural network in the analysis of city systems: J. Kropp

Table 1 The 21 variables in the dataset

1 Non-German residents	12 Single-room flats
2 Total city area	13 Double-room flats
3 Built-up area	14 Triple-room flats
4 Number of motorcycles	15 Flats with 4 rooms
5 Total power consumption	16 Flats with 5 rooms
6 Total gas consumption	17 Flats with 6 rooms
7 Total water consumption	18 Flats with > 6 rooms
8 Gas consumption by households	19 Net tax yield
9 Gas consumption by authorities	20 Trade tax yield
10 Water consumption by households	21 Social expenditure
11 Number of flats	

Self organizing maps (SOM) transform multi-dimensional data into lower dimensions.

Sorting vectors of city characteristics to find cluster of cities.

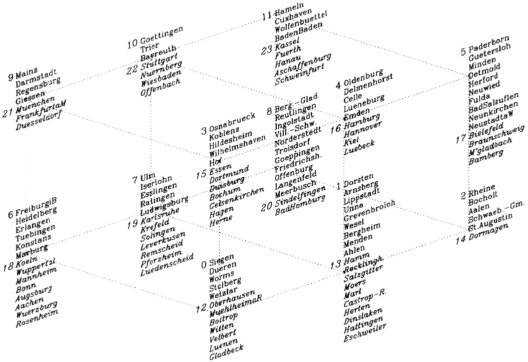
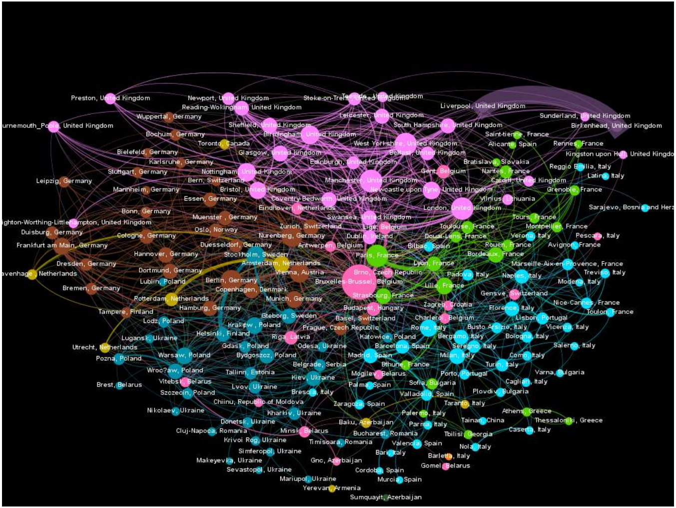


Figure 3 Presentation of the city distribution on a $3 \times 2 \times 2 \times 2$ network. Each corner node has four neighbours and each edge node five adjacent sites. For a better illustration the fourth dimension is presented in an italic font

Kropp (1998)

Spoiler alert for Jason's upcoming presentation

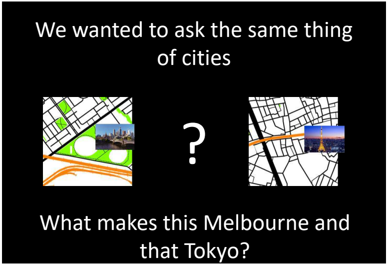


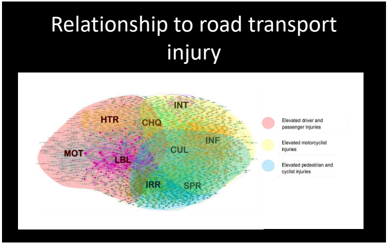
Thompson et al. (2018)

Clusters of 1667 cities using neural networks and city maps and social network graphs.

Previous work in our research hub to cluster cities

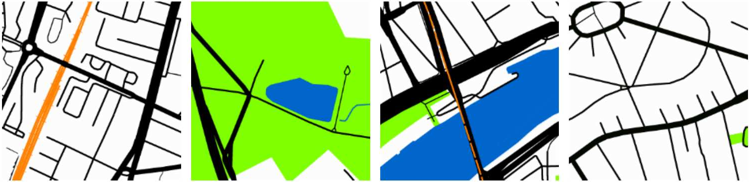
Clustering using neural network confusion recognizing maps of similar cities.





Thompson et al. (2018)

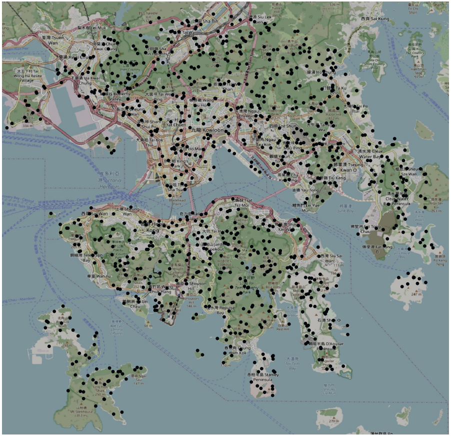
Block typologies - Maps



Four sample Google Maps used as the basis for block typologies (from Paris, France)

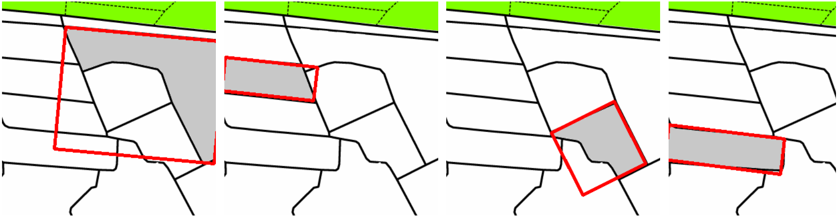
Google Maps (2017).

Block typologies - Sampling map imagery



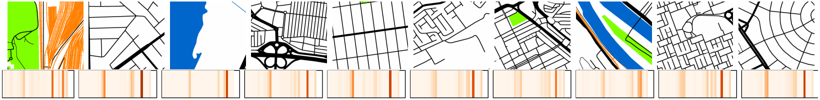
Sampling locations for map imagery (from Hong Kong). 1000 locations for each of the 1667 cities.

Block typologies - Calculating block size and regularity



Results of flood filled city blocks showing flood fills of each individual region to determine region size (count of pixels in grey). Differences between region size and pixel counts within bounding boxes (outlined in red) are used as a measure of regularity.

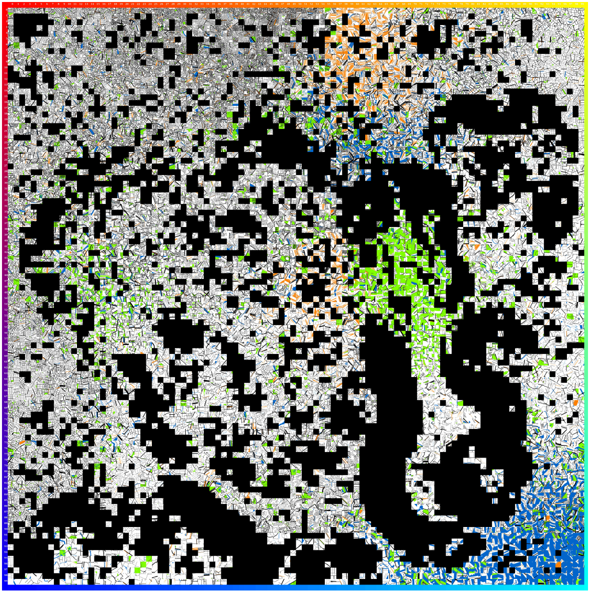
Block typologies - Generating vectors for each map



Samples of map regions (top) and resulting histograms (bottom). Region size, regularity, and colour counts are joined into a combined histogram vector, with size frequencies in the first 15 bins, regularity in the second 15 bins and colour pixel counts in the remaining 5 bins.

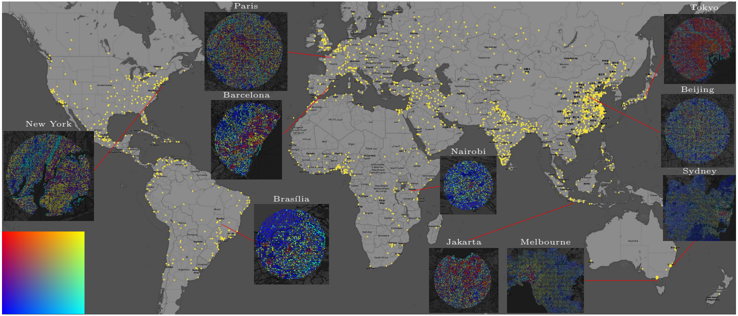
Block typologies-Detail of sorted vectors in SOM

Block typologies - Self organizing map (SOM)



A visualisation of the 2-dimensional 100x100 SOM trained with 1.7 million map images from 1667 cities. Each x,y point shows a representative map section associated with each node while nodes without associated maps are shown in black.

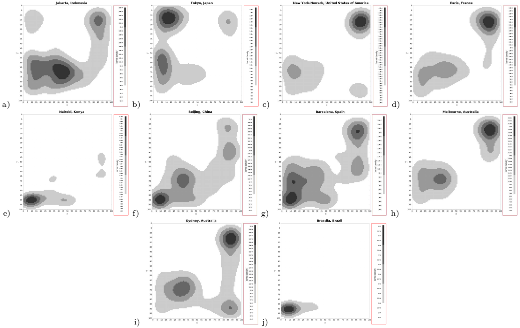
Block typologies - City mixes of neighbourhood types

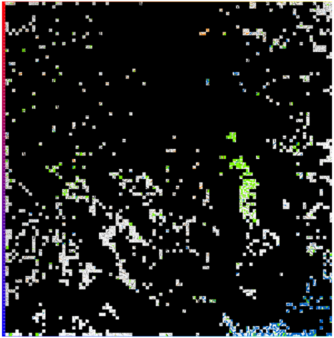


Sampled world cities with inserts showing detail of New York, Paris, Barcelona, Brasília, Nairobi, Jakarta, Melbourne, Tokyo, Beijing, and Sydney. City detail maps use the same SOM (x,y) location colour scheme as the colour map insert image (lower left).

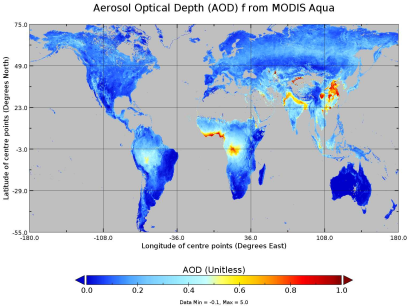
Sample representative maps from top SOM (x,y) locations for cities a) Jakarta, b) Tokyo, c) New York, d) Paris, e) Nairobi, f) Beijing, g) Barcelona, h) Melbourne, i) Sydney, and j) Brasília.

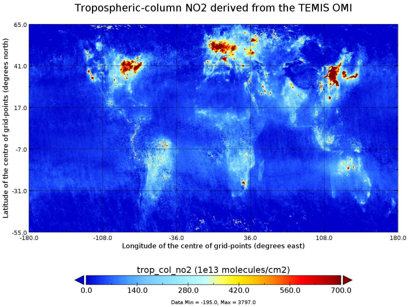
Kernel density maps of SOM x,y locations for cities a) Jakarta, b) Tokyo, c) New York, d) Paris, e) Nairobi, f) Beijing, g) Barcelona, h) Melbourne, i) Sydney, and j) Brasília. And SOM contents for Sydney, Australia.





AOD and NO_2 data to illustrate utility of methodology





Urban form data derived from Google Street View to illustrate utility of methodology

Fractions of urban form calculated at 65 million locations.

Fig. 6. Sample image segmentation results illustrating segmentations with an accuracy > 95% (a-h) and an accuracy < 95% (i-p).

	C	D	E	F	G	H	I	J	K
1	lat	lon	SVF	sky	trees	buildings	impervious	pervious	moving
2	57.717995	11.630221	0.996987	0.485037	0.023018	0.056254	0.192865	0.23	0.012823
3	57.718049	11.630386	0.997812	0.481468	0.029968	0.051524	0.28154	0.151153	0.004344
4	57.718075	11.630586	0.997348	0.477467	0.091775	0.061661	0.187932	0.178814	0.002348
5	57.718092	11.630725	0.996549	0.479935	0.120809	0.068809	0.167166	0.16215	0.001127
6	57.718109	11.630877	0.99694	0.476993	0.147418	0.087006	0.156854	0.127331	0.004395
7	57.718122	11.631035	0.995682	0.473536	0.146056	0.077152	0.182086	0.118607	0.00256
8	57.718134	11.631197	0.99438	0.47053	0.183309	0.055186	0.17516	0.11159	0.004222
9	57.718147	11.631367	0.988137	0.461256	0.204525	0.04471	0.153951	0.127741	0.007814
10	57.718163	11.631537	0.989625	0.460789	0.161371	0.043455	0.191761	0.135381	0.00724
11	57.718173	11.631714	0.982388	0.45967	0.178257	0.046254	0.126903	0.178414	0.0105
12	57.718011	11.634571	0.991897	0.452877	0.141415	0.026227	0.242257	0.132501	0.004721
13	57.71802	11.634374	0.989383	0.438416	0.176193	0.027302	0.212179	0.143836	0.002072
14	57.718029	11.63418	0.866461	0.357879	0.315427	0.016691	0.178969	0.128411	0.00262
15	57.718039	11.633989	0.915021	0.387039	0.317269	0.01552	0.102004	0.174836	0.003329
16	57.718051	11.633799	0.990619	0.446274	0.277448	0.022925	0.090466	0.159313	0.003571
17	57.718066	11.63361	0.980783	0.443012	0.265137	0.018055	0.107088	0.1636	0.003104
18	57.718077	11.63342	0.99467	0.465449	0.220873	0.03562	0.118876	0.152821	0.006358
19	57.718085	11.633294	0.993699	0.469972	0.161084	0.040814	0.130178	0.190912	0.007037
20	57.718097	11.633109	0.996831	0.473794	0.101678	0.032957	0.159859	0.228787	0.002921
21	57.718101	11.633049	0.995906	0.470261	0.109171	0.035886	0.124251	0.254797	0.005632
22	57.718113	11.632863	0.995256	0.46736	0.152428	0.044519	0.13538	0.193315	0.006997
23	57.718127	11.632667	0.988803	0.455166	0.123028	0.114345	0.152902	0.148896	0.00566
24	57.71814	11.63247	0.975605	0.446769	0.106835	0.087098	0.162365	0.191513	0.005416
25	57.718156	11.632271	0.985818	0.451704	0.163496	0.048937	0.12153	0.209173	0.005157
26	57.718167	11.632077	0.991059	0.455809	0.148122	0.063689	0.11912	0.208493	0.004764
27	57.718174	11.631896	0.983854	0.454593	0.152837	0.079664	0.139591	0.169416	0.003896
28	57.713688	11.635032	0.9927	0.44077	0.018627	0.117373	0.389549	0.022231	0.011446
29	57.700515	11.635322	0.952409	0.374936	0.16565	0.081012	0.211525	0.159782	0.007093
30	57.717331	11.637259	0.965771	0.410449	0.183449	0.053905	0.252638	0.092344	0.007212
31	57.717412	11.637111	0.978393	0.427039	0.187904	0.041493	0.254699	0.081652	0.00721

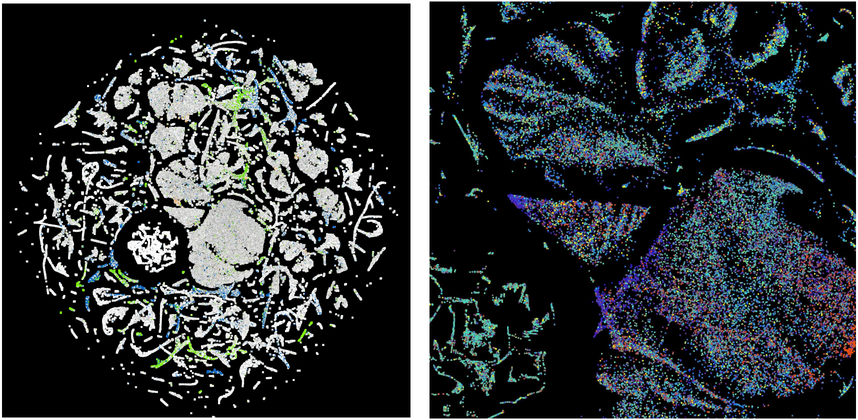
Middel et al. (2019)

	A	B	D	E	G	H	J
1	city	aodAquaObs	xyAodAqua	aodTerraObs	xyAodTerra	no2Obs	xyNo2
2	Tokyo, Japan	.3375	.3296	.3472	.3526	791.0735	513.8885
3	New York-Newark, United States of America	.1601	.3057	.2011	.3345	748.5637	471.6009
4	Kunming, China	.0999	.3692	.1428	.3985	194.0702	487.7979
5	Worcester, United States of America	.1165	.3247	.1556	.3541	367.2458	487.6344
6	Nurenberg, Germany	.1429	.3081	.2025	.3368	503.0870	484.8274

Parameter	Correlation value
Movable objects fraction	0.97
Impervious surfaces fraction	0.86
Sky fraction	0.75
Building fraction	0.56
AOD	0.58
NO_2	0.57

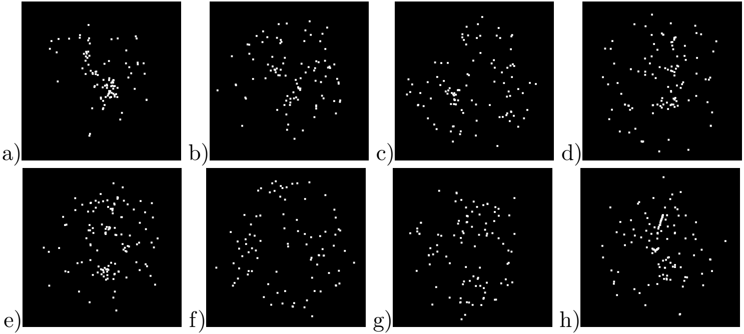
Correlations between mean average values by city and by city mix of (x,y) location within the SOM.

Block typologies - Alternative methods with T-SNE



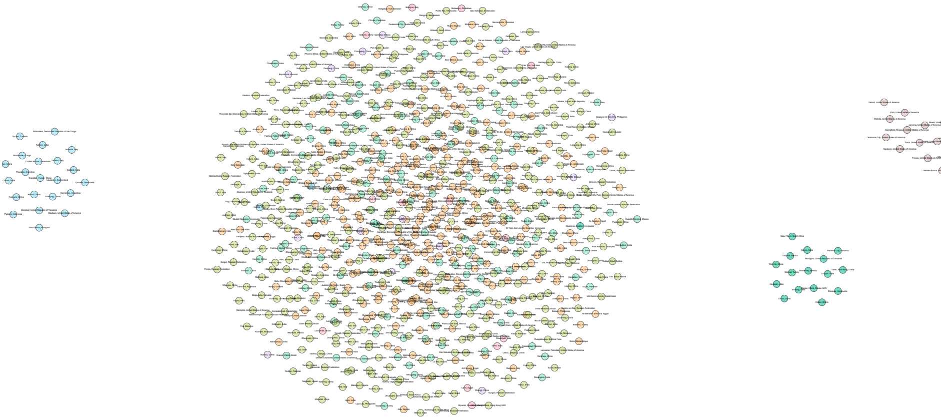
Clustering of map segments from 1667 cities using T-SNE showing representative maps and colour plots using lat/lon.

Block typologies - T-SNE - City fingerprints



(x,y) T-SNE locations for a) Tokyo, b) Jakarta, c) Brasília, d) Barcelona, e) Paris, f) Nairobi. g) Beijing, h) New York.

Block typologies - City clustering experiements



Experimental city clustering using block typologies

Block typologies summary

- Block typologies enables inter- and intra-city comparisons.
- Method uses size and regularity of city blocks and amounts of public transport and green and blue space (through pixel counts).
- City 'fingerprints' reveal that most cities have similar mixes of neighbourhood types but with slight variations (but some cities are completely different). Same basic ingredients but different sauces.
- Can evaluate how the mix and spatial distribution of neighbourhoods impacts performance indicators of each city.
- Method is extendible. Sorted vectors can include any additional spatial parameters (traffic counts, urban form elements, demographics, etc.).
- Future work: to use block typologies to examine urban form impacts on public health, transportation safety, active transport, etc.

Google Maps (2017), Google Static Maps API, Available from https://developers.google.com/maps/documentation/static-maps. (accessed 15 June 2017).

Kropp, J. (1998), A neural network approach to the analysis of city systems. *Applied Geography*, 18(1):pp. 83–96.

Louf, R. and Barthelemy, M. (2014), A typology of street patterns. *J. R. Soc. Interface*, 11:pp. 1–7.

Middel, A., Lukasczyk, J., Zakrzewski, S., Arnold, M. and Maciejewski, R. (2019), Urban form and composition of street canyons: A human-centric big data and deep learning approach. *Landscape and Urban Planning*, 183:pp. 122–132.

Porta, S., Crucitti, P. and Latora, V. (2006a), The network analysis of urban streets: A dual approach. *Physica A: Statistical Mechanics and its Applications*, 369(2):pp. 853–866.

Porta, S., Crucitti, P. and Latora, V. (2006b), The network analysis of urban streets: A primal approach. *Environment and Planning B: Planning and Design*, 33(5):pp. 705–725.

Strano, E., Nicosia, V., Latora, V., Porta, S. and Barthélemy, M. (2012), Elementary processes governing the evolution of road networks. *Scientific Reports*, 2.

Thompson, J., Stevenson, M., Wijnands, J.S., Nice, K., Aschwanden, G., Silver, J., Nieuwenhuijsen, M., Rayner, P., Schofield, R., Hariharan, R. and Morrison, C.N. (2018), Injured by Design: A Global Perspective on Urban Design and Road Transport Injury. *SSRN*.

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