Spatial heterogeneity & dependence:

Night satellite images and functional relationship in the rural-urban environment and the economy?

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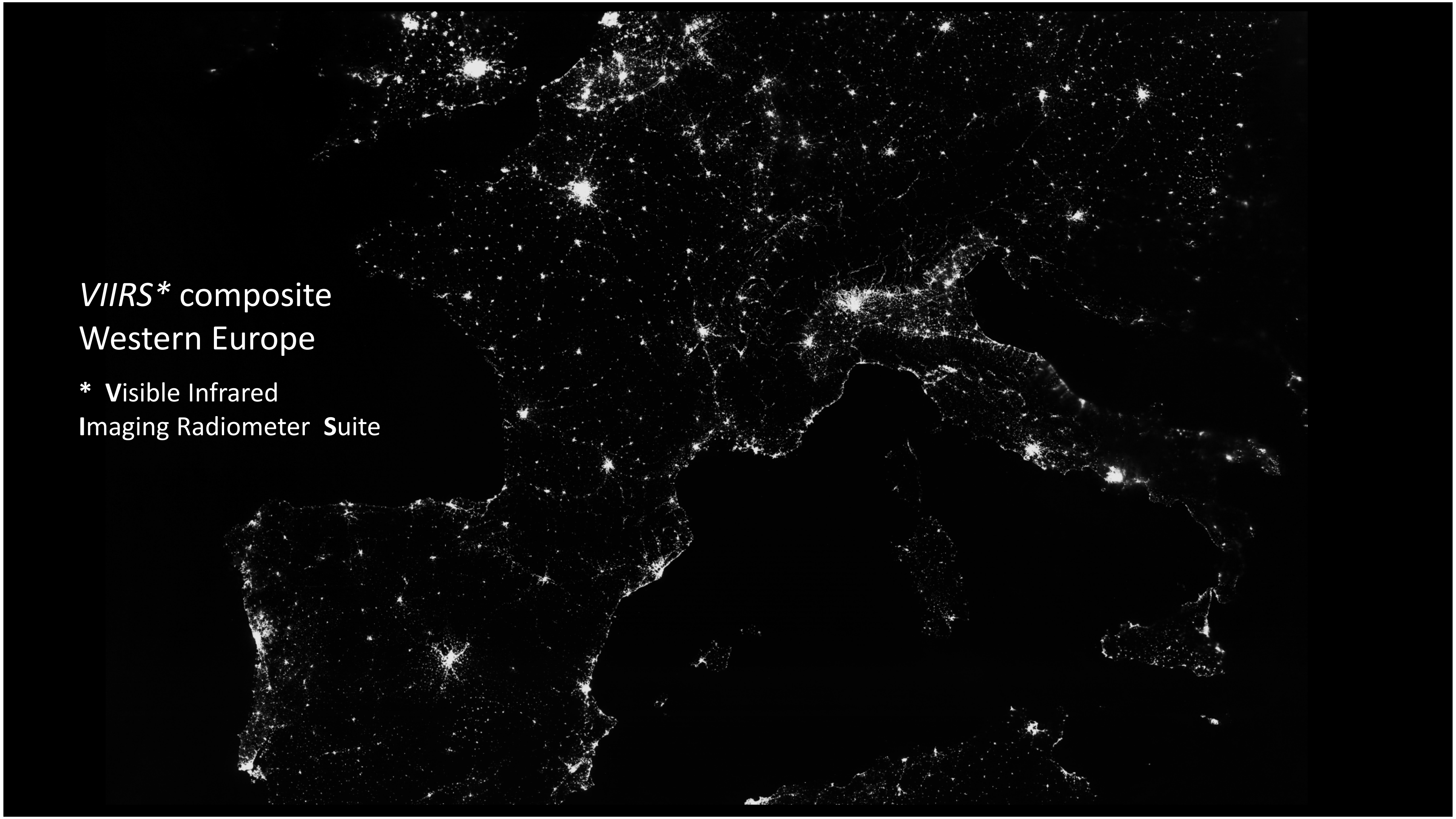
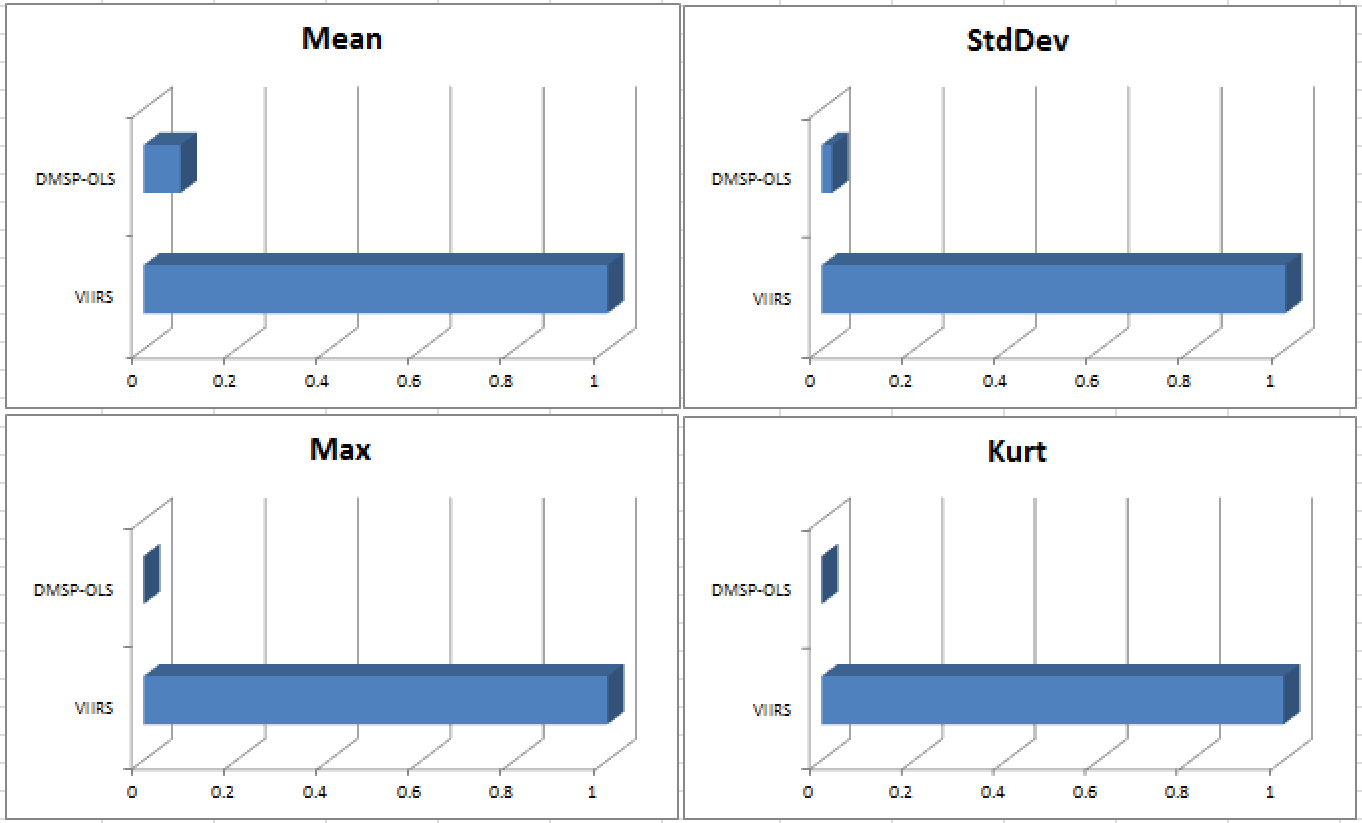

*VIIRS** composite
Western Europe
* **V**isible Infrared
Imaging Radiometer **S**uite

Assumed advantage of the use of VIIRS in regional science

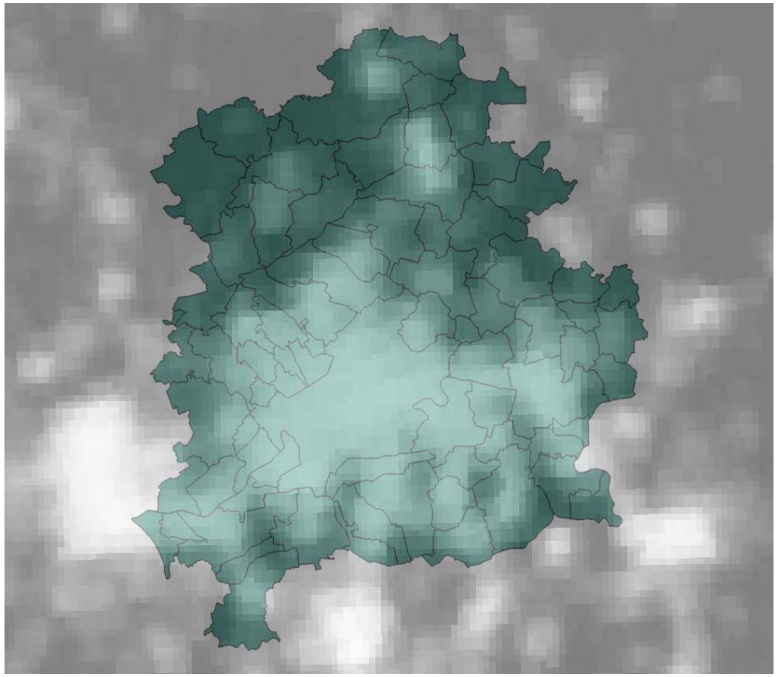
- **Three properties**: (i) a high spatial resolution, (ii) a close statistical association with the economy and the environment, and (iii) a strong variation of detected light emission

- **Two solutions**: (i) a precise statistical segmentation of functional space, and (ii) continuous monitoring and forecasting of rural-urban change at smallest spatial scale.

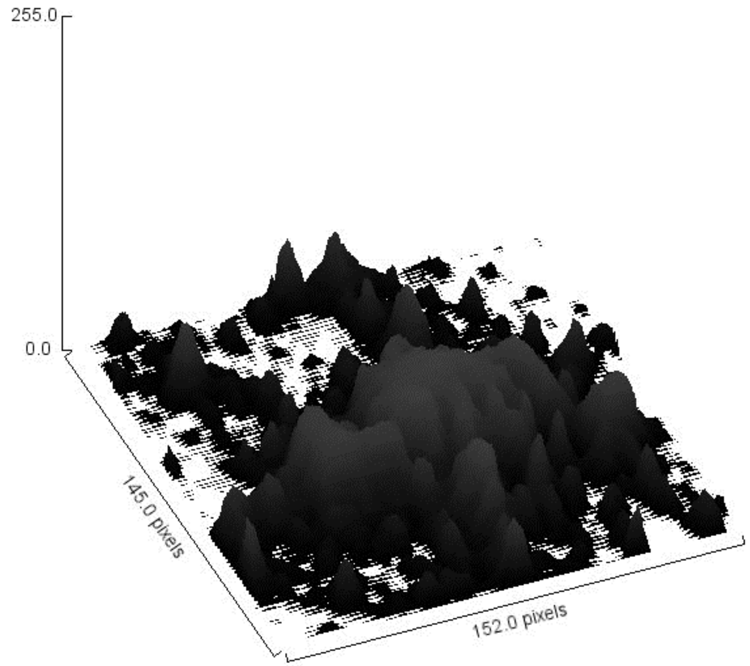
VIIRS and DMSP-OLS compared



Comparison of the old DMSP-OLS and the new VIIRS images I (1992)

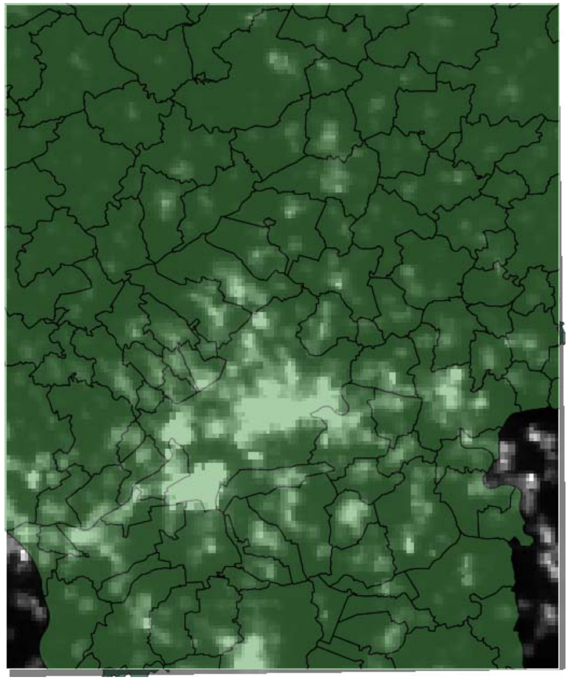


DMSP-OLS stable lights

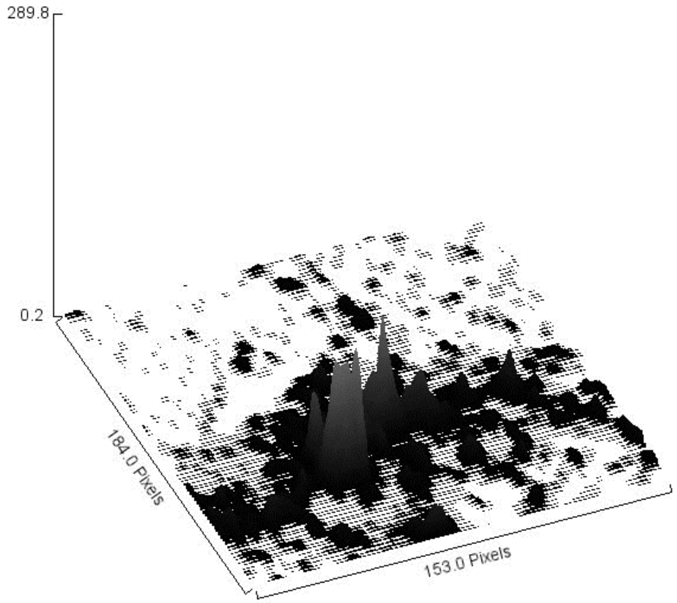


6 bit: <64; Kurt(x) = 0.66

Comparison of the old DMSP-OLS and the new VIIRS images II (2012)



VIIRS



14 bit: < 16,384; Kurt(x) = 186.40

Three ROBUST-related questions

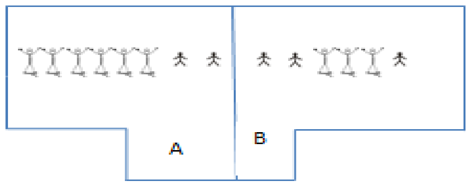
Issues to be addressed

- The **M**odifiable **A**real **U**nit **P**roblem (**MAUP**);
- Urbanization / Urban sprawl / Dissolution of urban and rural functionality;
- Lack of socio-economic and environmental information at neighbourhood level

MAUP

MAUP

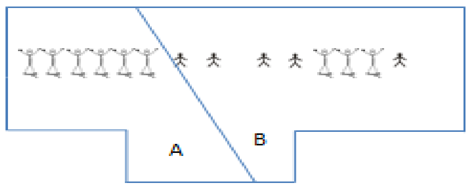
Original administrative boundary



A: 25 percent unemployment

B: 50 percent unemployment

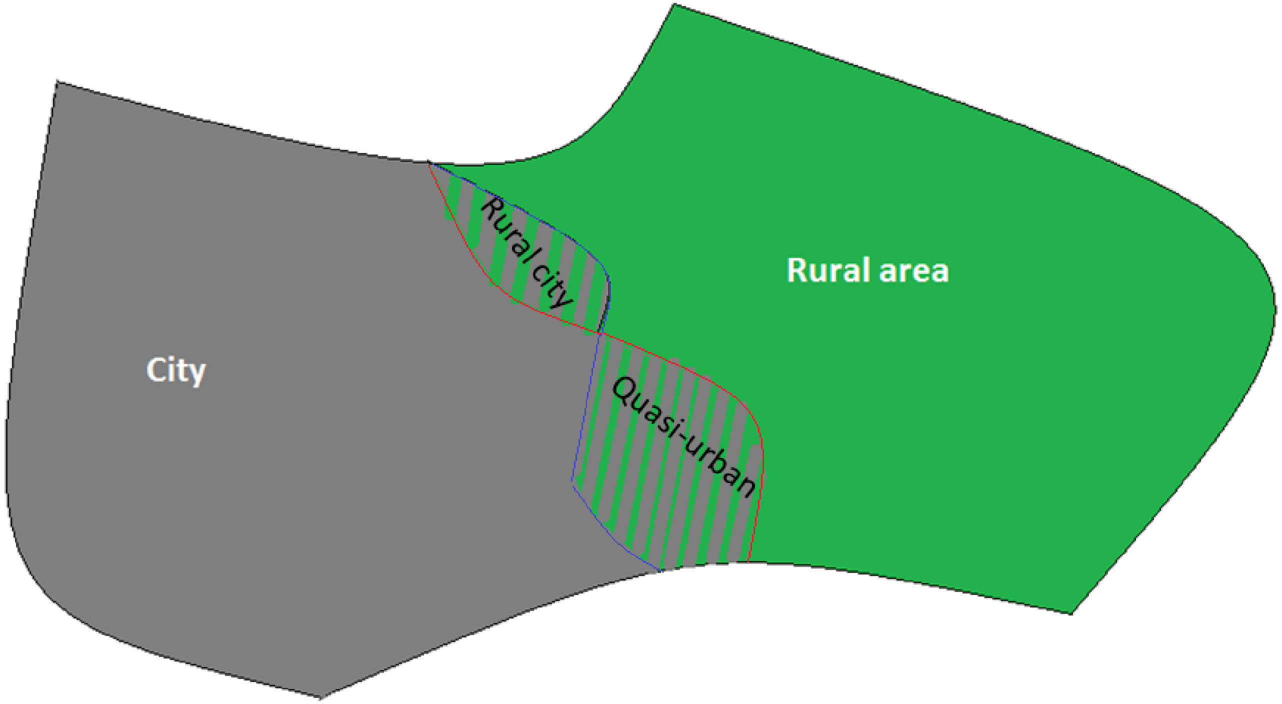
Changed administrative boundary



A: zero percent unemployment

B: 62.5 percent unemployment

The rural-urban MAUP



The „natural“ and „administrative“ mismatch of space along the urban fringe

City of Frankfurt

Eschborn (peri-urban area close to Frankfurt)

So what did we do?

Thresholding & statistical **segmentation** of functional urban and non-urban space in the images;

Analysis and simulation of changing **spatial dependence** at grid level;

Exploring the **strength of association** between night lights and several socio-economic/environmental variables at grid level

I. Segmentation of functional space

- Extraction of the national VIIRS image with QGIS (based on a shapefile)
- Trimming the upper tail of the pixel distribution (outlier removal 0.5% or estimation with an adjusted boxplot algorithm*) ;
- Statistical thresholding (k-means or Isodata segmentation with QGIS, ImageJ or Stata™);
- Testing the resulting segmentation (with Zipf's law);
- Extracting the study region (with QGIS)

* *Vandervieren-Huber* adjusted box-plot for skewed distributions

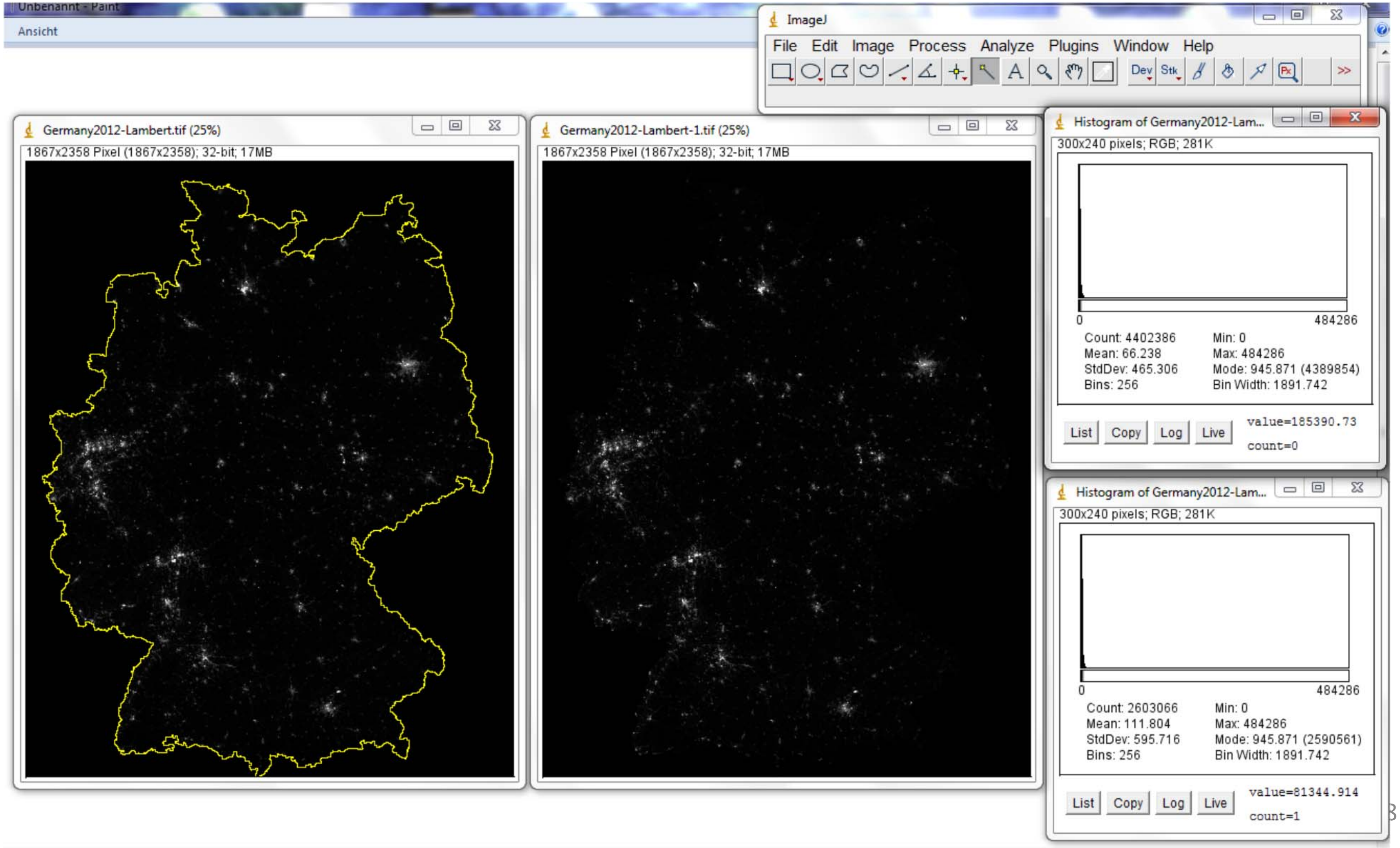
Steps (Quantum-GIS)

- The database (VIIRS composites) can be found at: https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html (download tile 2 for Europe; VCMCFG files)
- The files are compressed (.tgz files) and need to be extracted. The final raw dataset is a geo-tiff image (thus geo-referenced)
- Download and open QGIS (https://qgis.org/en/site/forusers/download.html)
- To produce the image you wish to analyse, add the geo-tiff image as a raster layer
- Then add the shapefile (country to be regarded) as a vector layer
- Extract the image by «Raster>extraction>clip raster by mask layer» and save the output geo-tiff as a separate file
- Re-project it by the «Raster>projections>warp» command (For EU spatial analyses/ INSPIRE directive: *Lambert-Azimuthal*/EPSG 3035) and save it

Geo-tiff image

Steps (ImageJ): preparation

- Create a new folder with a copy of the sole tiff-image to use it for image analysis
- Download (https://imagej.nih.gov/ij/)/open ImageJ (or Fiji) and load the Tiff image
- Radiance becomes visible by multiplying the pixels by e.g. 100
- The image is a rectangle and contains „outer space“ (zero or NaN pixels)
- Select the region to analyse by freehand selection, polygon selection or by using the Wand tool (more precise, but more demanding)
- Generate basic moments, the distribution and a surface plot to recognize the character («analyse>histogram», «analyse>surface plot »)



Unbenannt - Paint
Ansicht
ImageJ
File Edit Image Process Analyze Plugins Window Help
Dev Stk
Germany2012-Lambert.tif (25%)
1867x2358 Pixel (1867x2358); 32-bit; 17MB
Germany2012-Lambert-1.tif (25%)
1867x2358 Pixel (1867x2358); 32-bit; 17MB
Histogram of Germany2012-Lam...
300x240 pixels; RGB; 281K
0
484286
Count: 4402386
Mean: 66.238
StdDev: 465.306
Bins: 256
Min: 0
Max: 484286
Mode: 945.871 (4389854)
Bin Width: 1891.742
List Copy Log Live
value=185390.73
count=0
Histogram of Germany2012-Lam...
300x240 pixels; RGB; 281K
0
484286
Count: 2603066
Mean: 111.804
StdDev: 595.716
Bins: 256
Min: 0
Max: 484286
Mode: 945.871 (2590561)
Bin Width: 1891.742
List Copy Log Live
value=81344.914
count=1

Steps (ImageJ): outlier removal - thresholding

- To remove outliers, either set the upper 0.5% of the power-distributed observations equal to the cut-off value or run a statistical procedure to trim the data (then you need a statistics software to estimate different parameters to find the precise threshold)
- Then again select the region to analyse and use the image>adjust>threshold command to segment the image by Isodata, k-means or other procedures
- Select from the pulldown: «Isodata»
- Alternatively: install the ImageJ segmentation plugin and run the k-means procedure
- Or: transform the pixel database into a numeric one and run a *k-means* clustering (K=2) by *Stata*. Insert the resulting threshold value into the ImageJ threshold procedure manually («image>adjust>threshold>set»)

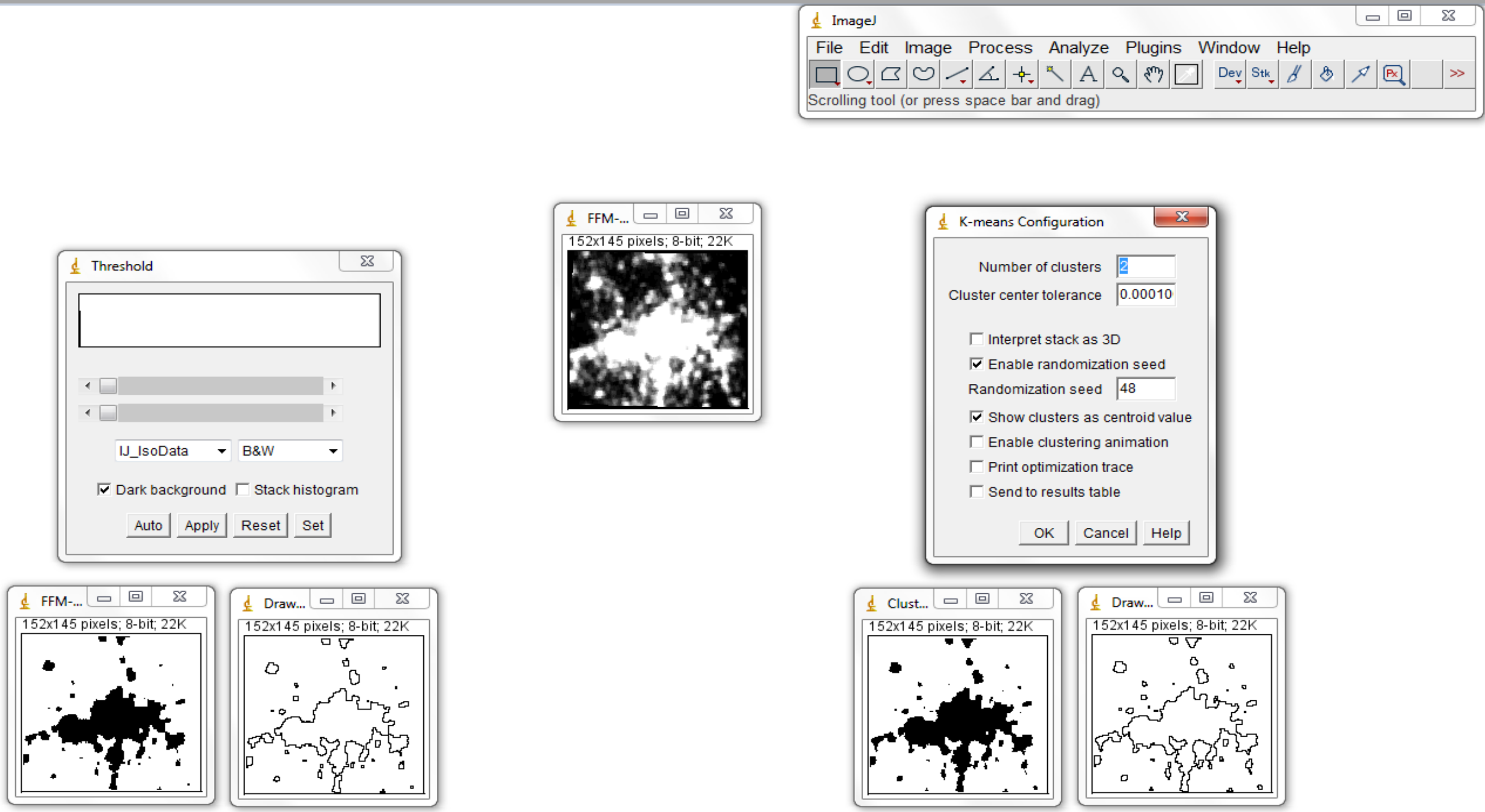
To summarize, the adjusted boxplot marks the observations that fall outside the interval

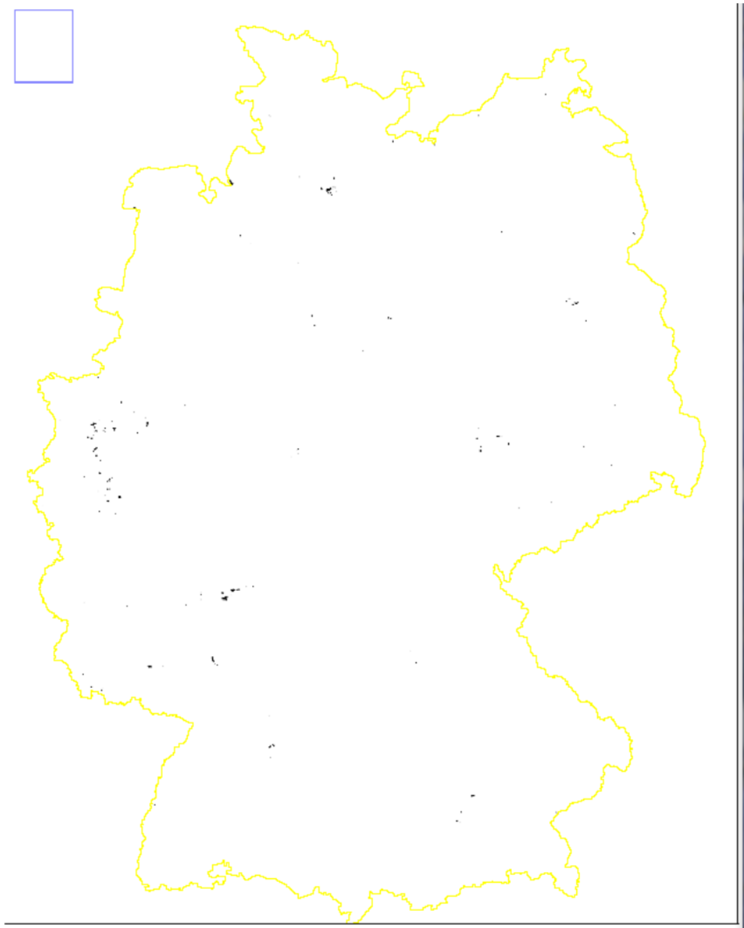
$$[Q_1 - 1.5\, e^{-3.5\,\mathrm{MC}}\, \mathrm{IQR}\ ;\ Q_3 + 1.5\, e^{4\,\mathrm{MC}}\, \mathrm{IQR}] \qquad (1)$$

		original boxplot			adjusted boxplot		
Distr	n	% L	% R	Tot %	% L	% R	Tot %
$N(0,1)$	100	0.600	0.700	1.300	1.180	0.800	1.980*
	500	0.358	0.402	0.760*	0.462*	0.634*	1.096*
	1000	0.335	0.362*	0.697*	0.484*	0.445*	0.929*
χ^2_1	100	0.000	7.350*	7.350*	0.000	0.180	0.180
	500	0.000	7.940**	7.940**	0.000	0.032	0.032
	1000	0.000	7.726**	7.726**	0.000	0.015	0.015
χ^2_{20}	100	0.060	1.360	1.420	0.880	0.780	1.660
	500	0.002	1.478*	1.480*	0.400*	0.392*	0.792*
	1000	0.002	1.456**	1.458**	0.382*	0.311*	0.693*
$\Gamma(0.1, 0.5)$	100	0.000	7.960*	7.960*	0.000	0.410	0.410
	500	0.000	7.716**	7.716**	0.000	0.030	0.030
	1000	0.000	7.708**	7.708**	0.000	0.019	0.019
Pareto(3,1)	100	0.000	8.130*	8.130*	0.280	0.950	1.230
	500	0.000	8.350**	8.350**	0.034	0.620*	0.654*
	1000	0.000	7.943**	7.943**	0.000	0.558*	0.558*
$F(90,10)$	100	0.000	5.210*	5.210*	1.480*	0.960	2.440*
	500	0.000	5.000**	5.000**	0.584*	0.636*	1.220*
	1000	0.000	5.230**	5.230**	0.485**	0.714*	1.199**
Pareto(1,3)	100	0.000	12.250*	12.250*	0.710*	2.490	3.200*
	500	0.000	12.338**	12.338**	0.000	2.314*	2.314*
	1000	0.000	12.461**	12.461**	0.000	2.166*	2.166*
G_3	100	0.000	16.300*	16.300*	0.000	3.290	3.290
	500	0.000	16.516*	16.516*	0.000	2.966*	2.966*
	1000	0.000	16.408**	16.408**	0.000	3.028**	3.028**

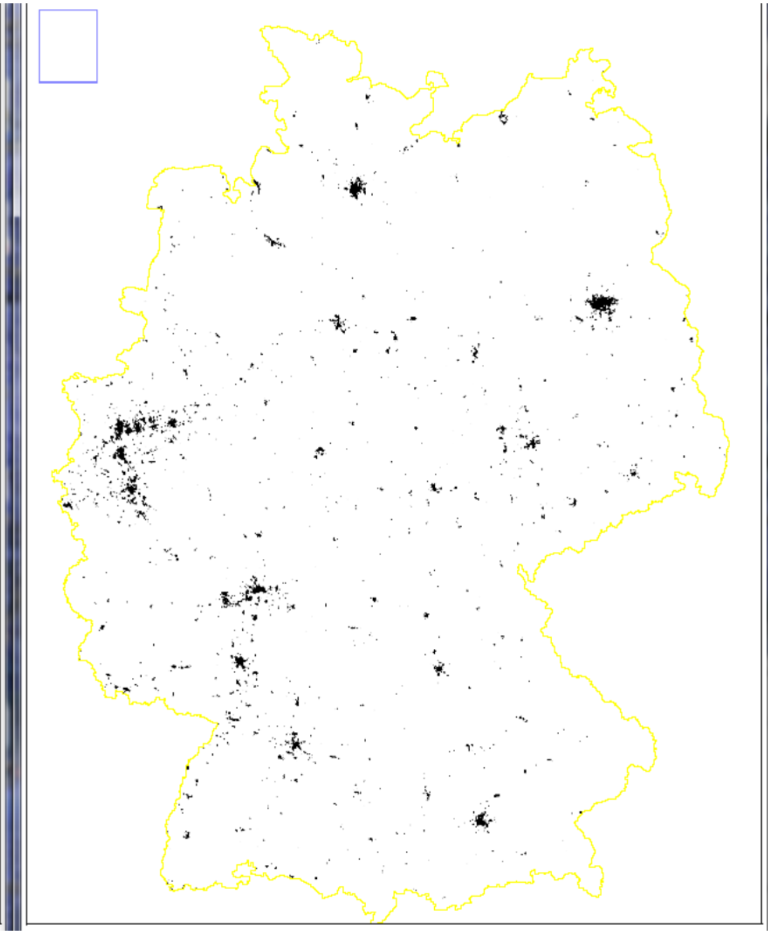
Table 2: For different distributions and samples sizes, the mean percentage of left outliers (% L), right outliers (% R) and the mean total percentage of outliers (Tot %) are reported, resulting from the original boxplot and the adjusted boxplot. The superscript $*$ means a standard error between 0.2% and 0.5%, $**$ between 0.5% and 0.9%. No superscript is set if the standard error is smaller than 0.2%.

ImageJ – Isodata versus k-means

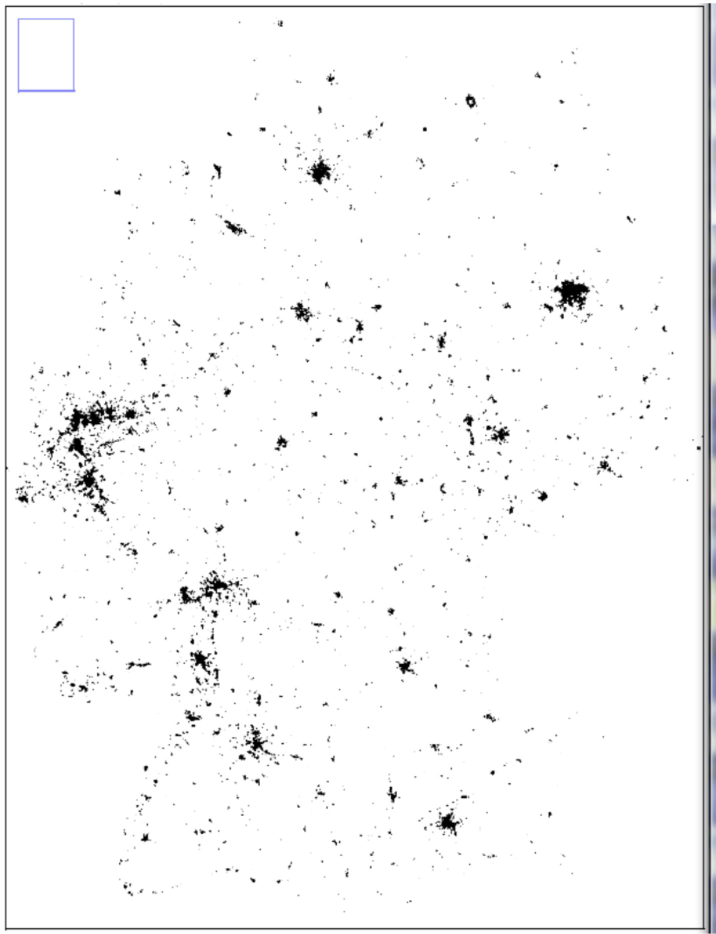




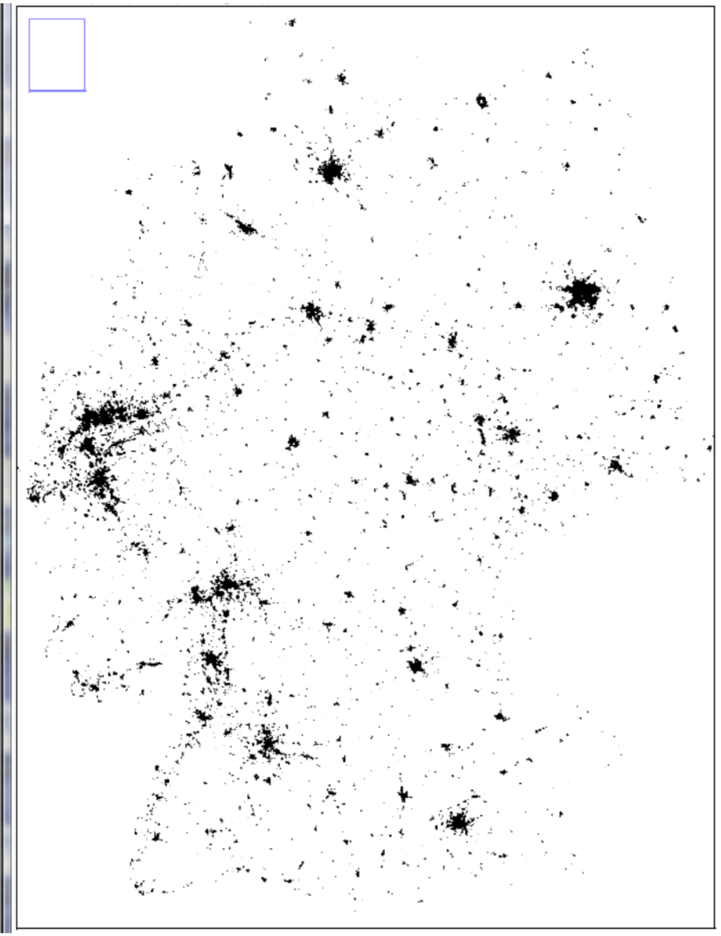
Isodata (untrimmed)



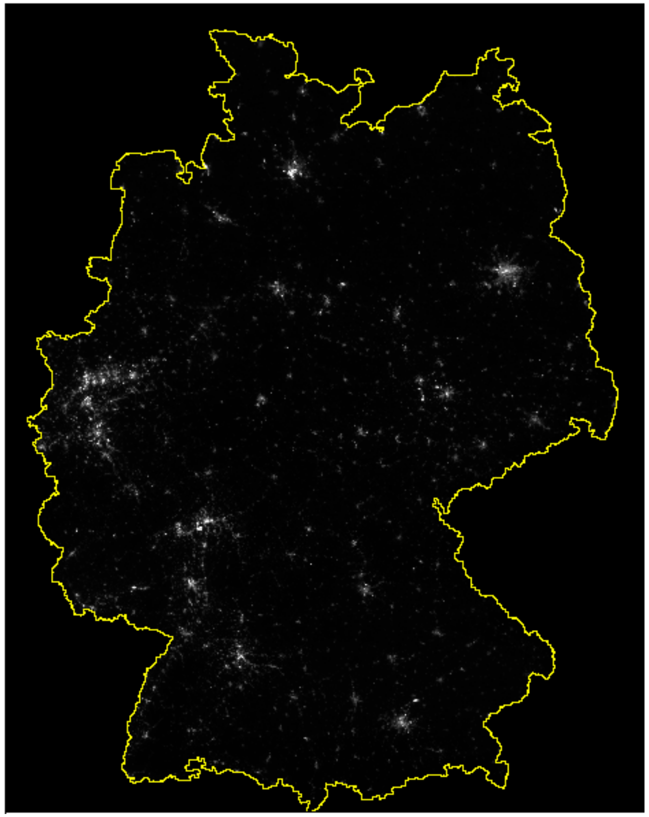
Isodata (trimmed)

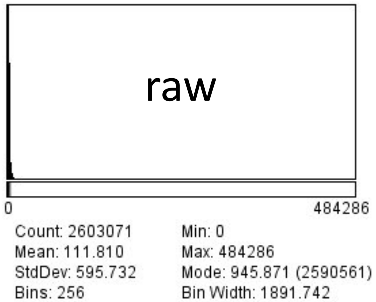


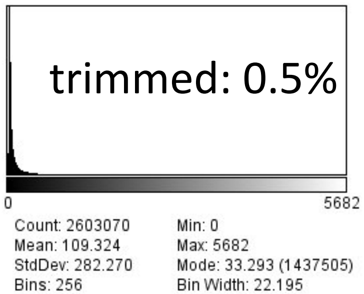
K-means (untrimmed)



K-means (trimmed)

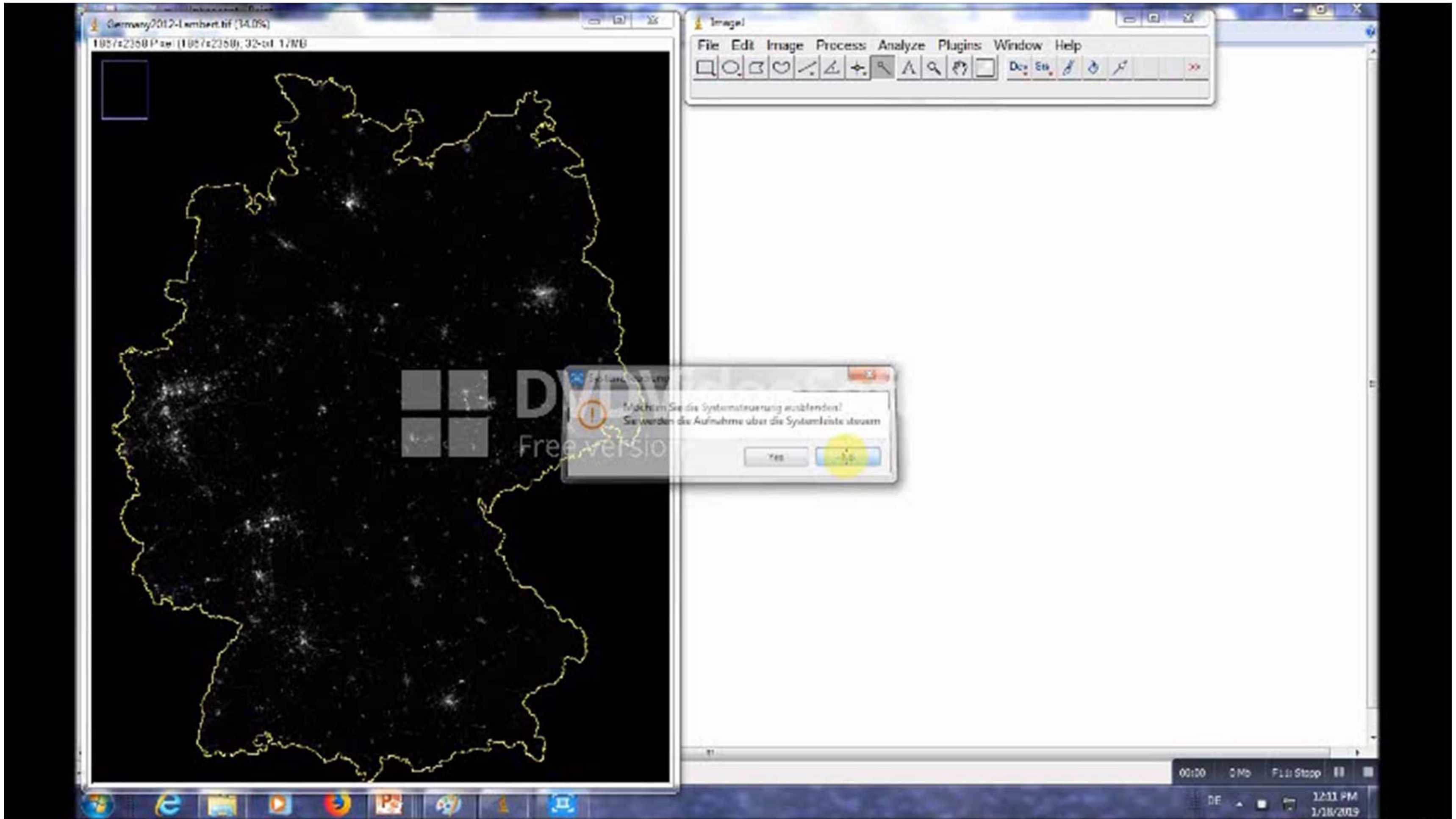






Segmentation with k-means clustering

Threshold: 735.32


File Edit Image Process Analyze Plugins Window Help

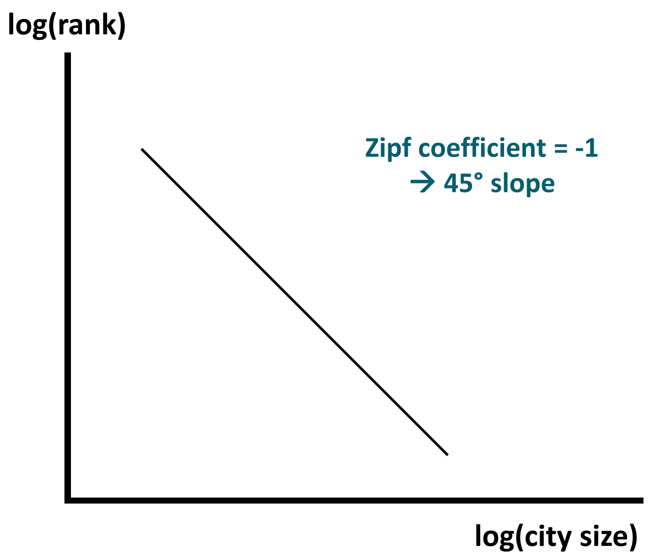
First and second order spatial heterogeneity

- Segmentation shows cities as on a map, but the distribution as such appears chaotic (first order spatial heterogeneity);

- However, the rank-size distribution of all cities (patches) reveals a systematic rule: **Zipf‘s law** (second order spatial heterogeneity);

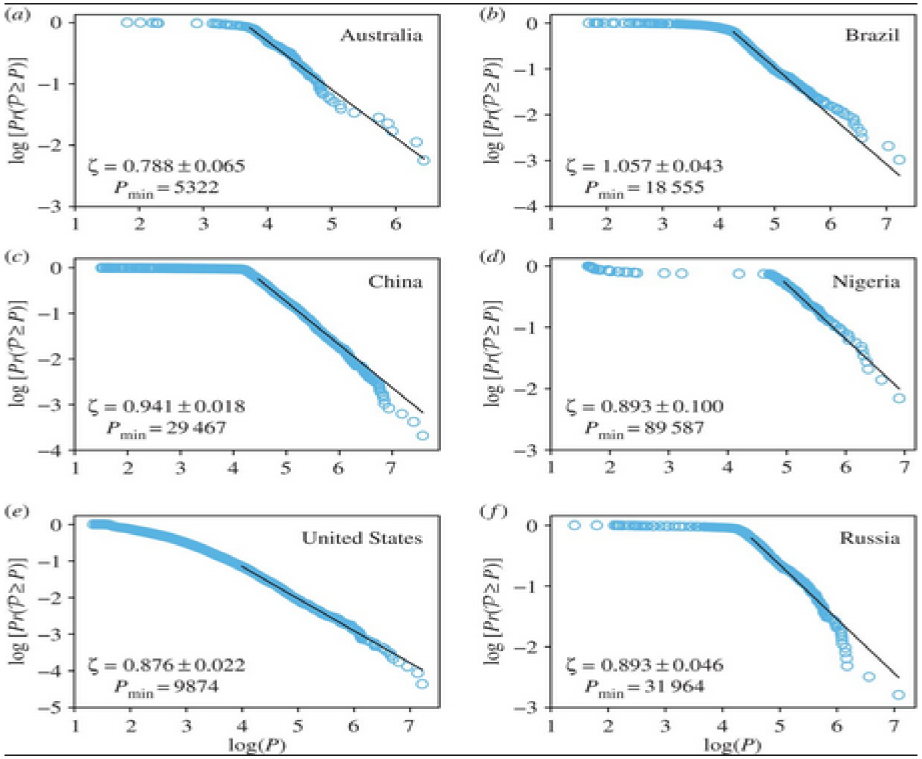
- This makes Zipf‘s law a candidate for testing the segmentation adequacy

Zipf‘s law for cities



Spooky Zipf's law →

- Ubiquitous pattern of city rank-size distribution (population of administrative cities)*:
- log [Pr(p≥P)] = Constant - ζ · log (P)
- ζ ≈ 1 [with some spatio-temporal variance of around ± 0.2 for most countries]

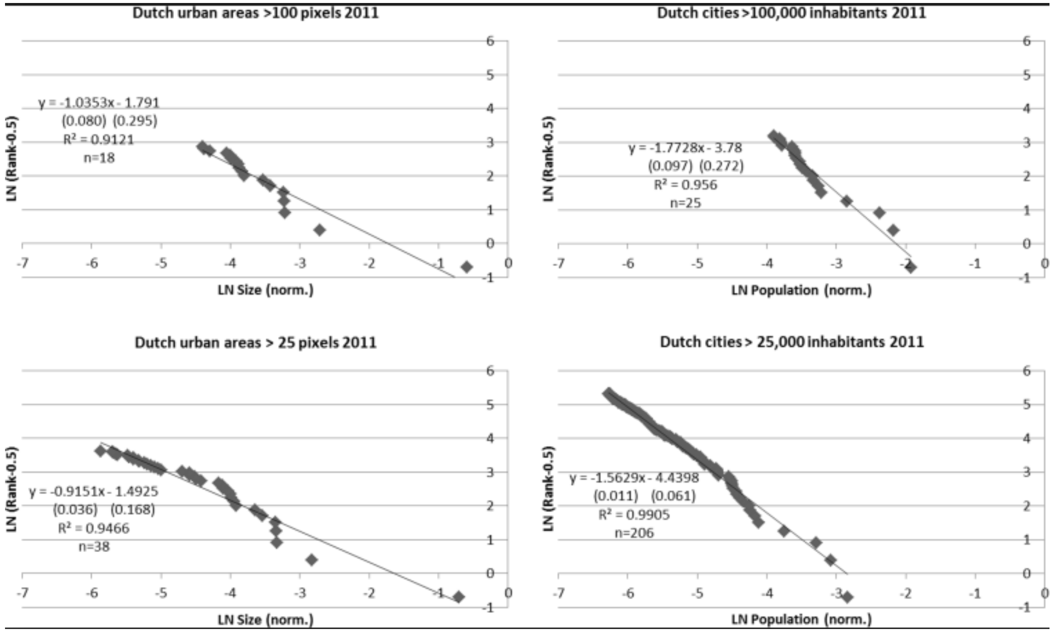


* *Simple logarithmic Zipf estimates*

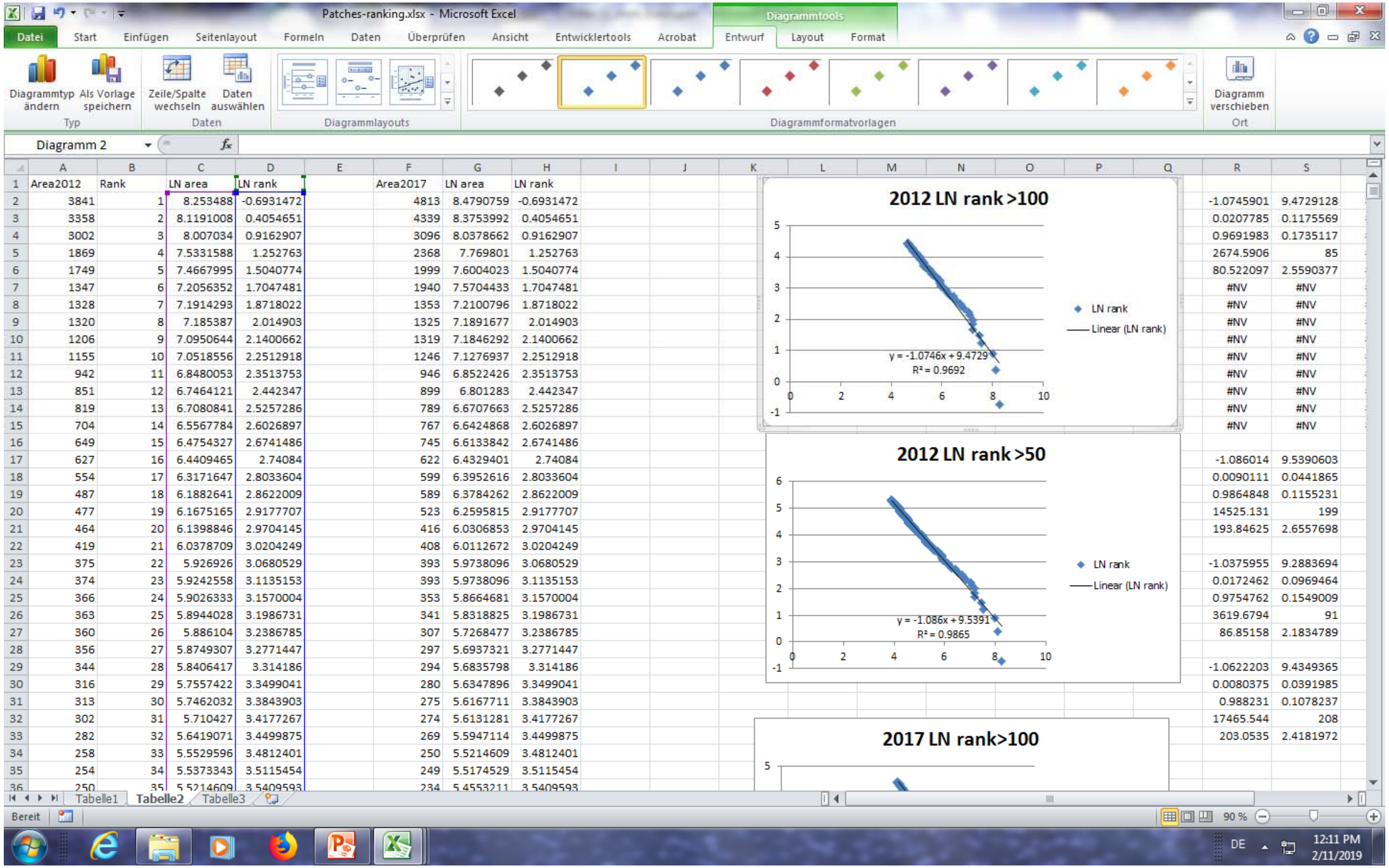
Spooky Zipf‘s law

Natural cities are better determined by Zipf‘s law than administrative cities:

log(R-1/2) = log(C) - ζ · log(S) *



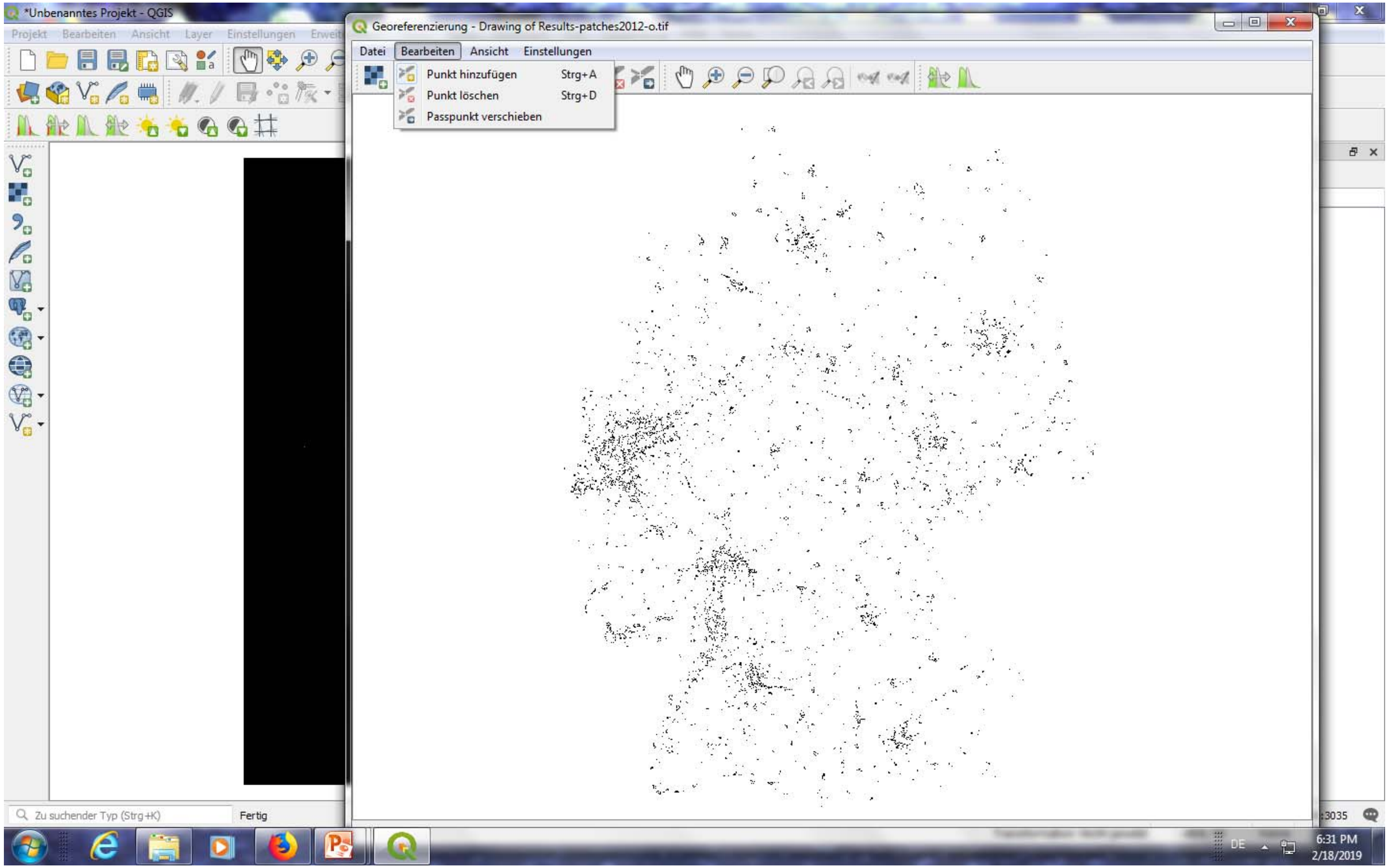
* *Gabaix-Ibragimov estimator*



	A	B	C	D	E	F	G	H	R	S
1	Area2012	Rank	LN area	LN rank		Area2017	LN area	LN rank		
2	3841	1	8.253488	-0.6931472		4813	8.4790759	-0.6931472	-1.0745901	9.4729128
3	3358	2	8.1191008	0.4054651		4339	8.3753992	0.4054651	0.0207785	0.1175569
4	3002	3	8.007034	0.9162907		3096	8.0378662	0.9162907	0.9691983	0.1735117
5	1869	4	7.5331588	1.252763		2368	7.769801	1.252763	2674.5906	85
6	1749	5	7.4667995	1.5040774		1999	7.6004023	1.5040774	80.522097	2.5590377
7	1347	6	7.2056352	1.7047481		1940	7.5704433	1.7047481	#NV	#NV
8	1328	7	7.1914293	1.8718022		1353	7.2100796	1.8718022	#NV	#NV
9	1320	8	7.185387	2.014903		1325	7.1891677	2.014903	#NV	#NV
10	1206	9	7.0950644	2.1400662		1319	7.1846292	2.1400662	#NV	#NV
11	1155	10	7.0518556	2.2512918		1246	7.1276937	2.2512918	#NV	#NV
12	942	11	6.8480053	2.3513753		946	6.8522426	2.3513753	#NV	#NV
13	851	12	6.7464121	2.442347		899	6.801283	2.442347	#NV	#NV
14	819	13	6.7080841	2.5257286		789	6.6707663	2.5257286	#NV	#NV
15	704	14	6.5567784	2.6026897		767	6.6424868	2.6026897	#NV	#NV
16	649	15	6.4754327	2.6741486		745	6.6133842	2.6741486		
17	627	16	6.4409465	2.74084		622	6.4329401	2.74084	-1.086014	9.5390603
18	554	17	6.3171647	2.8033604		599	6.3952616	2.8033604	0.0090111	0.0441865
19	487	18	6.1882641	2.8622009		589	6.3784262	2.8622009	0.9864848	0.1155231
20	477	19	6.1675165	2.9177707		523	6.2595815	2.9177707	14525.131	199
21	464	20	6.1398846	2.9704145		416	6.0306853	2.9704145	193.84625	2.6557698
22	419	21	6.0378709	3.0204249		408	6.0112672	3.0204249		
23	375	22	5.926926	3.0680529		393	5.9738096	3.0680529	-1.0375955	9.2883694
24	374	23	5.9242558	3.1135153		393	5.9738096	3.1135153	0.0172462	0.0969464
25	366	24	5.9026333	3.1570004		353	5.8664681	3.1570004	0.9754762	0.1549009
26	363	25	5.8944028	3.1986731		341	5.8318825	3.1986731	3619.6794	91
27	360	26	5.886104	3.2386785		307	5.7268477	3.2386785	86.85158	2.1834789
28	356	27	5.8749307	3.2771447		297	5.6937321	3.2771447		
29	344	28	5.8406417	3.314186		294	5.6835798	3.314186	-1.0622203	9.4349365
30	316	29	5.7557422	3.3499041		280	5.6347896	3.3499041	0.0080375	0.0391985
31	313	30	5.7462032	3.3843903		275	5.6167711	3.3843903	0.988231	0.1078237
32	302	31	5.710427	3.4177267		274	5.6131281	3.4177267	17465.544	208
33	282	32	5.6419071	3.4499875		269	5.5947114	3.4499875	203.0535	2.4181972
34	258	33	5.5529596	3.4812401		250	5.5214609	3.4812401		
35	254	34	5.5373343	3.5115454		249	5.5174529	3.5115454		
36	250	35	5.5214609	3.5409593		234	5.4553211	3.5409593		

Testing the segmentation with Zipf's law (estimates for patches >50 and >100 px)

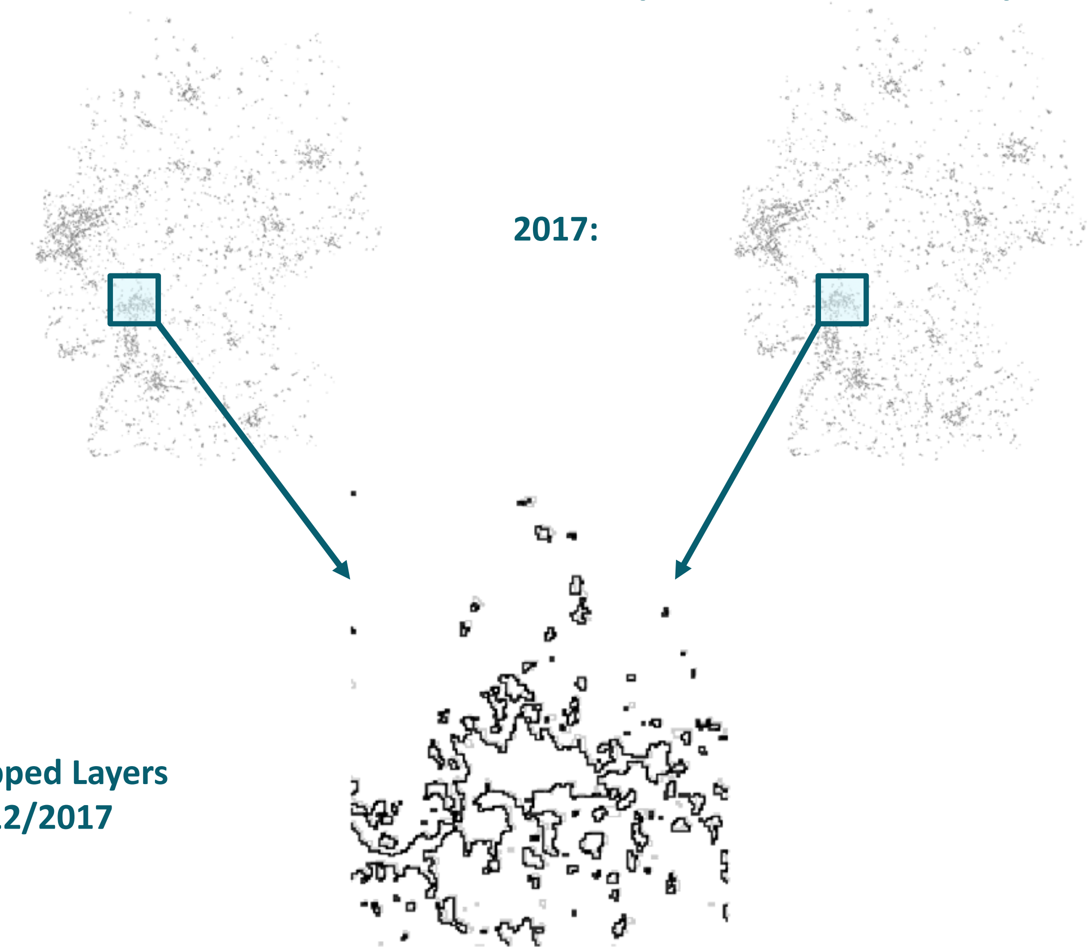
	2012	2017
>100 px	$y = -1.0746x + 9.4729$ $R^2 = 0.9692$	$y = -1.0376x + 9.2884$ $R^2 = 0.9755$
>50 px	$y = -1.086x + 9.5391$ $R^2 = 0.9865$	$y = -1.0622x + 9.4349$ $R^2 = 0.9882$


*Unbenanntes Projekt - QGIS
Projekt Bearbeiten Ansicht Layer Einstellungen
Georeferenzierung - Drawing of Results-patches2012-o.tif
Datei Bearbeiten Ansicht Einstellungen
Punkt hinzufügen Strg+A
Punkt löschen Strg+D
Passpunkt verschieben
Zu suchender Typ (Strg+K)
Fertig
6:31 PM
2/18/2019

Segmentation result 2012 and 2017 (national and local)

2012:

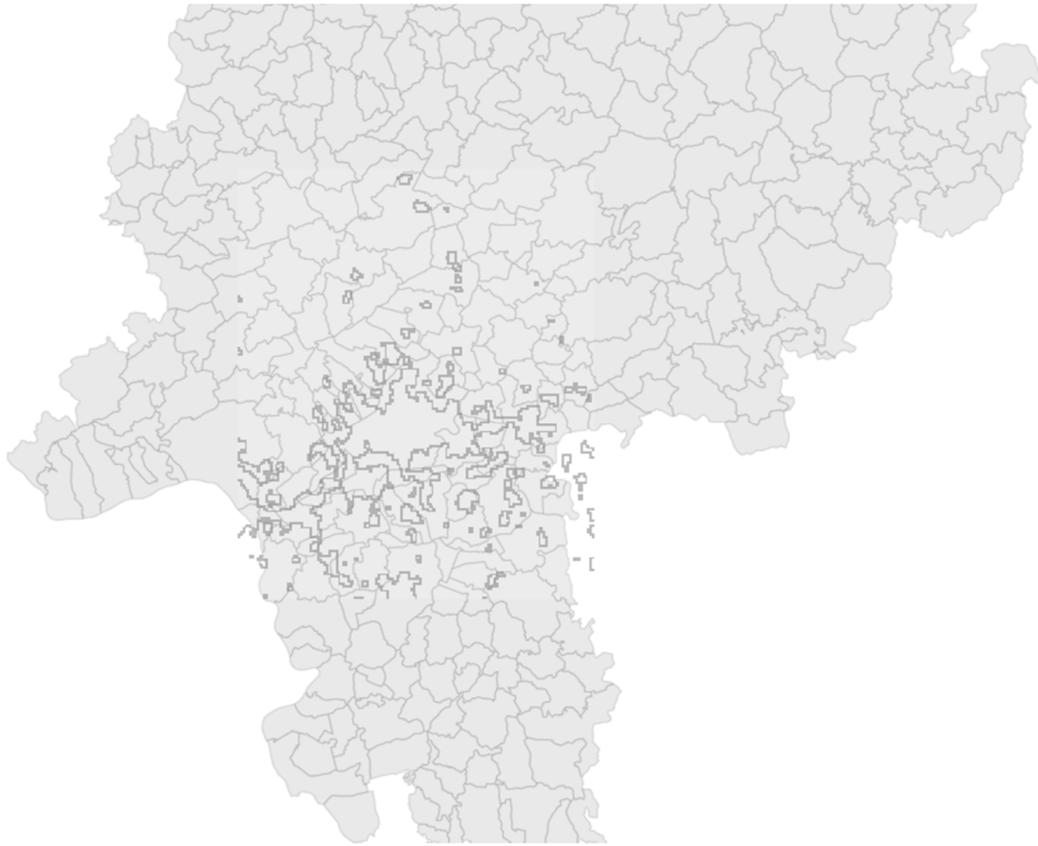
2017:



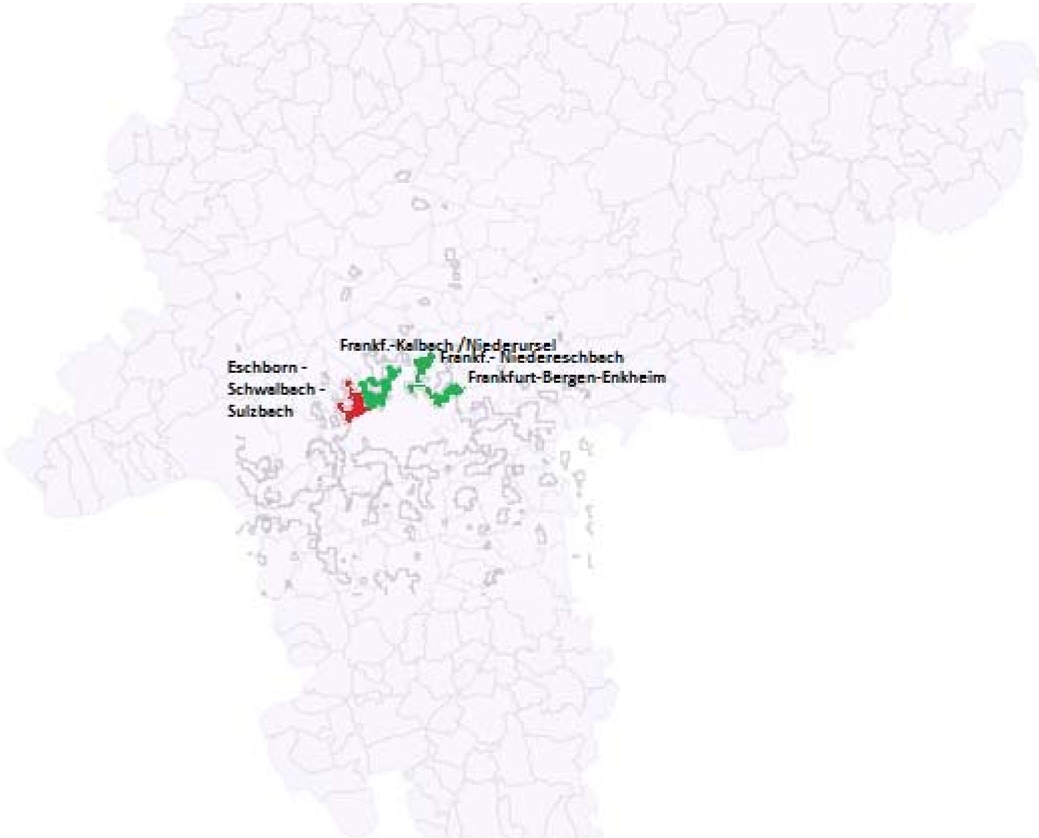
Clipped Layers
2012/2017

Natural versus administrative urban space: RVFRM 2012

Natural versus urban space RVFRM 2017



Rural-urban mismatch: RVFRM 2017



Policy- and planning-relevant Implications

- Deviations of natural urban space from administrative space are remarkable;
- While administrative space is fixed, natural (functional space) evolves continuously;
- Rural-urban planning needs could be better identified by evolving natural space instead of static administrative boundaries

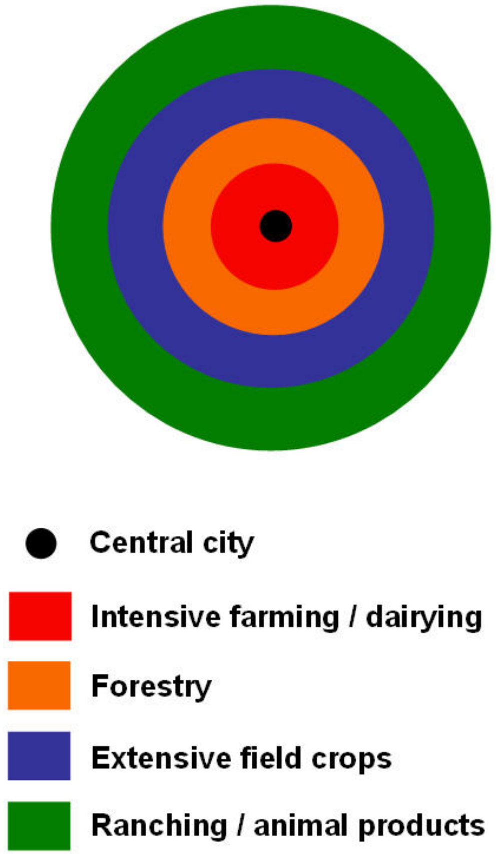
II. Addressing dissolution of rural-urban functionality

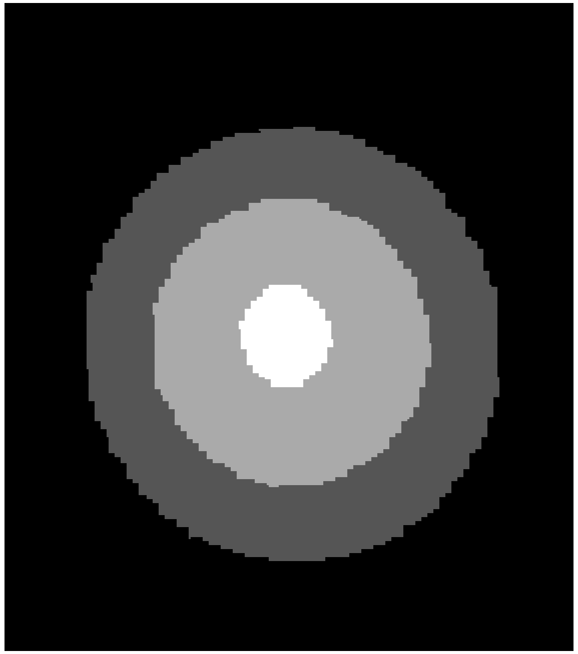
- Urban fringe zones have important ecological functions (to avoid urban sprawl, to prevent neighboring towns from merging, to maintain fresh air passage and urban regeneration);
- Those areas are never immune to soil sealing and development (temptation to develop residual open space);
- Any kind of land use conflict is eventually the result of historically defined boundaries

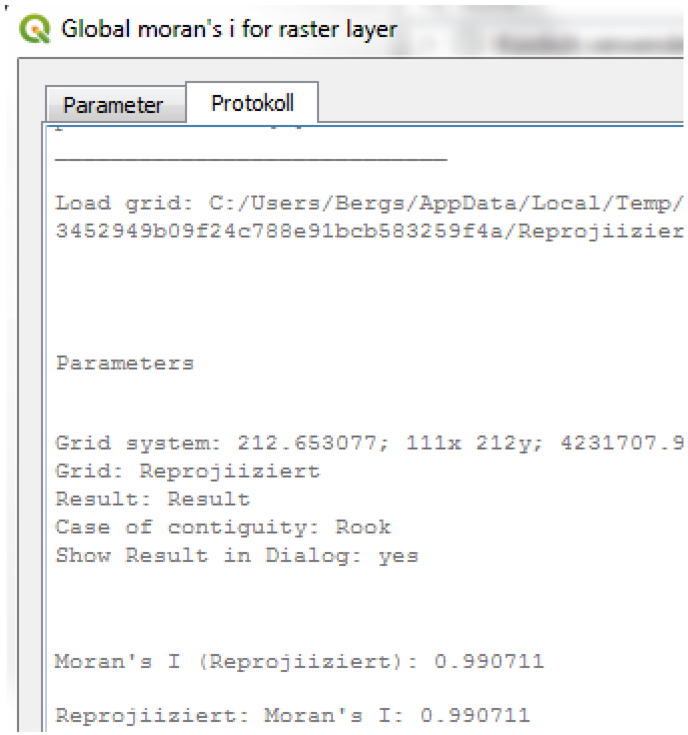
Contribution to policy insight: Longitudinal analysis of spatial dependence

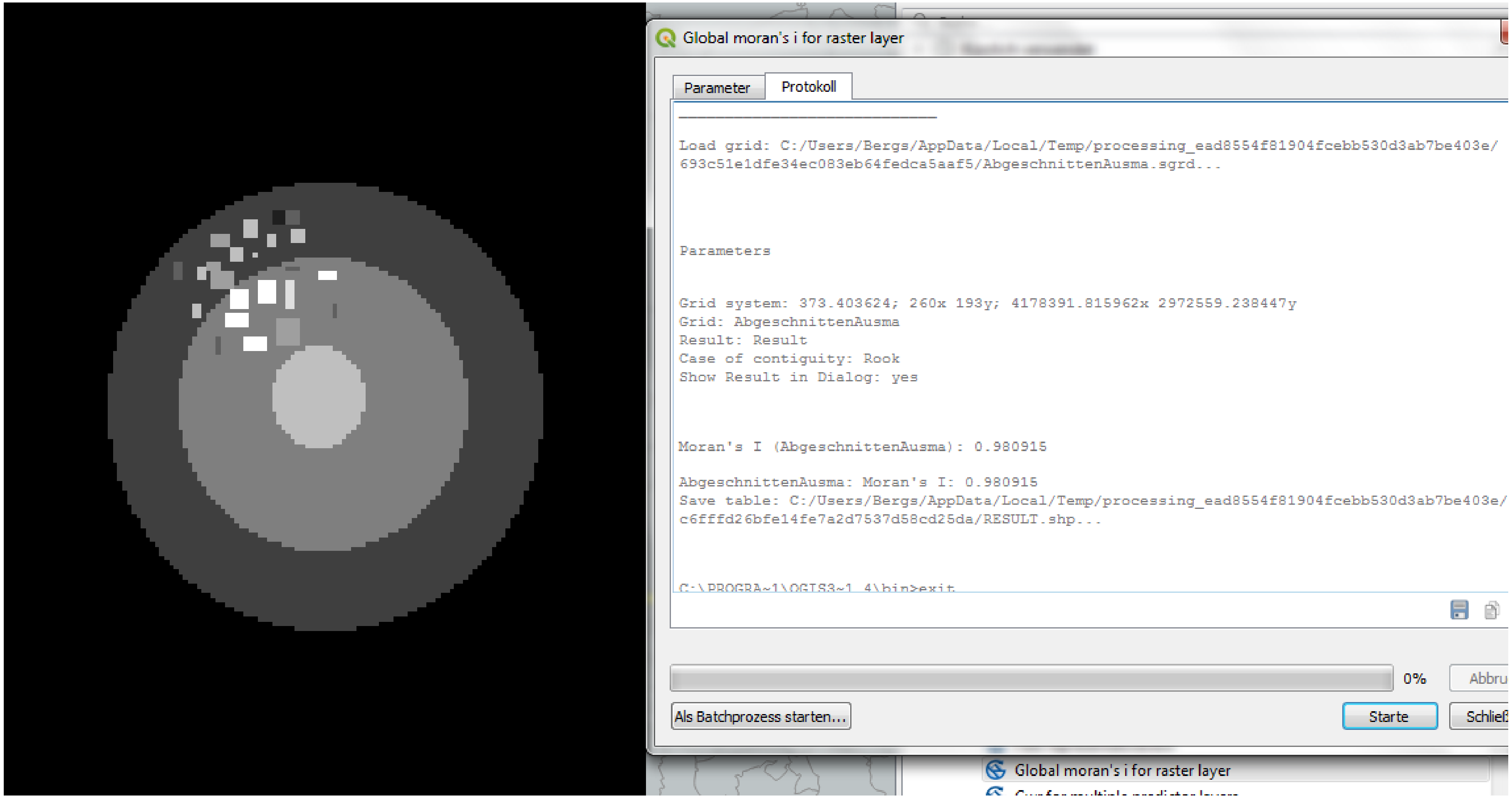
- “Everything is related to everything else, but near things are more related than distant things” (*Tobler’s law*);
- Urban and rural space is relational to each other (at local levels much more than globally);
- Spatial autocorrelation is characterized by a correlation in a signal among nearby locations in space. If autocorrelation ≠ 0, then observations are not **independent** from one another.
- Changing spatial **dependence** (e.g. in an urban fringe area) can thus indicate a change of rural-urban functionality

Example of rural-urban functionality:
The *von Thunen* rings

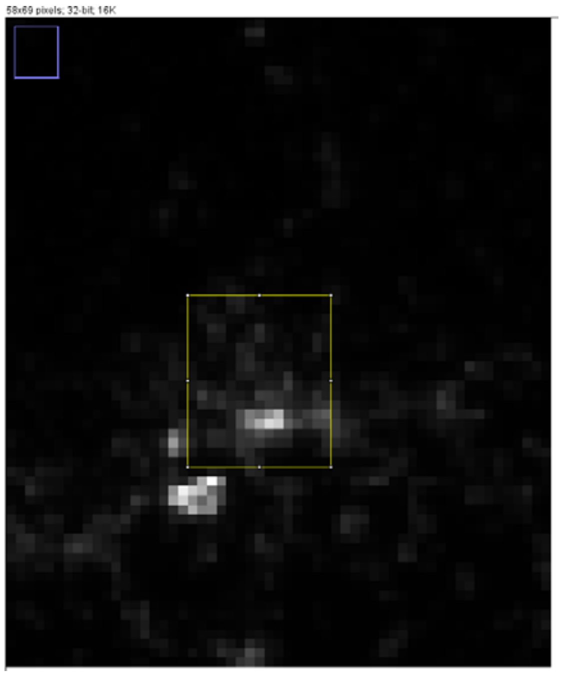


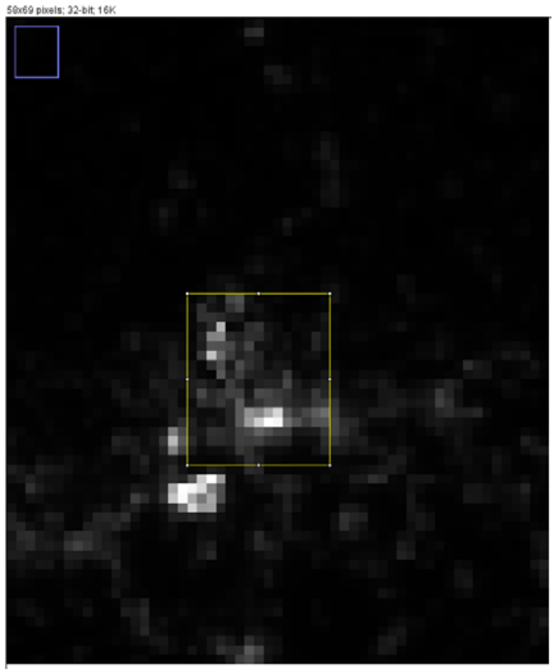



Global moran's i for raster layer
Parameter
Protokoll
Load grid: C:/Users/Bergs/AppData/Local/Temp/
3452949b09f24c788e91bcb583259f4a/Reprojiizier
Parameters
Grid system: 212.653077; 111x 212y; 4231707.9
Grid: Reprojiiziert
Result: Result
Case of contiguity: Rook
Show Result in Dialog: yes
Moran's I (Reprojiiziert): 0.990711
Reprojiiziert: Moran's I: 0.990711


Global moran's i for raster layer
Parameter
Protokoll
Load grid: C:/Users/Bergs/AppData/Local/Temp/processing_ead8554f81904fcebb530d3ab7be403e/
693c51e1dfe34ec083eb64fedca5aaf5/AbgeschnittenAusma.sgrd...
Parameters
Grid system: 373.403624; 260x 193y; 4178391.815962x 2972559.238447y
Grid: AbgeschnittenAusma
Result: Result
Case of contiguity: Rook
Show Result in Dialog: yes
Moran's I (AbgeschnittenAusma): 0.980915
AbgeschnittenAusma: Moran's I: 0.980915
Save table: C:/Users/Bergs/AppData/Local/Temp/processing_ead8554f81904fcebb530d3ab7be403e/
c6fffd26bfe14fe7a2d7537d58cd25da/RESULT.shp...
0%
Als Batchprozess starten...
Starte
Global moran's i for raster layer

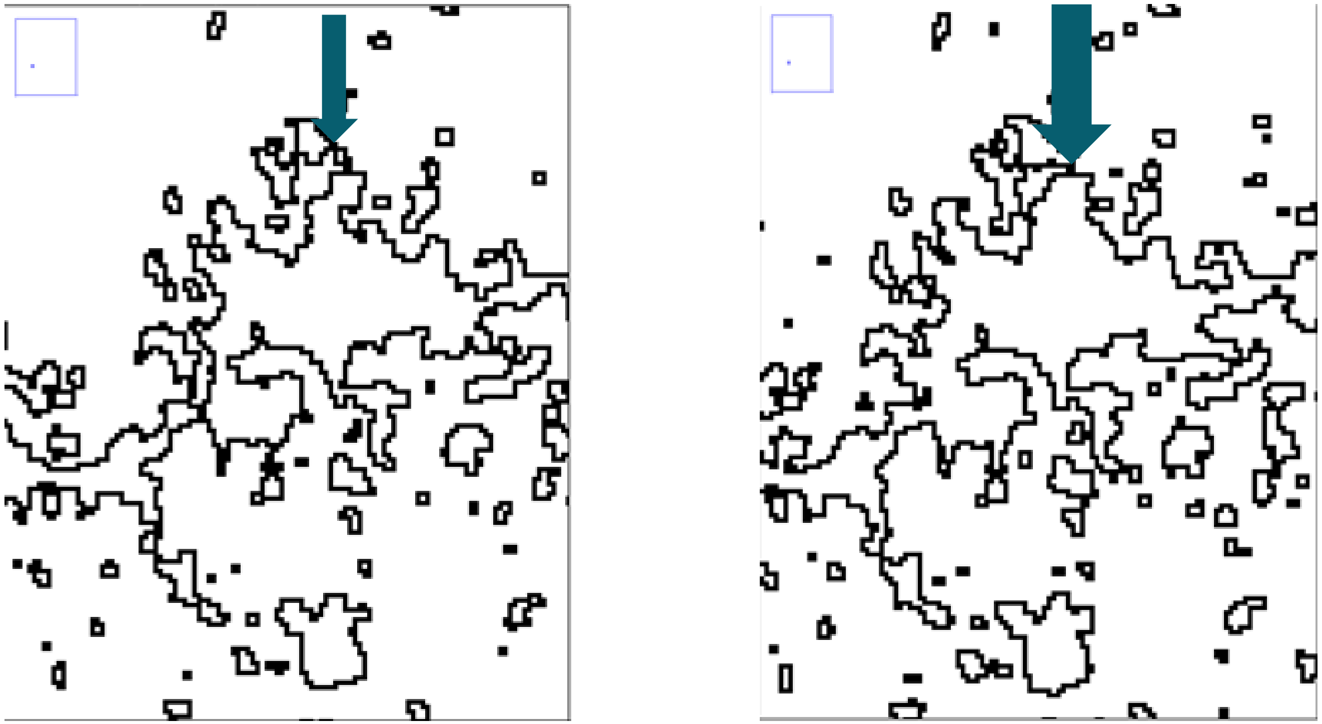
Spatial autocorrelation compared





Year	Moran I
Moran's I (Frankfurt2017KM)	0.792200
Moran's I (Frankfurt2027KM)	0.690827

Urbanization and dissolution of rural-urban functionality



	1996	2011
K=2		

Policy- & planning-relevant findings

- Unequal increase of light emission largely affects the size and relationship of functional areas;
- Functionality can become dissolved and natural cities may grow over-proportionally;
- Risk of urban sprawl/merging cities can be detected by image simulation

III. Lack of socio-economic and environmental information

- Figures at NUTS 3 level represent just mean values;

- Since space is never homogeneous, there is an unobservable variance around the mean values (i.e. at neighbourhood level there might be substantial deviations from the mean);

- Policy & planning coordination at neighbourhood level is thus hampered by an information deficit

Global correlation of light emission with socio-economic variables

log (GDP) +

log (Electricity cons.) +

log (Population) +

log (CO_2) +

Poverty -

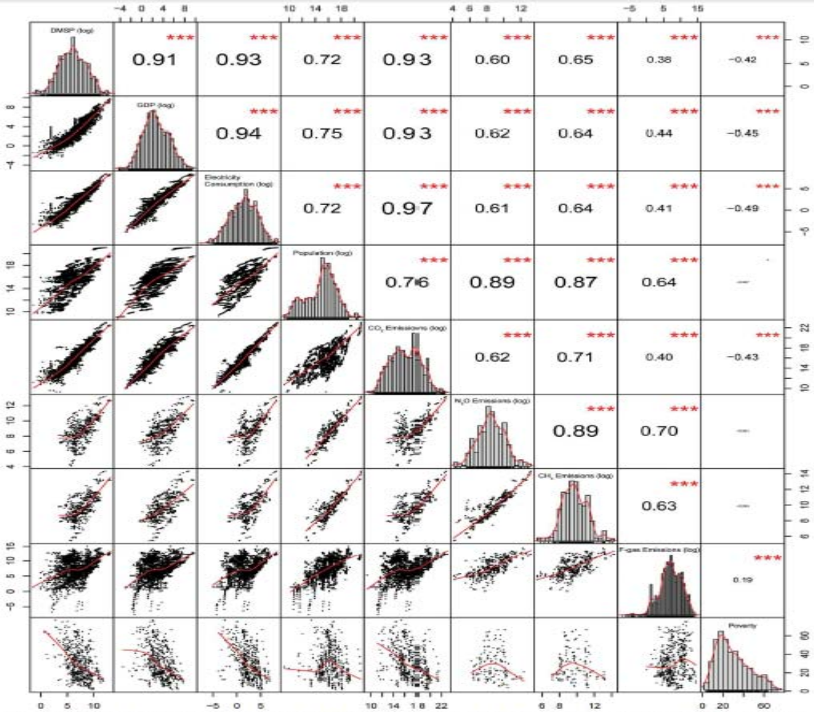


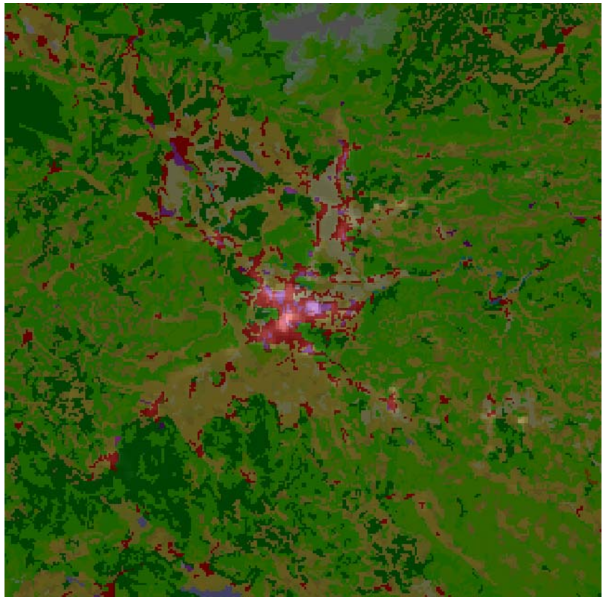
Fig 1. Correlation between area lit and a collection of socio-economic indicators. The matrix above shows links between logarithms of Area Lit, GDP, Electric Power Consumption, Population, CO_2 Emissions, N_2O Emissions, CH_4 Emissions, F-gas Emissions, and non-log Poverty Headcount Ratio, respectively. Numbers on the top-right side of the matrix denote Pearson's *r* values (font size ∝ value), and stars represent significance level (***, $p < 0.05$).

https://doi.org/10.1371/journal.pone.0174610.g001

… but: global correlations are not necessarily the same as local ones!!

The challenge is to find local spatial levels (e.g. urban or rural) where correlations are systematically stronger.

Visual association between night satellite imagery and land use (CORINE)



LUR (2012)

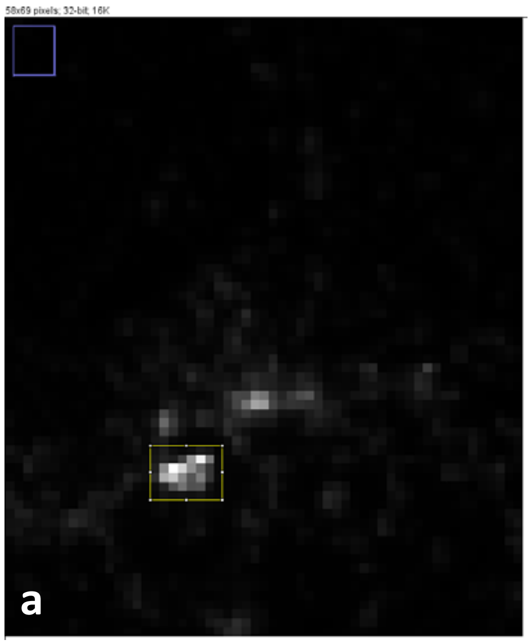
Findings by visual inspection (LUR)

- Red CORINE areas represent core city land use, violet areas represent commercial land use
- On semi-transparent CORINE + VIIRS layers, higher luminosity is visible on red and violet areas
- By visual inspection, high luminosity seems thus well associated with economic activity („people at work“)

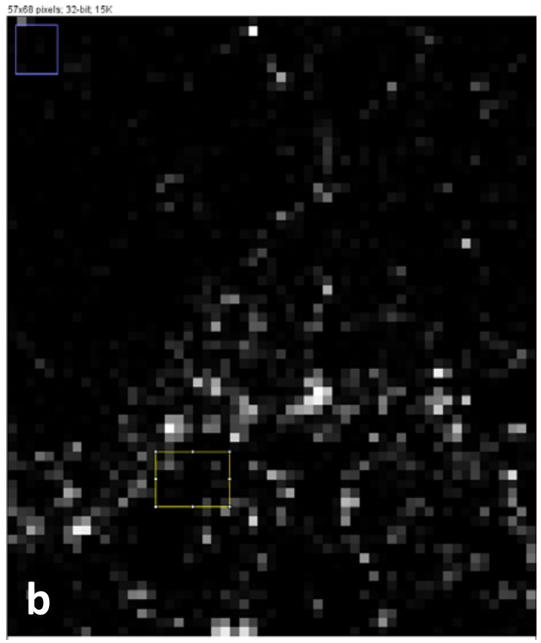
Correlation with IÖR Monitor variables at one square kilometer grid level (RVFRM)

Variable / Year	Image correlation: Pearson r (2011/2012)	Image correlation: Pearson r (2016/2017)
Areal share of commercial estate	0.36***	0.40***
Motor traffic density	0.39***	0.42***
Areal share of sealed ground	0.60***	n.a.
Housing density	0.28**	n.a.

The problem of variable definition: The example of land use definition of airports



r = 0.36***



RVFRM: Comparison of light emission **(a)** with share of commercial estate **(b)** 2011/2012

Correlation with an IÖR Monitor composite variable* at grid level (RVFRM)

Area	Size (km^2)	Image correlation 2011/2012 (Pearson r)
Entire area of the Regionalverband (gross size based on edge coordinates)	4,002	0.56***
Larger city area Frankfurt	494	0.51***
Selected area in the north-west of the RVFRM	735	0.77***

*Multiplicative composite variable consisting of shares of housing, commercial estate and transport infrastructure

Spatial econometric procedure (larger city area)

Model	ML-SAR	ML-SEM
Composite (X)	0.34	0.54
	(0.000)	(0.000)
Constant	8.63	32.55
	(0.000)	(0.000)
ρ	0.65	
	(0.000)	
λ		0.67
		(0.000)
Log likelihood	-1262.28	-1264.40
Wald test of ρ=0 / λ=0	156.266	154.101
	(0.000)	(0.000)

Major questions revisited

Can VIIRS images show the rural and the urban (and the continuum in- between)?

Statistically they show the functional urban and the non-urban (by k-means cluster segmentation + Zipf's law)

Can these images identify the peri-urban range?

Theoretically yes (after sub-segmenting the non-urban space), but without a test of evidence.

Major questions revisited

Can these images contribute to better urban-rural synergies?

The images allow insight into the dynamics of spatial heterogeneity and dependence. It is possible to detect risks of urban sprawl, disturbance of spatial functionality and environmental degradation.

Do these images show rural-urban synergies?

Indirectly, these images may offer important information on synergetic functional urban and rural development (e.g. active avoidance of sprawl).

Feedback – questions

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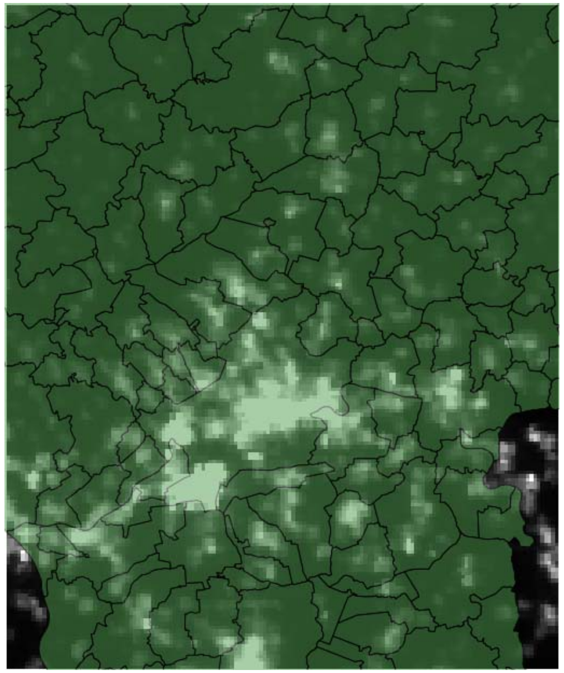
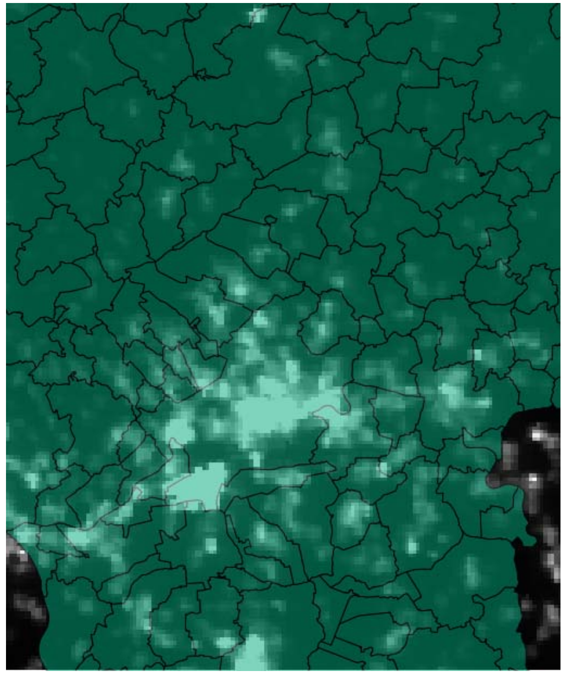
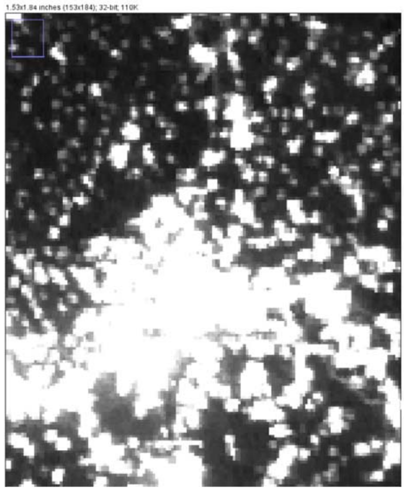
ANNEX: AUXILLIARY SLIDES

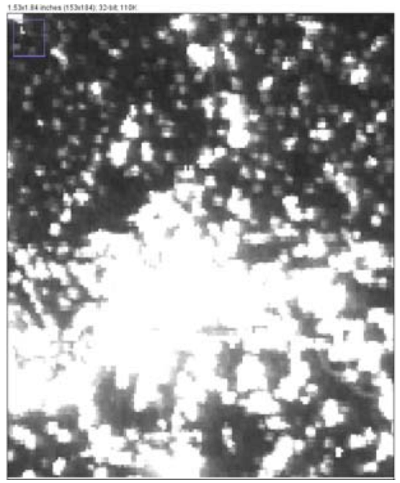


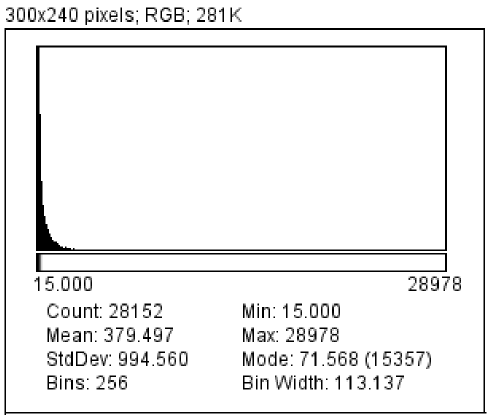


Radiance 2012 and 2017 (municipalities) ←

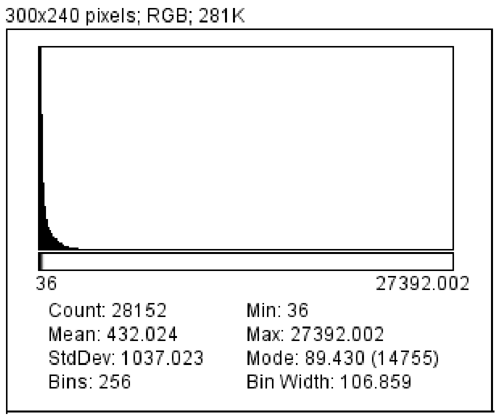


VIIRS images of the Regionalverband Frankfurt-Rhein-Main 2012 and 2017





Distribution and moments



Numerically transformed image: Frankfurt/Rhein-Main 2017 (left upper edge: North-West)

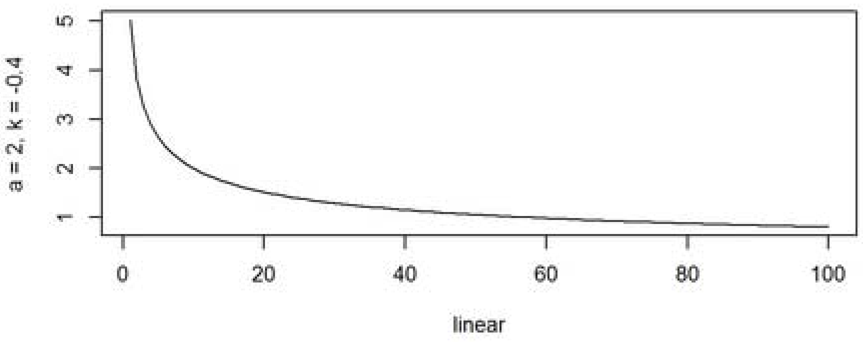
A1

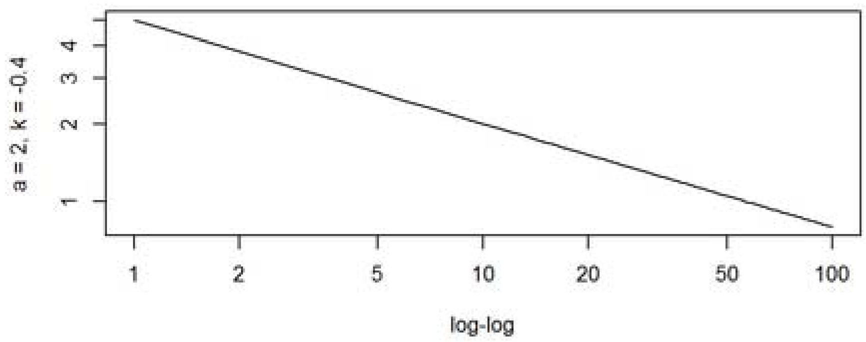
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1															
2															
3	Summe von mean2017_m	Spaltenbeschriftungen													
4	Zeilenbeschriftungen	4198000	4199000	4200000	4201000	4202000	4203000	4204000	4205000	4206000	4207000	4208000	4209000	4210000	421
5	(Leer)														
6	3042000	3.099999905	4.460000038	2.946666718	0.745000005	0.62166667	0.601666659	0.838333338	0.582499981	0.544999997	0.533333331	0.517499983	0.474999994	0.508333325	0.4874
7	3041000	1.030000001	1.383333315	2.356666644	0.965000004	0.630000005	0.580000013	0.596666664	0.719999999	0.819999993	0.676666667	0.587500006	0.48999999	0.563333342	0.5500
8	3040000	0.573333343	0.626666658	1.043333352	0.75666666	0.573333326	0.652222213	0.682222234	0.62166666	0.968888892	0.623333335	0.625	0.492222223	0.502222223	0.6383
9	3039000	0.523333331	0.572222226	1.015555561	0.696666673	0.653333339	0.650000003	0.702222215	0.558333327	0.775555571	0.671111094	0.468333329	0.500000003	0.692222228	1.0033
10	3038000	0.479999989	0.49666666	0.529999981	0.439999998	0.543333332	0.573333333	0.706666658	0.609999999	0.88499999	0.694999993	0.457499996	0.488333335	0.506666655	0.6024
11	3037000	0.48999999	0.861111104	0.661111103	0.568333338	0.698888881	0.514444437	0.804444452	1.900000016	1.149999996	0.567777773	0.463333334	0.477777779	0.456666658	0.4699
12	3036000	0.476666669	0.457777775	0.532222225	0.583333333	0.634444435	0.50888888	0.750000007	2.196666698	2.245555593	0.727777772	0.603333324	0.662222217	0.524444431	
13	3035000	0.583333313	0.667777783	0.702222228	0.50833333	0.489999996	0.474444439	0.543333335	0.498333335	1.42555554	0.971111086	0.594999989	0.644444452	0.546666665	0.4916
14	3034000	0.524999976	0.610000014	0.818333338	0.542500004	0.49333333	0.513333316	0.761666665	0.5625	0.885	0.655000001	0.527499989	0.513333331	0.564999998	0.5374
15	3033000	0.50666667	0.508888887	0.535555555	0.524999991	0.832222223	0.623333332	0.725555552	0.694999983	0.592222227	0.49888889	0.50333334	0.511111104	0.554444439	0.5833
16	3032000	0.623333335	0.579999997	0.546666662	0.630000005	0.928888884	0.676666657	0.533333321	0.643333326	0.567777779	0.531111101	0.703333328	1.028888881	1.145555523	2.7150
17	3031000	0.555000007	0.541666667	0.62500001	1.477500021	0.638333336	0.516666671	0.48666666	0.542500019	0.806666672	0.709999988	0.727500007	1.156666656	1.471666654	6.0749
18	3030000	0.700000008	0.516666664	0.577777776	0.921666672	0.531111108	0.476666666	0.511111104	0.585000008	0.633333332	0.745555553	0.550000002	0.553333329	0.91777777	2.2049
19	3029000	0.549999992	0.512222221	0.732222219	1.068333308	0.553333322	0.476666662	0.547777779	1.021666686	0.694444438	0.677777774	0.610000004	0.938888888	0.664444447	0.8500
20	3028000	0.50999999	0.498333325	0.63166667	0.982499987	0.590000004	0.486666674	0.514999996	0.537499994	0.560000002	1.060000002	0.637499988	0.896666686	0.588333329	0.5349
21	3027000	0.526666661	0.527777778	0.497777777	0.473333329	0.526666658	0.574444443	0.534444431	0.773333331	0.568888889	0.597777777	0.594999999	0.691111108	0.521111104	0.5116
22	3026000	0.653333326	0.576666666	0.503333333	0.528333326	0.620000005	1.569999993	0.732222226	1.521666666	1.103333334	0.574444446	0.569999993	0.779999991	0.563333333	0.5850
23	3025000	0.645000011	0.573333313	0.48833333	0.469999999	0.476666659	0.613333344	0.591666659	0.919999987	0.838333329	0.559999992	0.597500011	0.748333335	0.533333331	0.5749
24	3024000	0.633333325	0.681111104	0.564444446	0.581666668	0.5	0.521111108	0.548888882	0.586666673	0.632222215	0.851111107	1.033333361	0.646666653	0.615555551	1.0383
25	3023000	0.770000021	0.982222226	0.794444448	0.758333325	0.607777788	0.542222222	0.574444433	0.553333342	0.621111115	0.855555554	1.350000004	0.772222221	0.632222215	0.9899
26	3022000	1.444999993	0.906666666	0.626666665	0.787499994	0.640000006	0.615	0.623333335	0.692499995	1.356666664	0.873333345	0.61999999	0.636666656	0.74333334	1.2249
27	3021000	2.75666674	1.226666662	0.716666659	0.610000004	0.566666669	0.582222223	0.576666673	0.671666672	1.092222227	0.828888893	0.724999994	0.889999999	0.787777788	2.2183
28	3020000	3.306666692	1.438888874	0.746666657	0.643333326	0.723333332	0.741111113	0.576666666	0.521666646	1.175555554	0.84111111	0.563333323	0.601111121	0.993333313	1.3616
29	3019000	1.120000005	0.896666686	0.693333348	0.594999999	1.059999992	1.545000017	0.656666676	0.719999999	0.623333335	0.62166666	0.609999999	1.005000015	1.423333307	1.1850

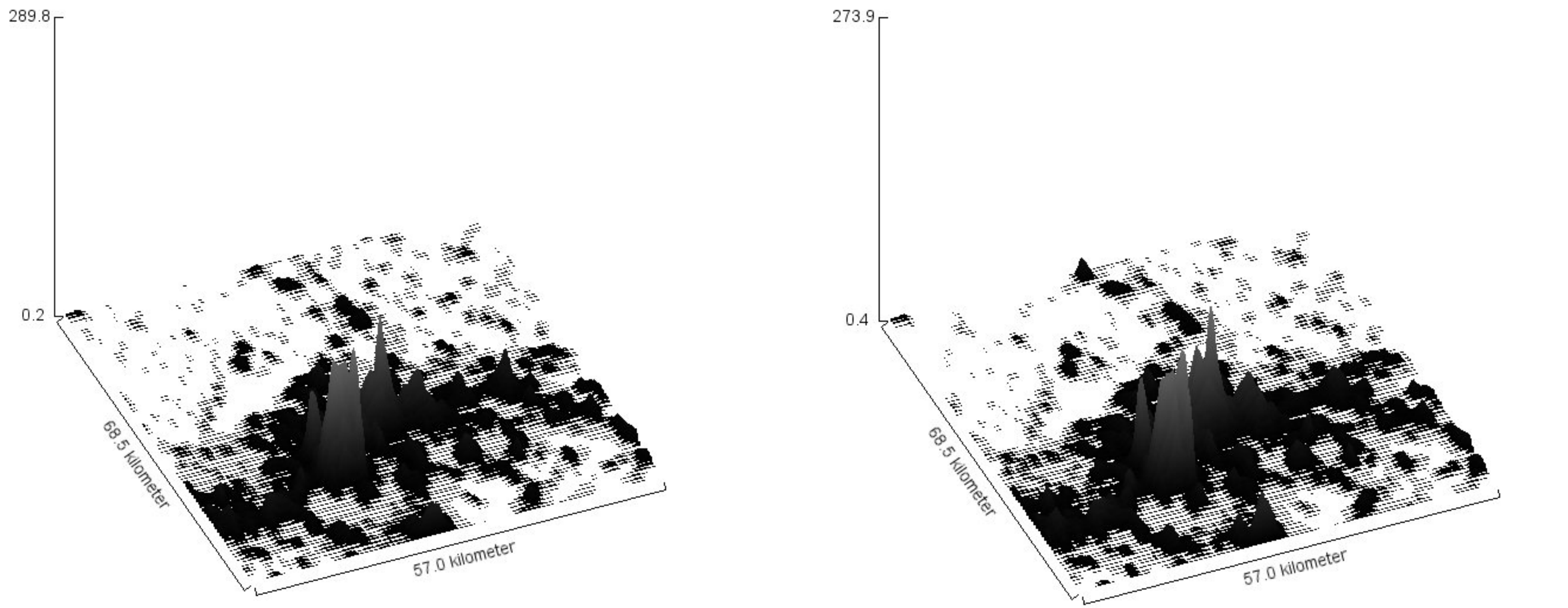
Pareto distribution: Many small items, few big ones

$Y = Constant \cdot X^{-\zeta}$

$Log\ (Y) = log(Constant) - \zeta \cdot log(X)$



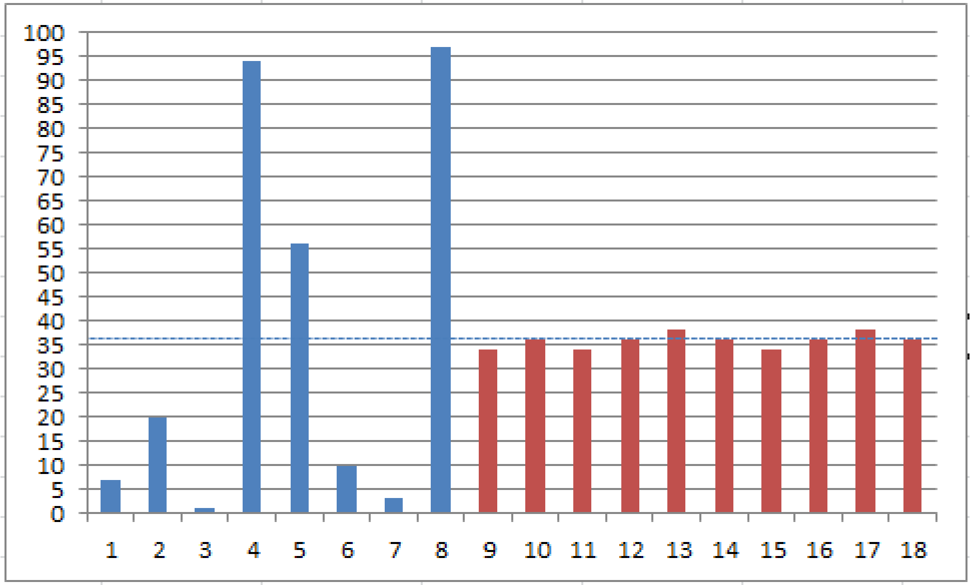




Surface plot Radiance 2012 and 2017 ($nWcm^{-2}\ sr^{-1}$)

←

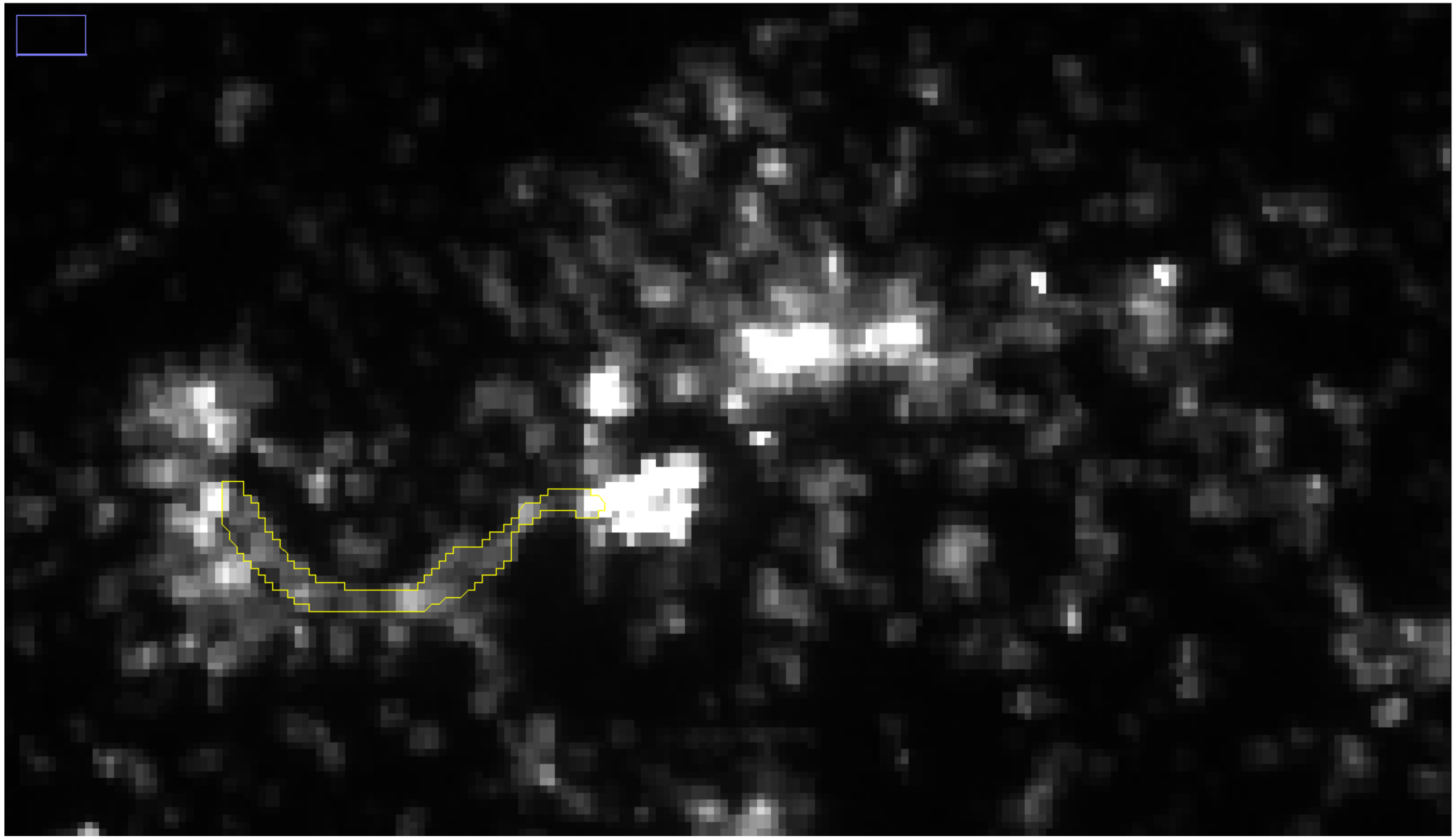
Mean & spread

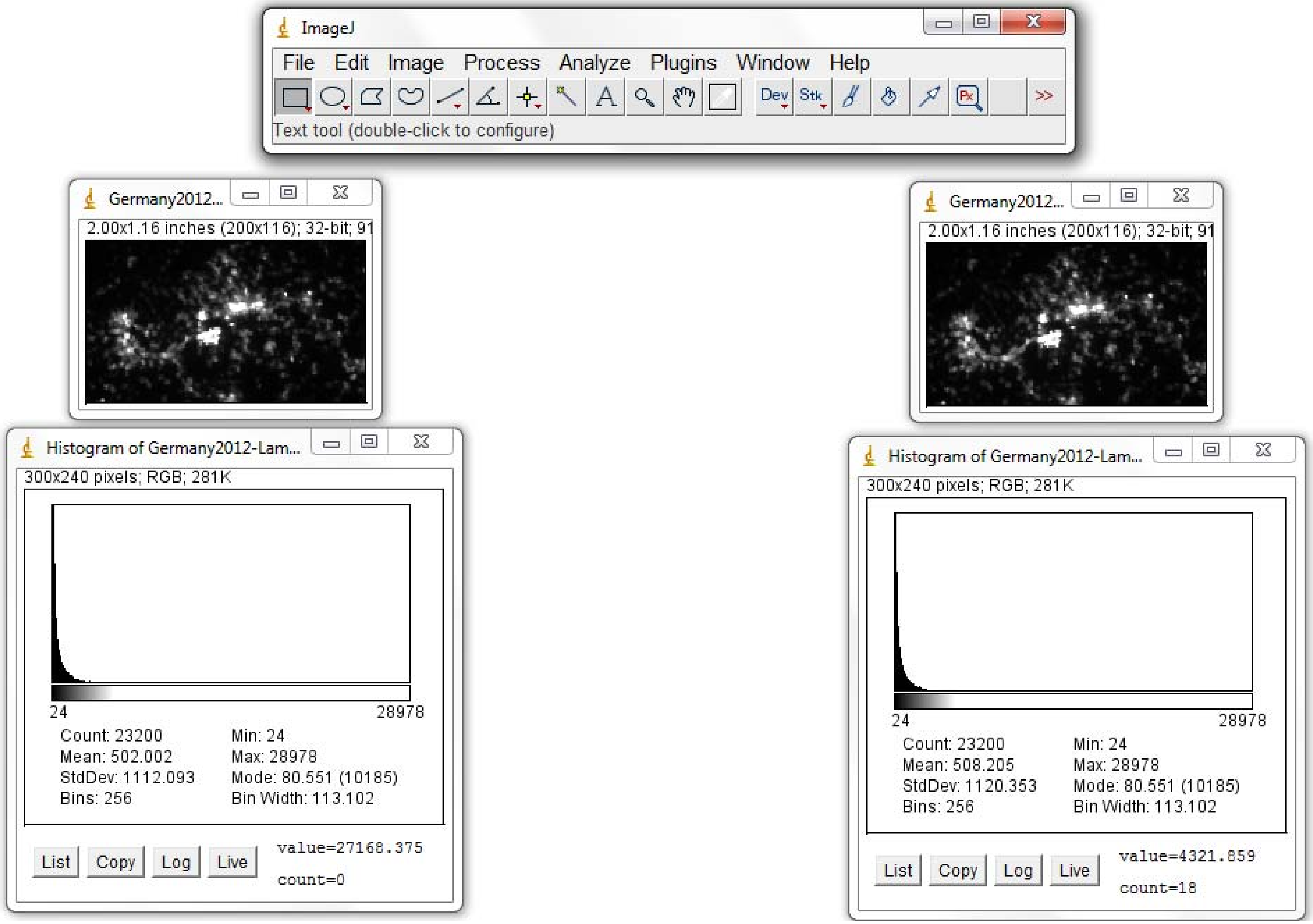


100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

←

Image manipulation

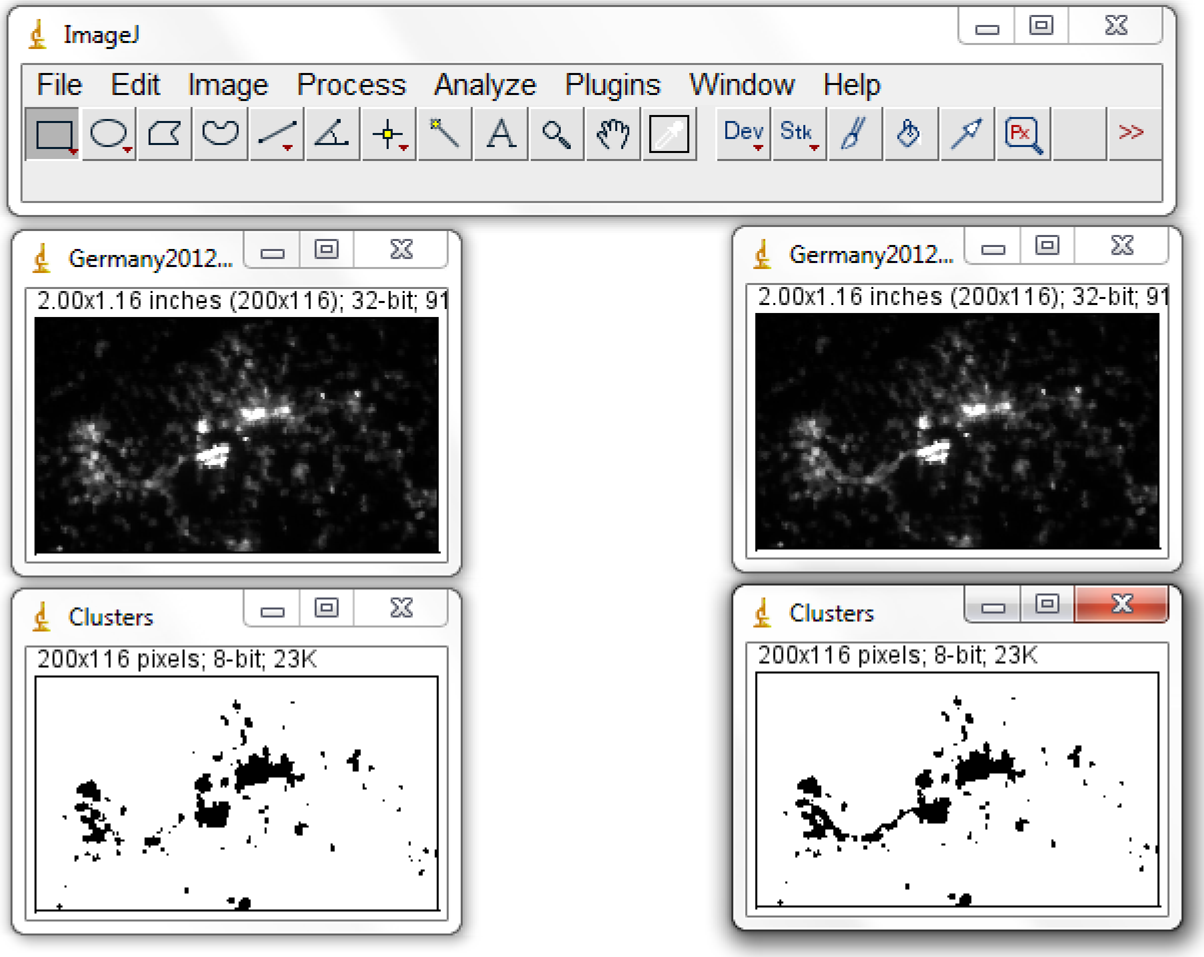



ImageJ
File Edit Image Process Analyze Plugins Window Help
Text tool (double-click to configure)
Germany2012...
2.00x1.16 inches (200x116); 32-bit; 91
Histogram of Germany2012-Lam...
300x240 pixels; RGB; 281K
24
28978
Count: 23200
Mean: 502.002
StdDev: 1112.093
Bins: 256
Min: 24
Max: 28978
Mode: 80.551 (10185)
Bin Width: 113.102
List Copy Log Live
value=27168.375
count=0
Germany2012...
2.00x1.16 inches (200x116); 32-bit; 91
Histogram of Germany2012-Lam...
300x240 pixels; RGB; 281K
24
28978
Count: 23200
Mean: 508.205
StdDev: 1120.353
Bins: 256
Min: 24
Max: 28978
Mode: 80.551 (10185)
Bin Width: 113.102
List Copy Log Live
value=4321.859
count=18

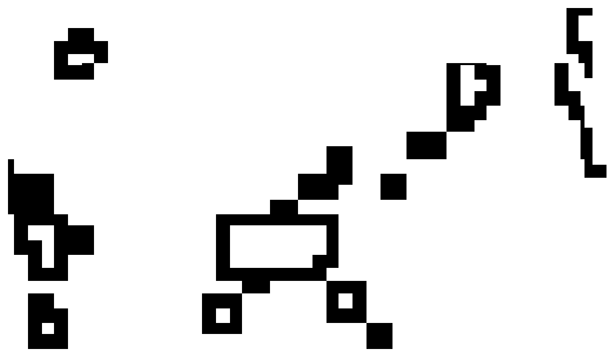
0.5% cutoff: original (left) & manipulated (right)

	A	B	C	D	E	F
40	4321.86	18		4321.86	18	
41	4434.96	9		4434.96	10	
42	4548.06	10		4548.06	11	
43	4661.16	9		4661.16	11	
44	4774.27	7		4774.27	8	
45	4887.37	8		4887.37	8	
46	5000.47	4		5000.47	4	
47	5113.57	6		5113.57	6	
48	5226.67	4		5226.67	4	
49	5339.77	8		5339.77	8	
50	5452.88	6		5452.88	4	
51	5565.98	3		5565.98	3	
52	5679.08	3		5679.08	3	
53	5792.18	7		5792.18	7	
54	5905.28	1		5905.28	1	
55	***6018.38***	***3***	0.5%cutoff	6018.38	3	
56	6131.48	7		6131.48	7	
57	6244.59	1		6244.59	1	
58	6357.69	6		6357.69	8	
59	6470.79	3		6470.79	3	
60	6583.89	6		***6583.89***	***6***	0.5%cutoff
61	6696.99	5		6696.99	5	
62	6810.09	2		6810.09	2	
63	6923.2	2		6923.2	2	
64	7036.3	2		7036.3	2	
65	7149.4	1		7149.4	1	
66	7262.5	0		7262.5	0	
67	7375.6	2		7375.6	2	
68	7488.7	5		7488.7	5	

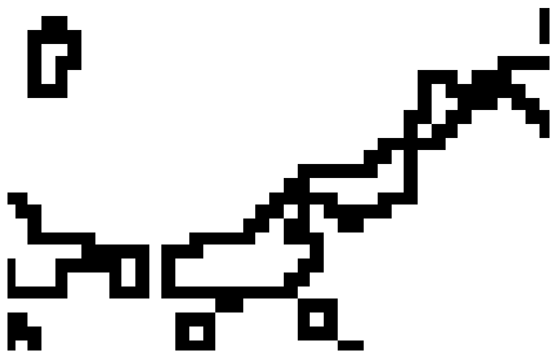
K-means segmentation: original (left) & manipulated (right)



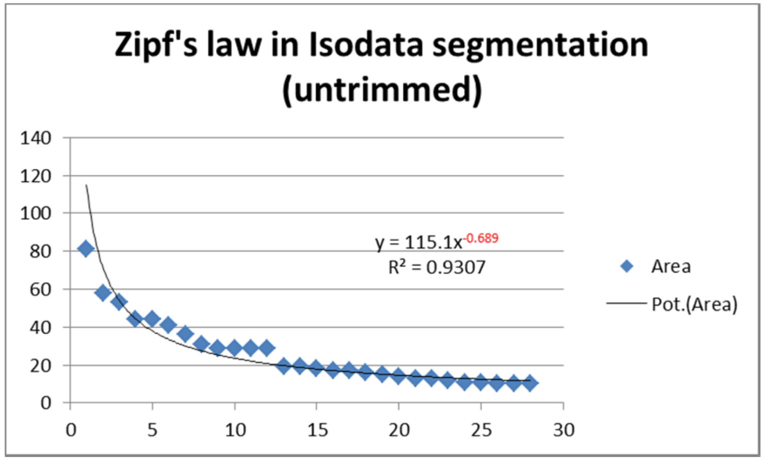
Original natural urban space

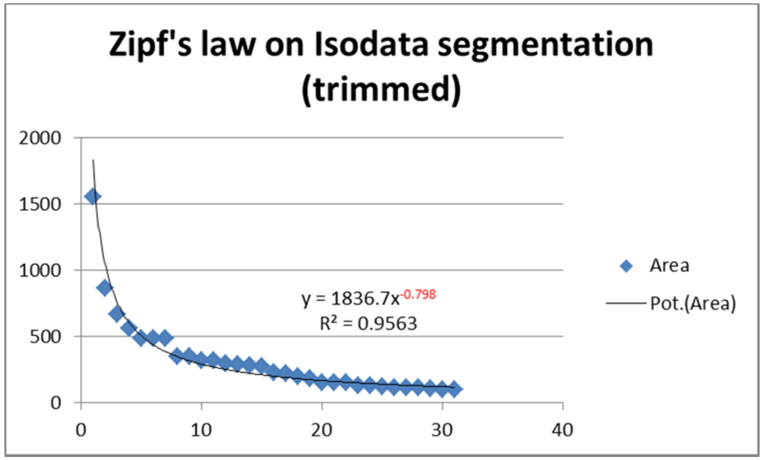


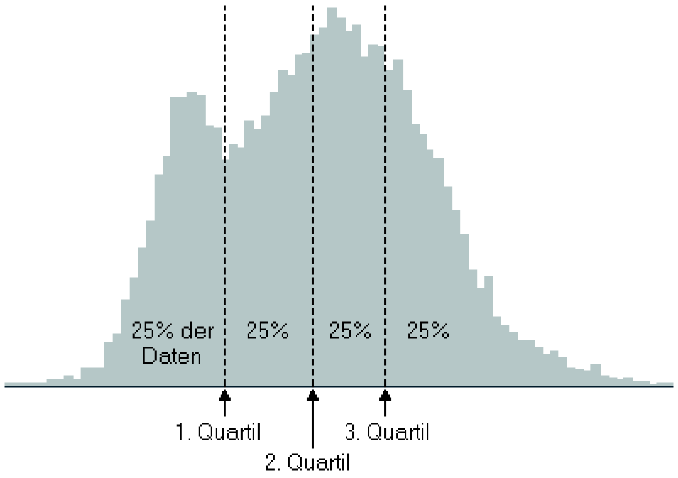
Simulated natural urban space

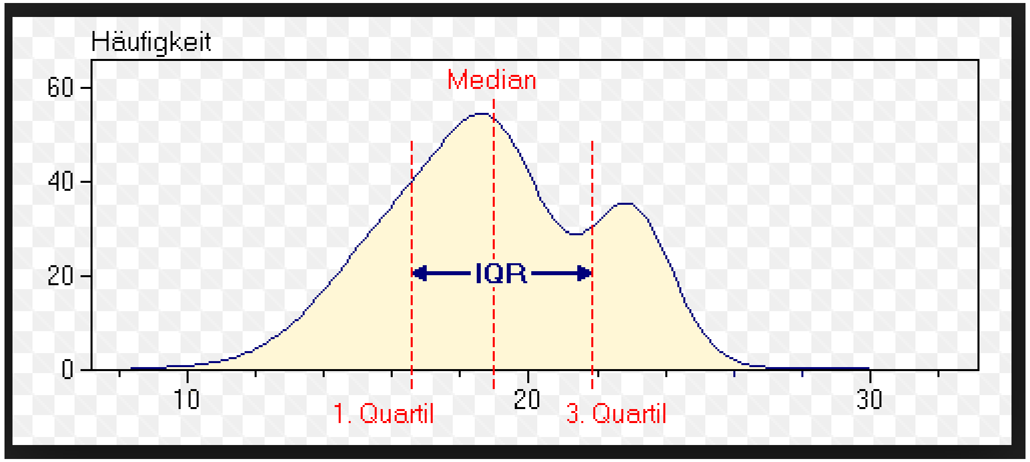


Pareto regression (Zipf‘s law) on Isodata segmentation









Vandervieren-Huber approach:

D5 f_x =((A5+1.5*(2.718281828^(4*B5))*C5))

	A	B	C	D	E	F
1	Skewed distributions: Box-plot upper tail					
2	Q3 + 1.5 $e^{4\,MC}$ IQR					
3						
4	Q3	MC	IQR	Result		
5	34.11	0.5174954	24.63	**326.887**		