

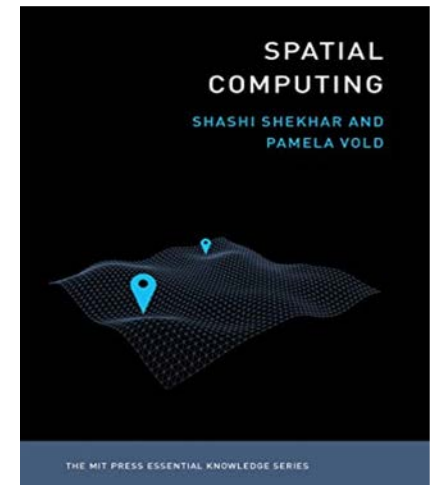
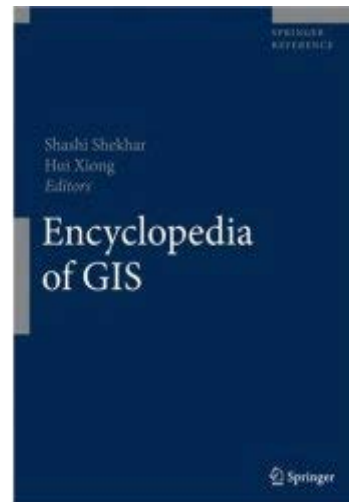
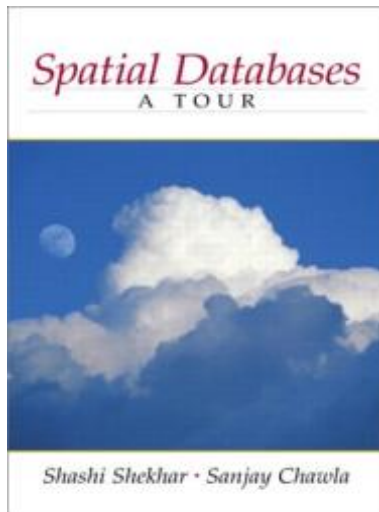
What is Special about **Spatial Data Science and GeoAI?**

Shashi Shekhar

McKnight Distinguished University Professor, University of Minnesota

www.cs.umn.edu/~shekhar, shekhar@umn.edu

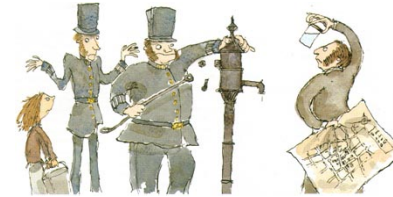
Acks: Collaborators, Sponsors (NSF, USDOD NGA, USDOE ARPA-E, USDA NIFA, NIH, ...)



A Spatial Data Science Story

1854: What causes Cholera?

Miasma theory



Collect &
Curate Data



Discover Patterns,
Generate Hypothesis

? water pump



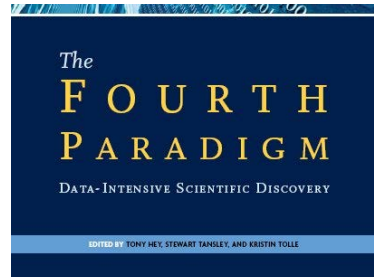
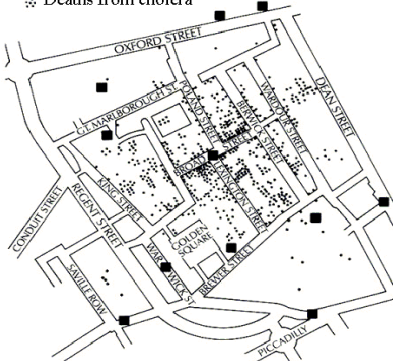
Test Hypothesis
(Experiments)

Remove pump handle



Develop
Theory

■ Pump sites
✱ Deaths from cholera



Impact: hygiene,
drinking water supply,
sewage system, ...

Q? What are Choleras of today?
Q? How may Spatial Data Sc. Help?

What has changed? Spatial Data Revolution

Spatial	Last Century	Last Decade
Data	Few satellites and sensors	Nano-satellites, Billions of GPS enabled smartphones
Data Access	Need special hardware and network	
Spatial Platforms	ESRI Arc/Info	
Spatial Data Science	Spatial Patterns, e.g., hotspots (SatScan, ESRI Geostatistics)	
Spatial Visualization	Quilt, e.g., MS Terraserver	

Spatial Computing is Ubiquitous Today!

- 2 billion GPS receivers in use, will hit 7 billion by 2022.
- Besides location, it **reference time** for critical infrastructure
 - Telecommunications industry
 - Banks
 - Airlines...
- GPS is the single point of failure for the entire modern economy.
- 50,000 incidents of deliberate (GPS) jamming last two years
 - Against Ubers, Waymo's self-driving cars, delivery drones from Amazon



Bloomberg Businessweek

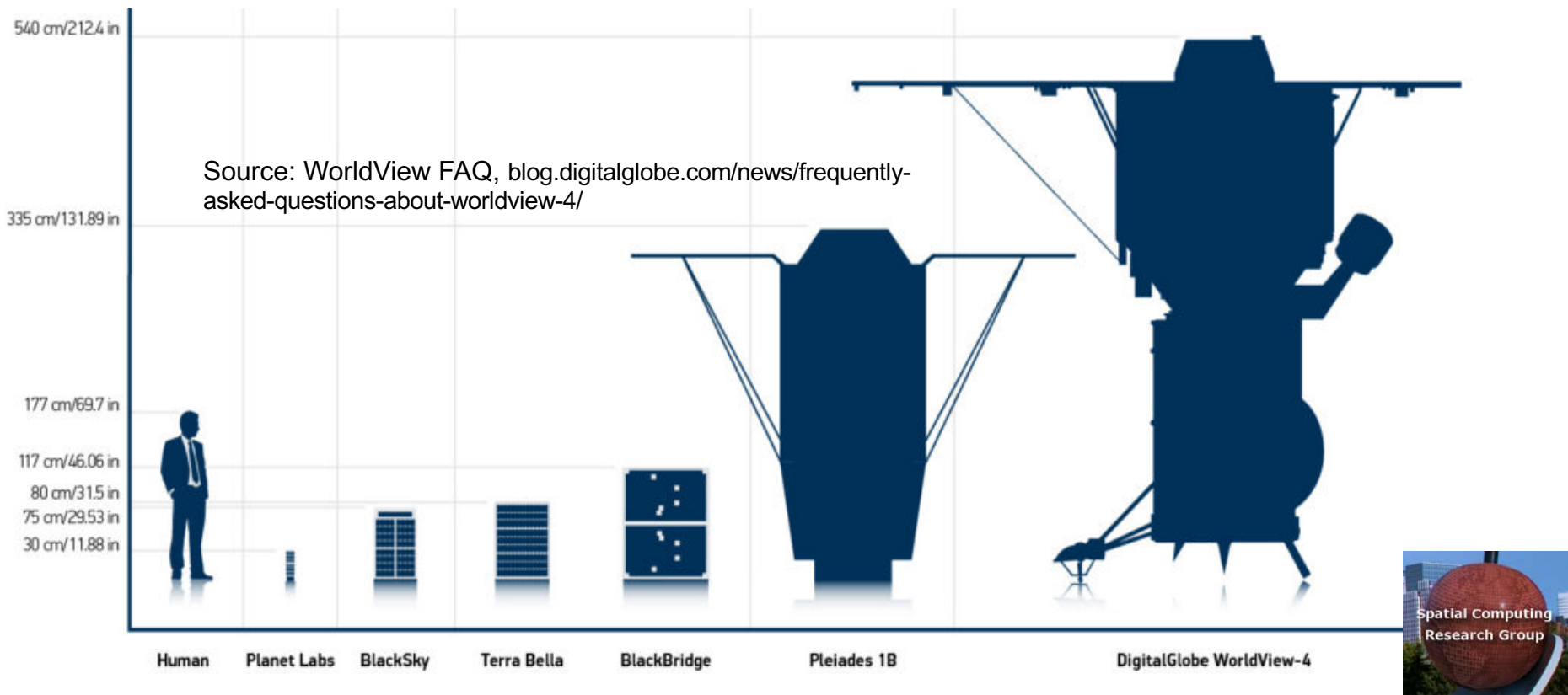
July 25, 2018, 4:00 AM CDT

The World Economy
Runs on GPS. It Needs a
Backup Plan

Source: <https://www.bloomberg.com/news/features/2018-07-25/the-world-economy-runs-on-gps-it-needs-a-backup-plan>

Large Constellations of Small Satellites

- Hi-frequency (e.g., daily or hourly) time-series of imagery of entire earth
- **Small Satellites: video (5-minutes):** <https://geospatialstream.com/sciencecasts-nasa-embraces-small-satellites/>
- **Large Constellations**
 - 2017: Planet Labs: 100 satellites: daily scan of Earth at 1m resolution in visible band



Spatial Data Revolution

1. GPS & Location traces

- 2 billion GPS receivers today (7 billion by 2022)
- Reference clock for telecom, banks, ...
- Help understand Spatio-temporal patterns of life



The World Economy
Runs on GPS. It Needs a
Backup Plan

Bloomberg Businessweek

July 25, 2018, 4:00 AM CDT

2. (Nano-)Satellite Imagery, ...

ENSURING RESOURCE AVAILABILITY

*Advanced technology, including many types of Earth information, will unlock up to **\$1.6 trillion** in economic savings for energy generation and use by 2035.*

Satellite observations can also help ensure water availability, which is particularly important to the 20% of the world now living in areas of water scarcity.

McKinsey Global Institute

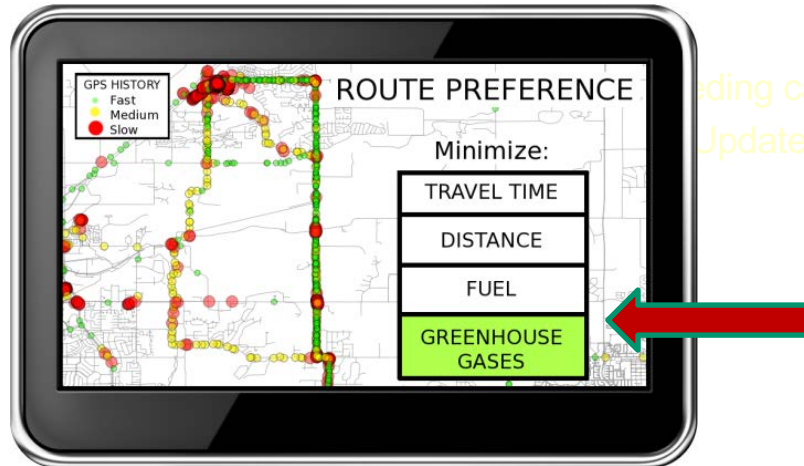
The study estimates that the use of **personal location data** could save consumers worldwide more than **\$600 billion** annually by **2020**. Computers determine users' whereabouts by tracking their mobile devices, like cellphones.

The New York Times

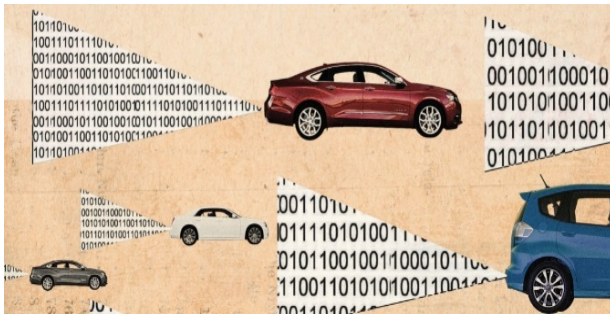
Published: May 13, 2011

Source: Y. Xie et al., [Transforming Smart Cities With Spatial Computing](#), Proc. [IEEE Intl. Conf. on Smart Cities](#), 2018.

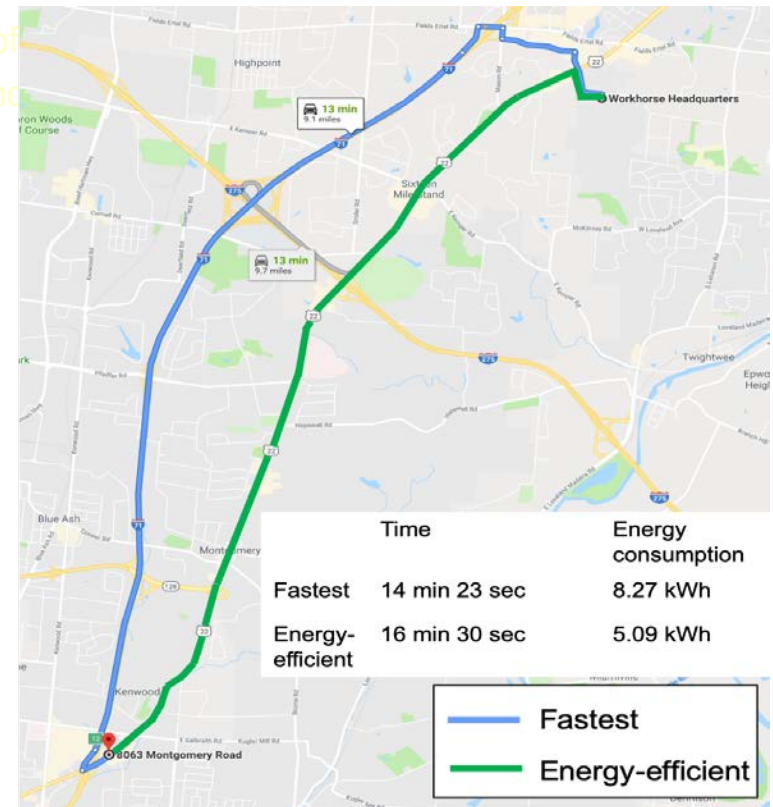
Next Generation Navigation App to Reduce Emission, Energy use



Reducing capacity of
(Update-rate) and



GPS Tracks + On Board Diagnostics Data



Details: Y. Li, P. Kotwal, P. Wang, Y. Xie, S. Shekhar, and W. Northrop, [Physics-guided Energy-efficient Path Selection Using On-board Diagnostics Data](#), ACM/IMS Trans. Data Sc. 1(3):1-28, Article 22, Oct. 2020.

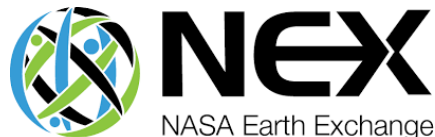
What has changed? **Spatial Data Access**

Spatial	Last Century	Last Decade
Data	Few satellites and sensors	Nano-satellites, Billions of GPS enabled smartphones
Data Access	Need special hardware and network	Cloud based repositories and analytics (e.g., DARPA GCA)
Spatial Platforms	ESRI Arc/Info	
Spatial Data Science	Spatial Patterns, e.g., hotspots (SatScan, ESRI Geostatistics)	
Spatial Visualization	Quilt, e.g., MS Terraserver	

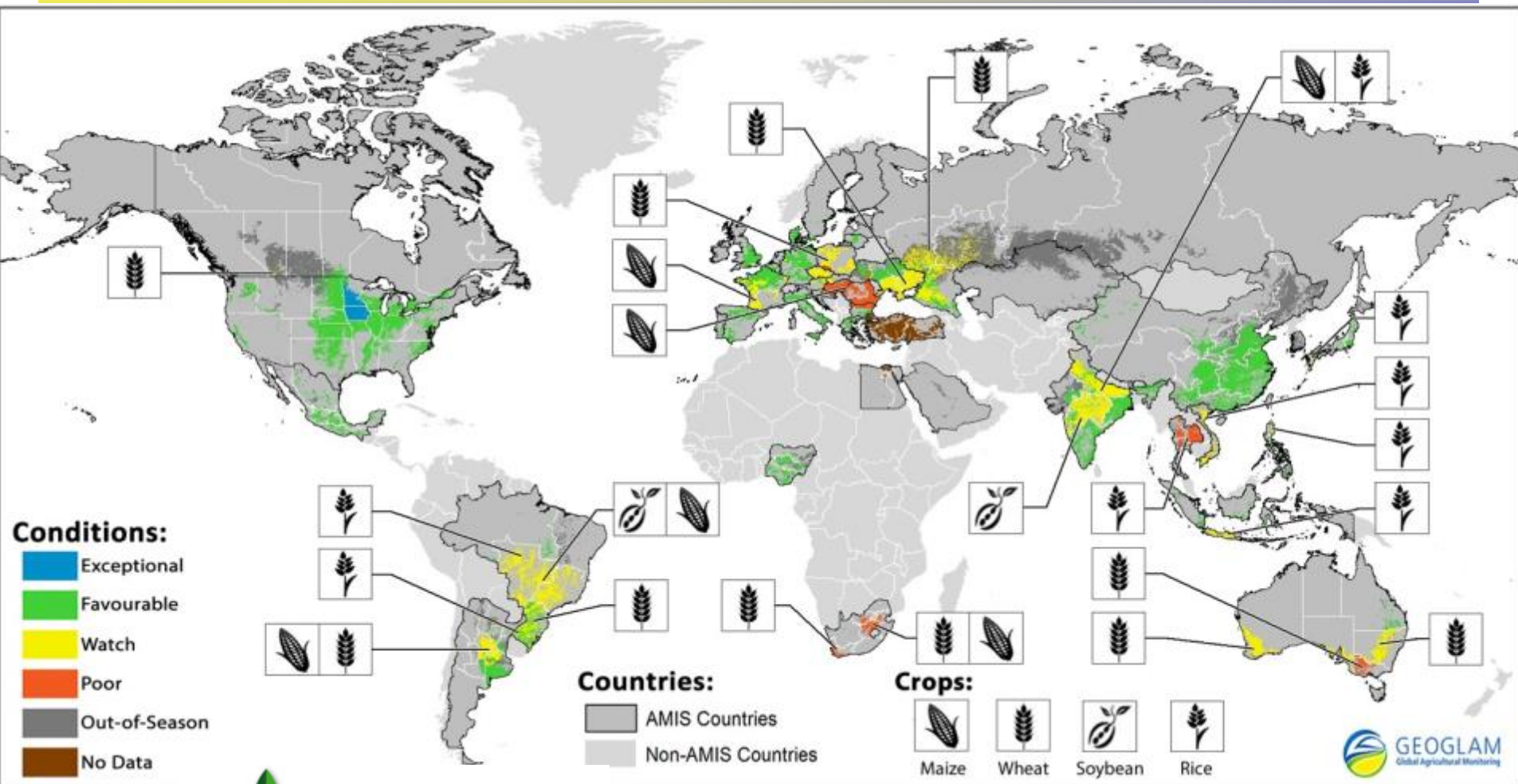
Easier Access: Cheap (or free) Cloud Repositories

- 2008: USGS gave away 35-year Landsat satellite imagery archive
 - Analog of public availability of GPS signal in late 1980s
- 2017: Cloud-based repositories of geospatial data
 - Explosion in machine learning on satellite imagery to map crops, water, buildings, roads, ...

	Google Earth Engines	NEX	AWS Earth
Elevation, Landsat, LOCA, MODIS, NAIP	x	x	x
NOAA	x		x
AVHRR, FIA, GIMMM, GlobCover, NARR, TRIMM, Sentinel-1	x	x	
IARPA, GDELT, MOGREPS, OpenStreetMap, Sentinel-2, SpaceNet (building/road labels for ML)			x
CHIRPS, GeoScience Australia, GSDMap, NASS, Oxford Map, PSDI, WHRC, WorldClim, WorldPop, WWF,	x		
BCCA, FLUXNET		x	



Global Agriculture Monitoring



Global Agriculture Monitoring

LATEST CONDITIONS PUBLISHED IN OUR REPORTS

Synthesis Conditions

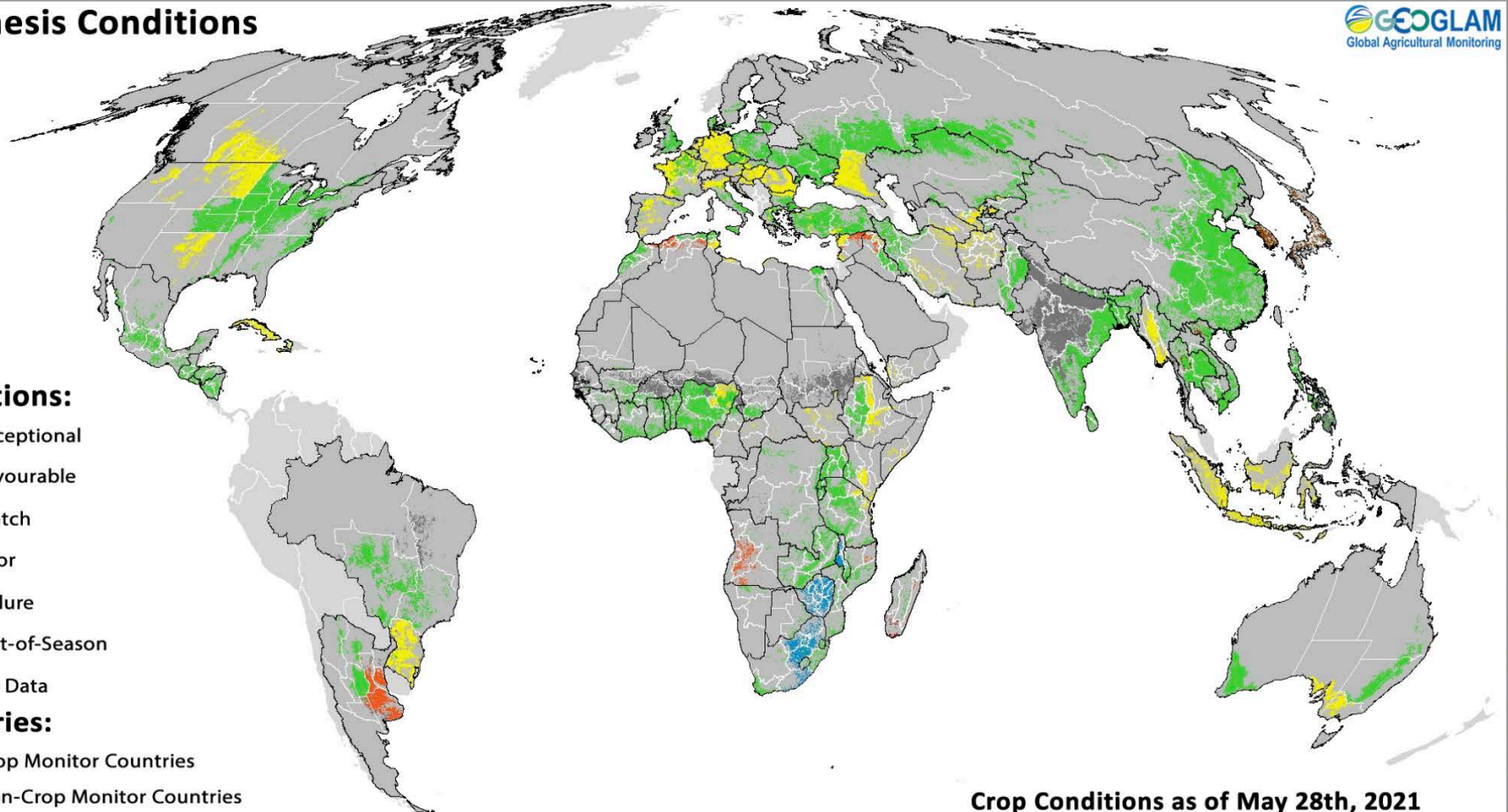
GEOGLAM
Global Agricultural Monitoring

Conditions:

- Exceptional
- Favourable
- Watch
- Poor
- Failure
- Out-of-Season
- No Data

Countries:

- Crop Monitor Countries
- Non-Crop Monitor Countries



Crop Conditions as of May 28th, 2021

AMIS & EARLY WARNING LATEST SYNTHESIS MAP



Agricultural Market
Information System



What has changed? Spatial Big Data Platforms

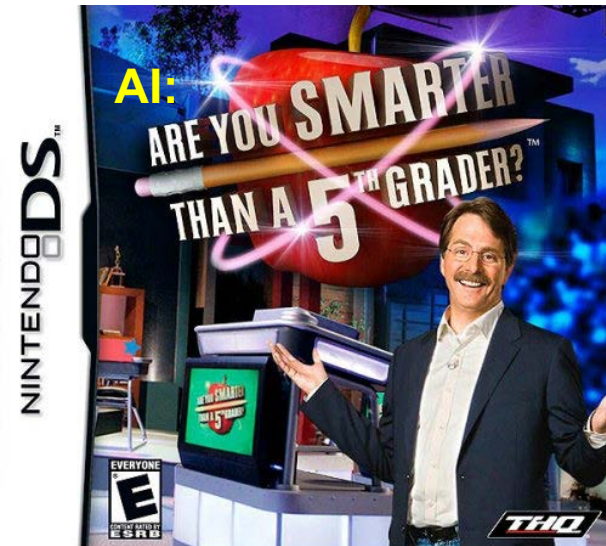
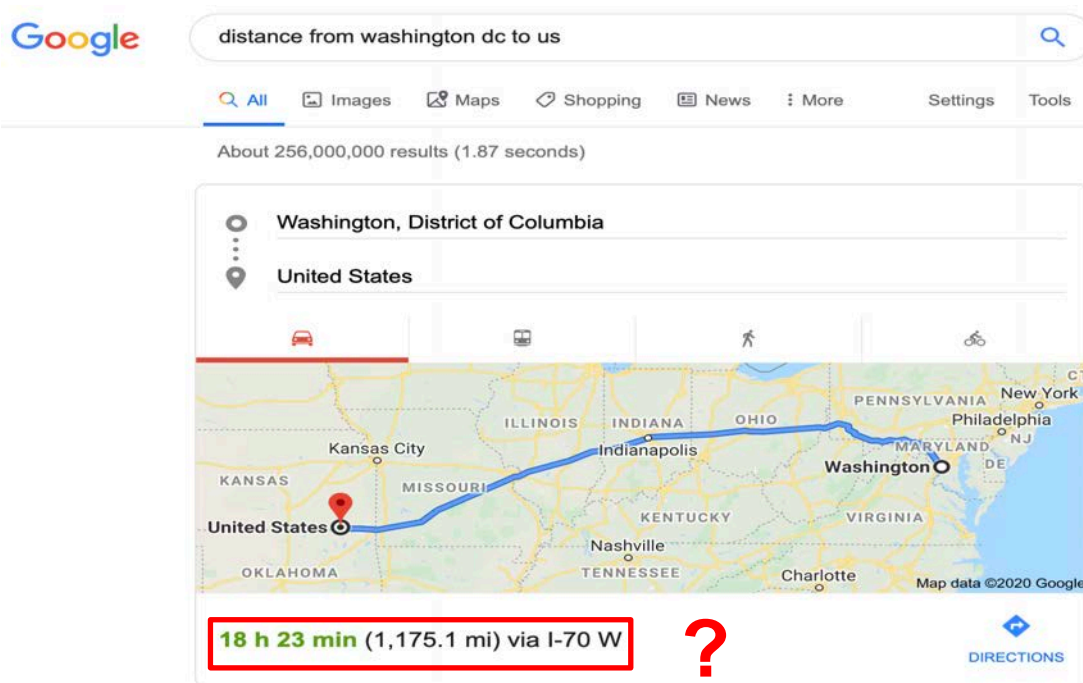
Spatial	Last Century	Last Decade
Data	Few satellites and sensors	Nano-satellites, Billions of GPS enabled smartphones
Data Access	Need special hardware and network	Cloud based repositories, e.g., Earth on AWS
Spatial Platforms	ESRI Arc/Info, SQL3/OGC, e.g., Postgis,	Geospatial Cloud Analytics (Monitor crops, fracking, illegal fishing), ESRI GIS Tools for Hadoop, ...



Spatial Data Types >> Points

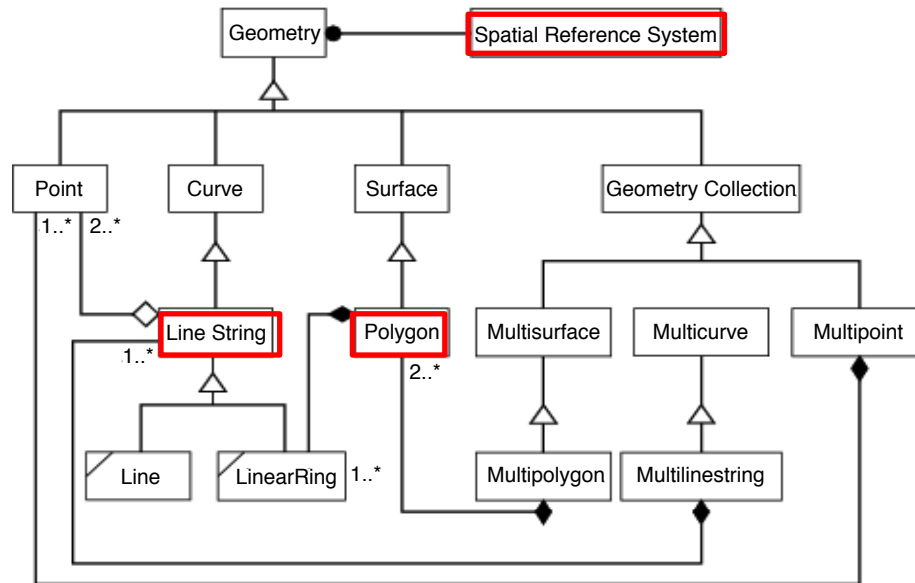
Q? What is distance between Washington D.C. and U.S.A.?

- Zero (Washington D.C. is **inside** U.S.A.)
- NSF OKN funded 2 grants on geo-knowledge networks!



Spatial Data Types: OGC Simple Features Standard

- Data types: Point, LineString, Polygon, Collections
- Relationships: Topological, Metric (e.g., distance)
- ML Challenge: implicit spatial relationships
 - Approach: pre-compute for feature extraction



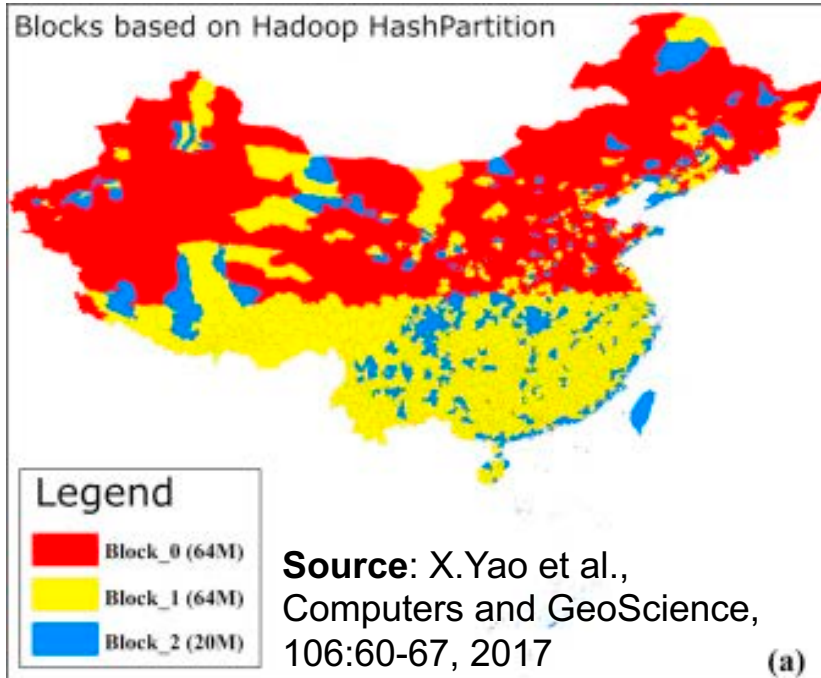
Basic Functions	SpatialReference ()
	Envelop ()
	Export ()
	IsEmpty ()
	IsSimple ()
	Boundary ()
Topological / Set Operators	Equal
	Disjoint
	Intersect
	Touch
	Cross
	Within
	Contains
	Overlap
Spatial Analysis	Distance
	Buffer
	ConvexHull
	Intersection
	Union
	Difference
	DymmDiff

Details: S. Shekhar et al., Spatial Databases: Accomplishments and Research Needs, IEEE Trans. on Knowledge and Data Eng., 11(1):45-55, Jan.-Feb. 1999.

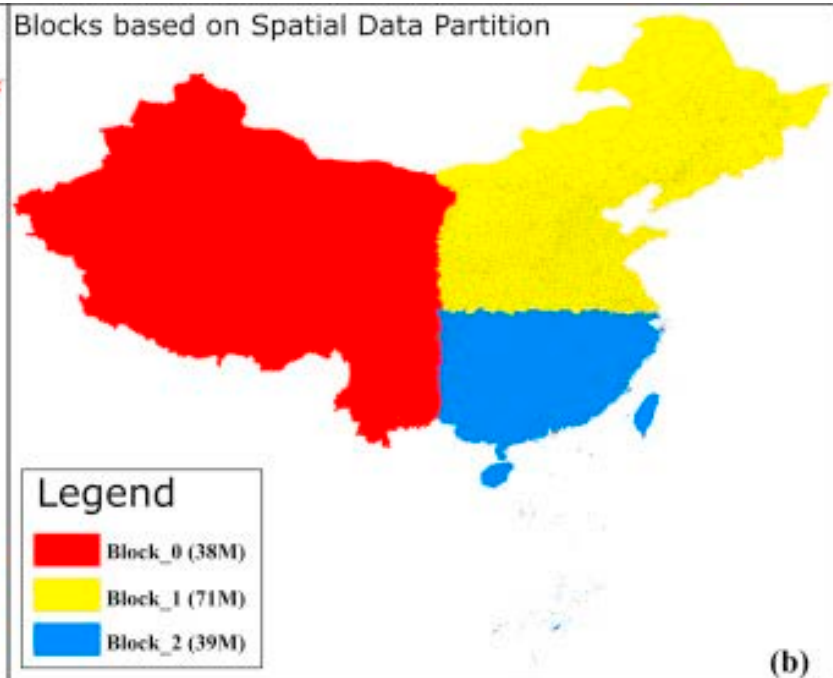
Spatial Big Data Platforms

Genre	Examples
Relational DBMS, Spatial Library	Oracle, IBM DB2, PostgreSQL, MS SQL Server OGC Simple Features, ...
Parallel DBMS	Teradata, Vertica, Greenplum, DataAllegro, ParAccel
Big Data Platforms	Hadoop, MapReduce, Spark, Hbase, Hive, ...
Spatial Big Data Platforms	ESRI GIS Tools for Hadoop, GeoWave, SpatialSpark, GeoSpark, Simba, Hadoop-GIS, SpatialHadoop, ST-Hadoop

Blocks based on Hadoop HashPartition



Blocks based on Spatial Data Partition



What has changed? **Spatial Data Science**

Spatial	Last Century	Last Decade
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Data Access	Need special hardware and network	Cloud based repositories, e.g., Earth on AWS
Spatial Platforms	ESRI Arc/Info	SQL3/OGC, e.g., Postgis, ESRI GIS Tools for Hadoop, Google Earth Engine
Spatial Data Science	Spatial Patterns, e.g., hotspots (SatScan, ESRI Geostatistics)	(a) Spatial Network Patterns, e.g., linear hotspots (b) Spatio-temporal (ST) patterns, e.g., Change time-series
Spatial Visualization	Quilt, e.g., MS Terraserver	

Spatial Challenges: Traditional Data Science

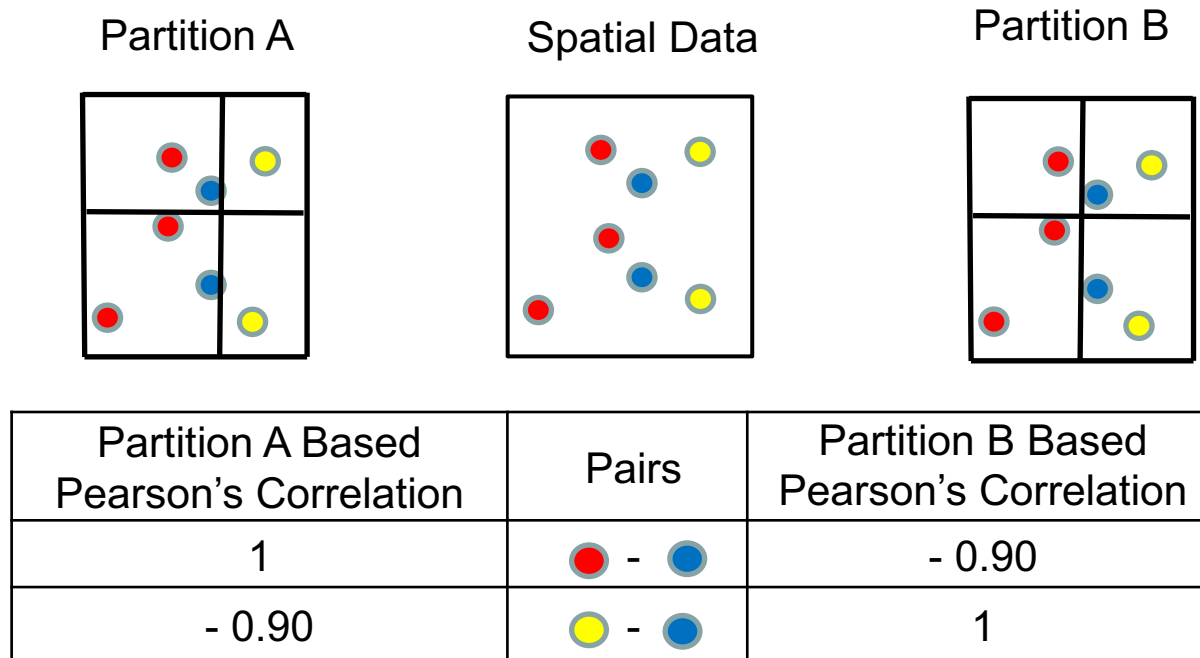


- Traditional methods not robust in face of
 - Challenge 1: Spatial continuity
 - Challenge 2: Auto-correlation, Heterogeneity , Edge-effect, ...
 - Challenge 3: Noise

Details: [Data Science for Earth: The Earth Day Report](#) , E. Eftelioglu, S. Shekhar, J. Hudson, L. Joppa, C. Baru, V. Janeja, et al. ACM SIGKDD Explorations Newsletter, 22(1), May 2020

Challenge 1: Continuous Space

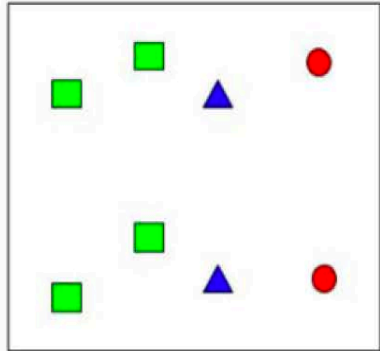
- Traditional methods not robust in face of **Spatial continuity**
 - Gerrymandering risk**: Classical methods not robust
 - Result changes if spatial partitioning changes
 - Formally, Modifiable Areal Unit Problem (MAUP)



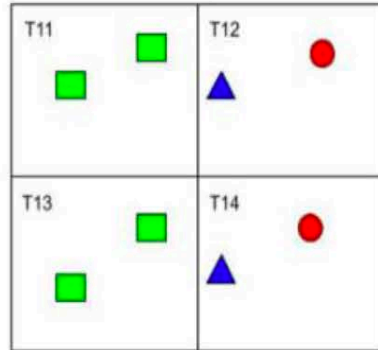
Details: [Data Science for Earth: The Earth Day Report](#) , E. Eftelioglu, S. Shekhar, J. Hudson, L. Joppa, C. Baru, V. Janeja, et al. ACM SIGKDD Explorations Newsletter, 22(1), May 2020

Classical Data Mining Methods not robust either!

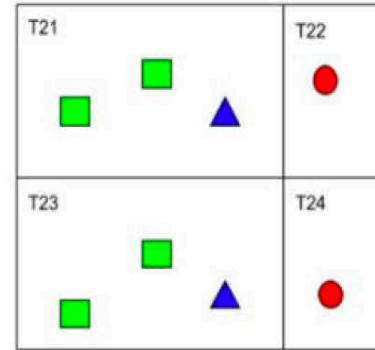
Consider the spatial Data in Figure (a)
Along with 3 alternative partitions in Figures (b), (c) and (d).



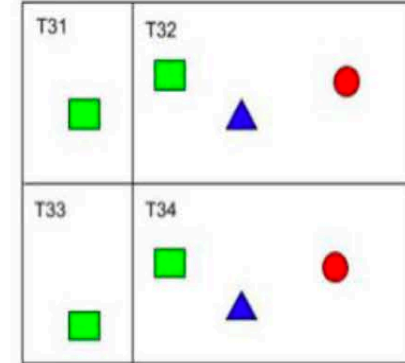
(a) Map of 3 item-types










(b) Spatial Partition P1



(c) Spatial Partition P2

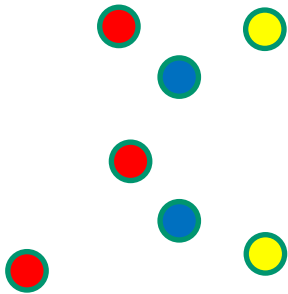


(d) Spatial Partition P3

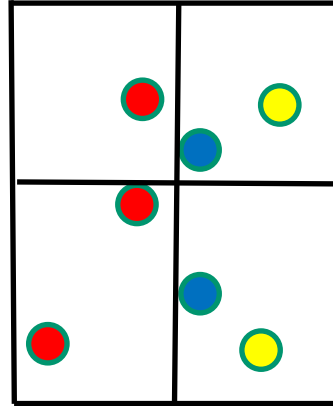
Spatial Partitioning Definition	P1	P2	P3
Transactions	T11, T12, T13, T14	T21, T22, T23, T24	T31, T32, T33, T44
Associations with support ≥ 0.5	( )	( )	(  )

Approach: Neighbor Graph

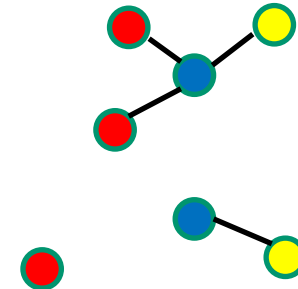
- Challenge: One size does not fit all
- Ex. Interaction patterns





(a) a map of 3 features



(b) Spatial Partitions



(c) Neighbor graph

	Pearson's Correlation	Ripley's cross-K	Participation Index
	-0.90	0.33	0.5
	1	0.5	1

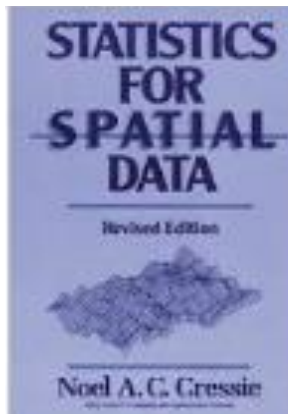
Details: Discovering Spatial Co-location Patterns: A General Approach,
IEEE Transactions on Knowledge and Data Eng., 16(12), December 2004 (w/ H.Yan, H.Xiong).

A Metric of Spatial Cross-Correlation

- Ripley's Cross K-Function Definition

$$K_{ij}(h) = \lambda_j^{-1} E \left[\begin{array}{l} \text{number of type } j \text{ event within distance } h \\ \text{of a randomly chosen type } i \text{ event} \end{array} \right]$$

- Cross K-function of some pair of spatial feature types
- Example
 - Which pairs are frequently co-located
 - Statistical significance



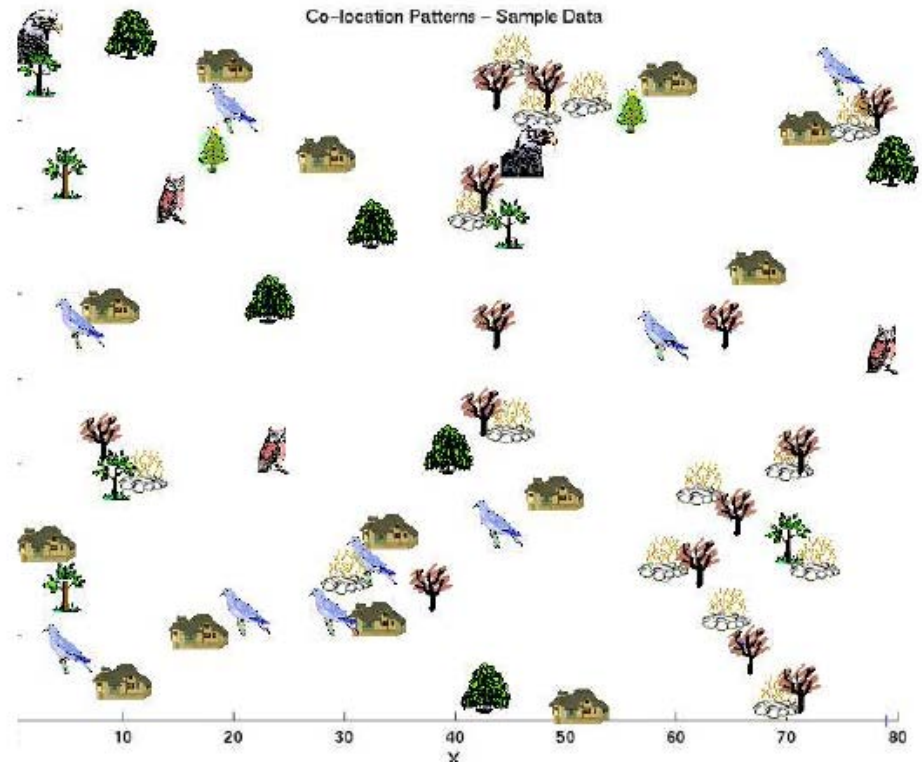
Co-locations

- Given: A collection of different types of spatial events
- Find: Co-located subsets of event types

Answers:



and

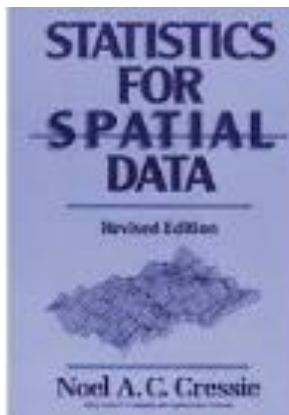
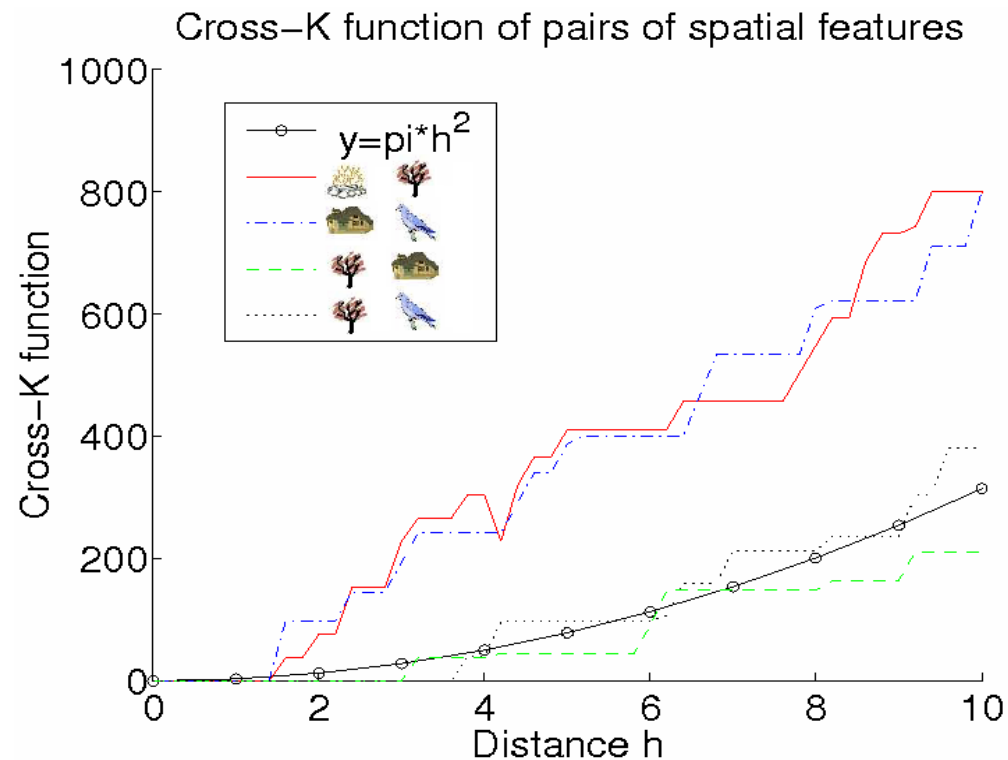


Source: Discovering Spatial Co-location Patterns: A General Approach, IEEE Transactions on Knowledge and Data Eng., 16(12), December 2004 (w/ H.Yan, H.Xiong).



Illustration of Cross-Correlation

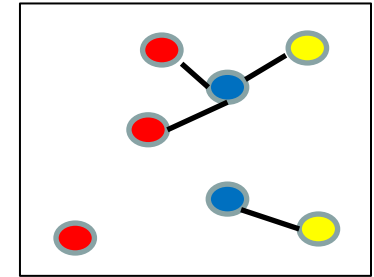
- Illustration of Cross K-function for Example Data



Spatial Colocation

Feature set: (●, ●, ●)

Feature Subsets:



Participation ratio (pr):

$\text{pr}(\text{red}, \text{[red, blue]}) = \text{fraction of red instances neighboring feature \{blue\}} = 2/3$

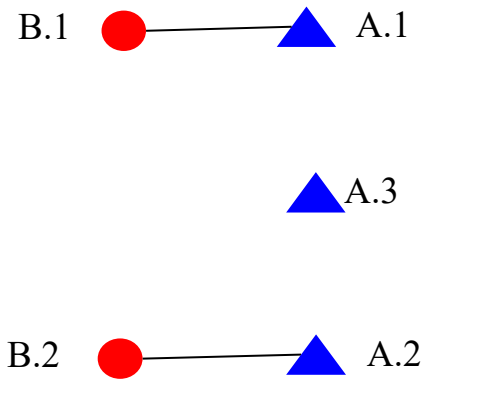
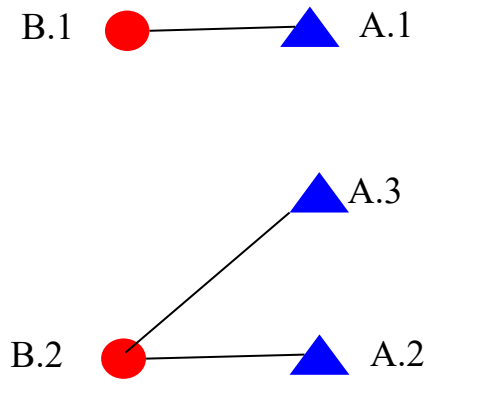
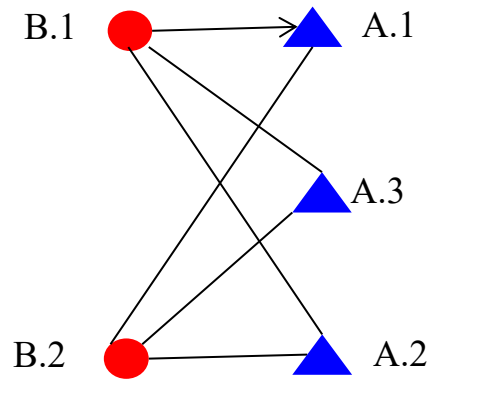
$\text{pr}(\text{blue}, \text{[red, blue]}) = 1/2$

Participation index $(\text{[red, blue]}) = \text{pi}(\text{[red, blue]})$
 $= \min\{ \text{pr}(\text{blue}, \text{[red, blue]}) , \text{pr}(\text{red}, \text{[red, blue]}) \}$
 $= \min(2/3, 1/2) = 1/2$

Participation Index Properties:

- (1) Computational: Non-monotonically decreasing like support measure
- (2) Statistical: Upper bound on Ripley's Cross-K function

Participation Index \geq Cross-K Function

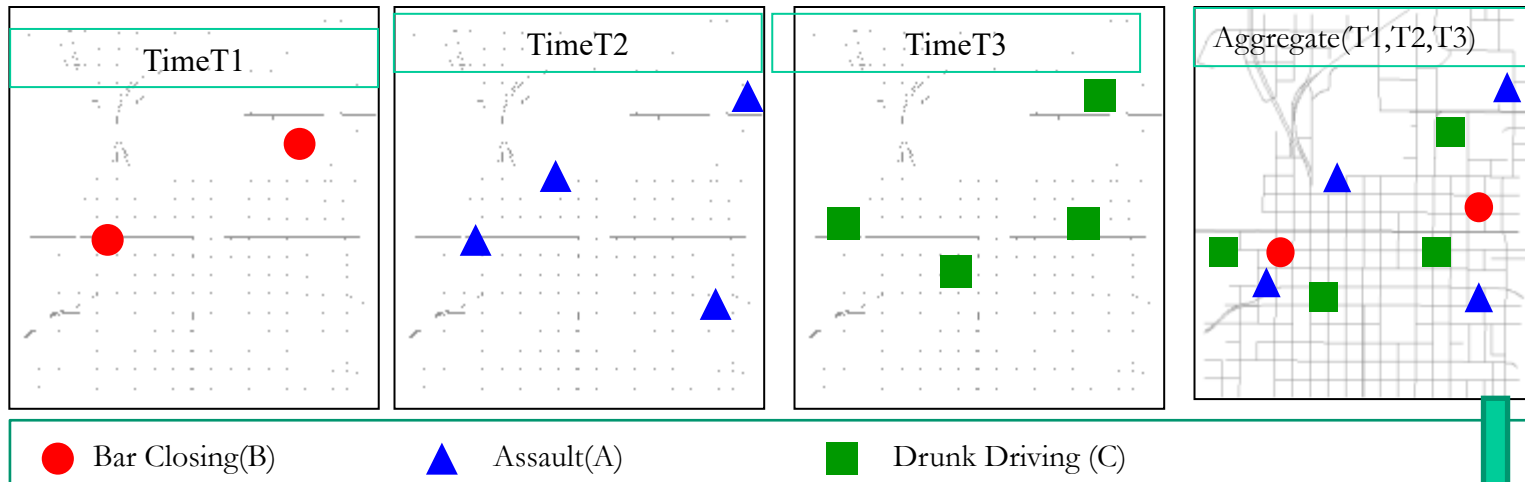
			
Cross-K (A,B)	$2/6 = 0.33$	$3/6 = 0.5$	$6/6 = 1$
PI (A,B)	$2/3 = 0.66$	1	1

Spatial Colocation: Trends

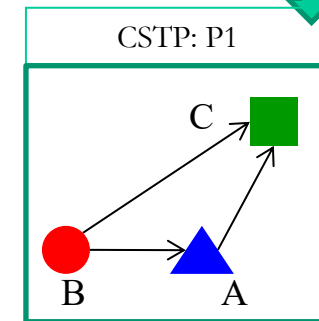
- Algorithms
 - Join-based algorithms
 - One spatial join per candidate colocation
 - Join-less algorithms
- Statistical Significance
 - ?Chance-patterns
- Spatio-temporal
 - Which events co-occur in space and time?
 - (bar-closing, minor offenses, drunk-driving citations)
 - Which types of objects move together?



Cascading spatio-temporal pattern (CSTP)



- ❑ **Input:** Urban Activity Reports
- ❑ **Output:** *CSTP*
 - ❑ *Partially ordered* subsets of ST event types.
 - ❑ Located together in space.
 - ❑ Occur in *stages* over time.
- ❑ Applications: Public Health, Public Safety, ...



Spatial Challenges: Traditional Data Science



- Traditional methods not robust in face of
 - Challenge 1: Spatial continuity
 - Challenge 2: Auto-correlation, Heterogeneity , Edge-effect, ...
 - Challenge 3: Noise

Details: [Data Science for Earth: The Earth Day Report](#) , E. Eftelioglu, S. Shekhar, J. Hudson, L. Joppa, C. Baru, V. Janeja, et al. ACM SIGKDD Explorations Newsletter, 22(1), May 2020

Challenge 2: Spatial Auto-correlation

- Traditional Statistics, ML, Data Mining
- Ubiquitous i. i. d. assumption
 - Data samples independent of each other
 - From identical distribution
- Problem
 - Ignores auto-correlation, heterogeneity
 - Salt n Pepper noise

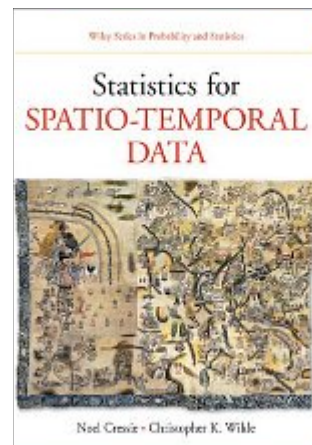
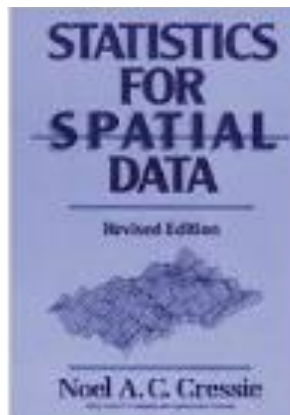
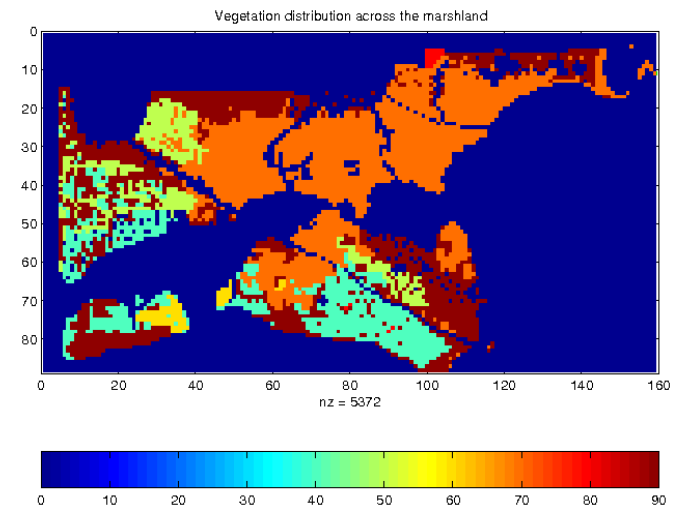
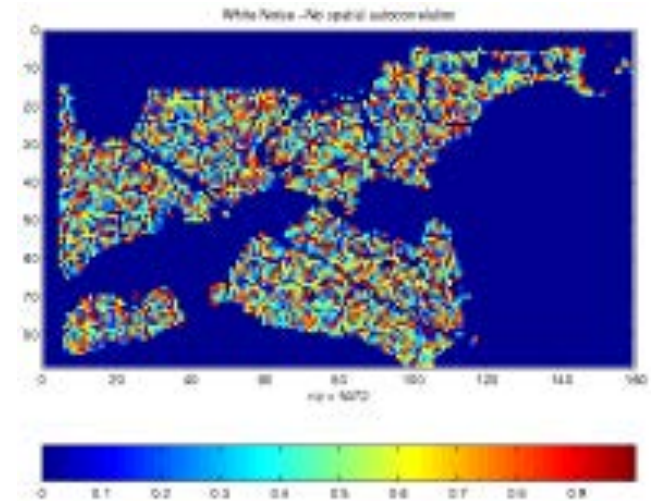
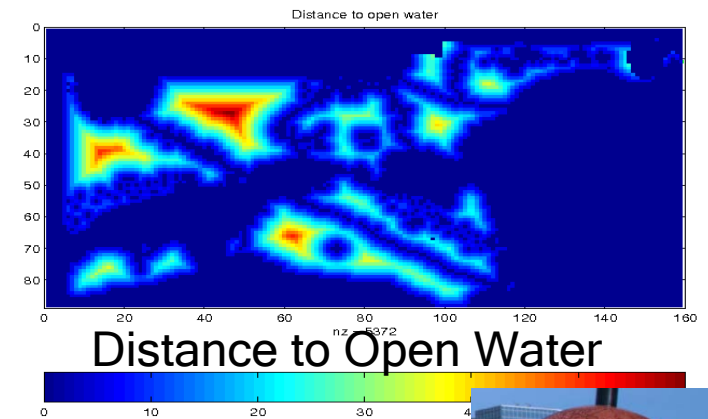
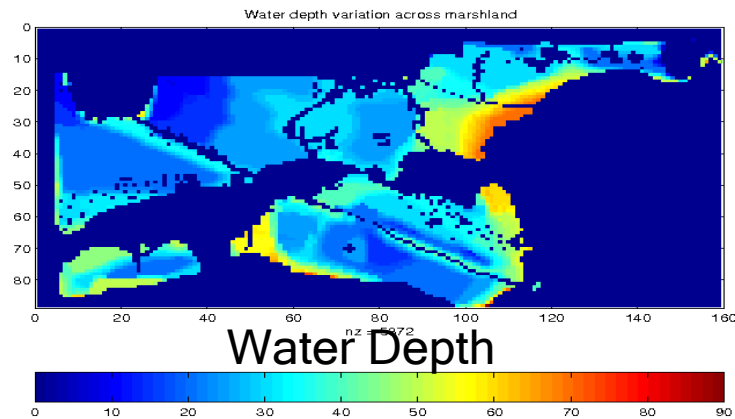
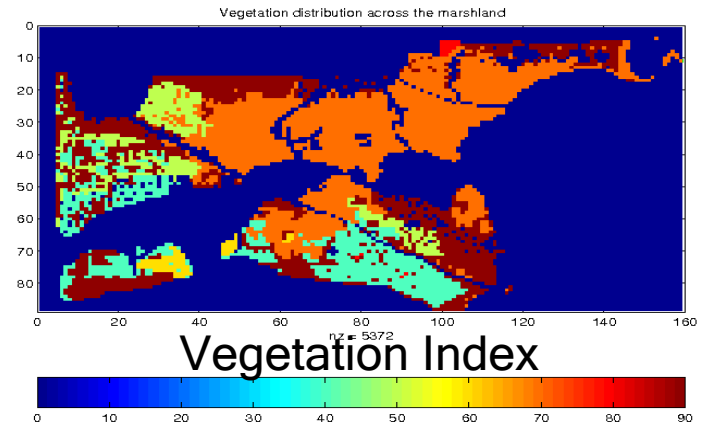
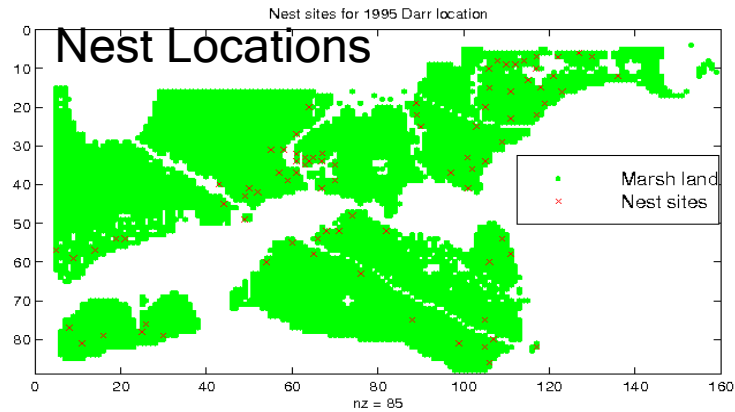


Illustration of Location Prediction Problem



Spatial Auto-Regression & Parameter Estimation

<i>Name</i>	<i>Model</i>
Classical Linear Regression	$\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$
Spatial Auto-Regression	$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$

ρ : the spatial auto - regression (auto - correlation) parameter

\mathbf{W} : n - by - n neighborhood matrix over spatial framework

- **Maximum Likelihood Estimation**

$$\ln(L) = \ln|\mathbf{I} - \rho\mathbf{W}| - \frac{n \ln(2\pi)}{2} - \frac{n \ln(\sigma^2)}{2} - SSE$$

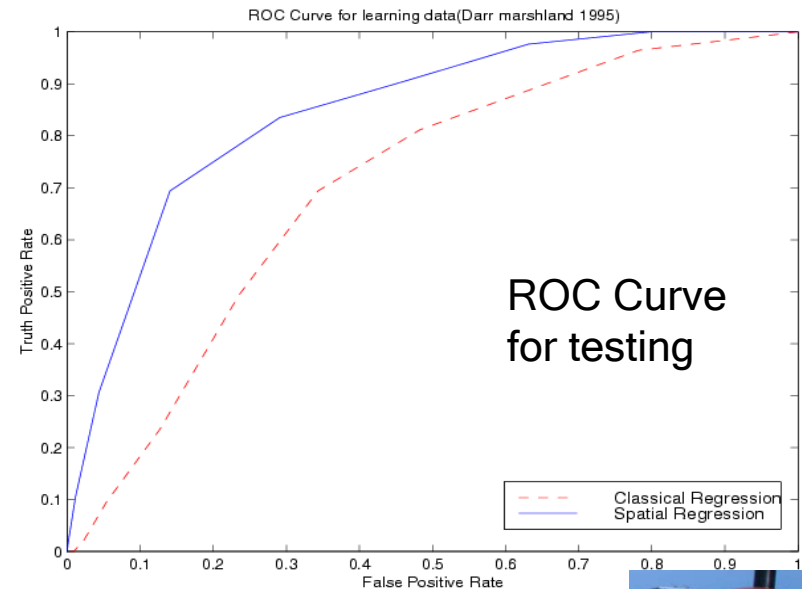
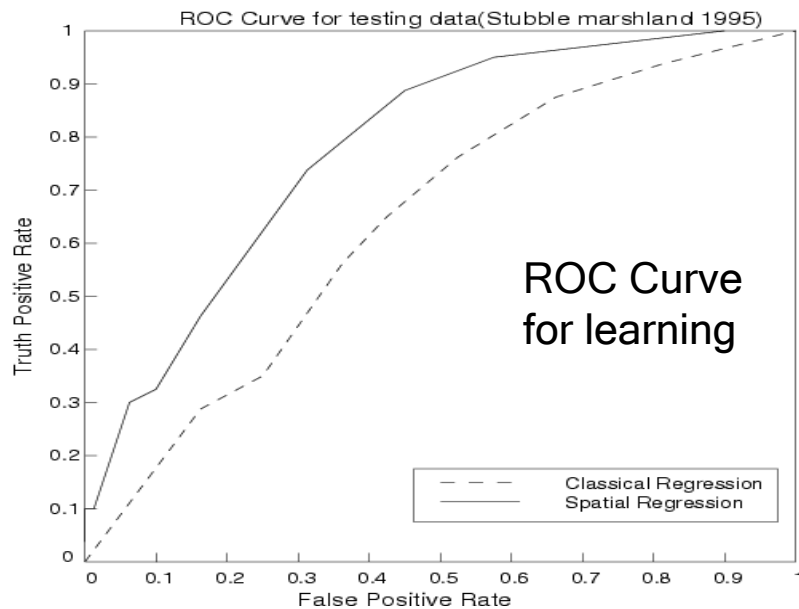
- **Computing determinant of large matrix is a hard (open) problem!**

- size(W) is **quadratic** in number of locations/pixels.
- Typical raster image has Millions of pixels
- W is sparse but not banded.

Details: A parallel formulation of the spatial auto-regression model for mining large geo-spatial datasets, SIAM Intl. Workshop on High Perf. and Distr. Data Mining, 2004. (with B. Kazar)

Comparing Traditional and Spatial Models

- Dataset: Bird Nest prediction
- Linear Regression
 - Lower prediction accuracy, coefficient of determination,
 - Residual error with spatial auto-correlation
- Spatial Auto-regression outperformed linear regression



Prediction Error and Bias Trade-off

- Linear Regression (LR)

$$y = X\beta + \varepsilon$$

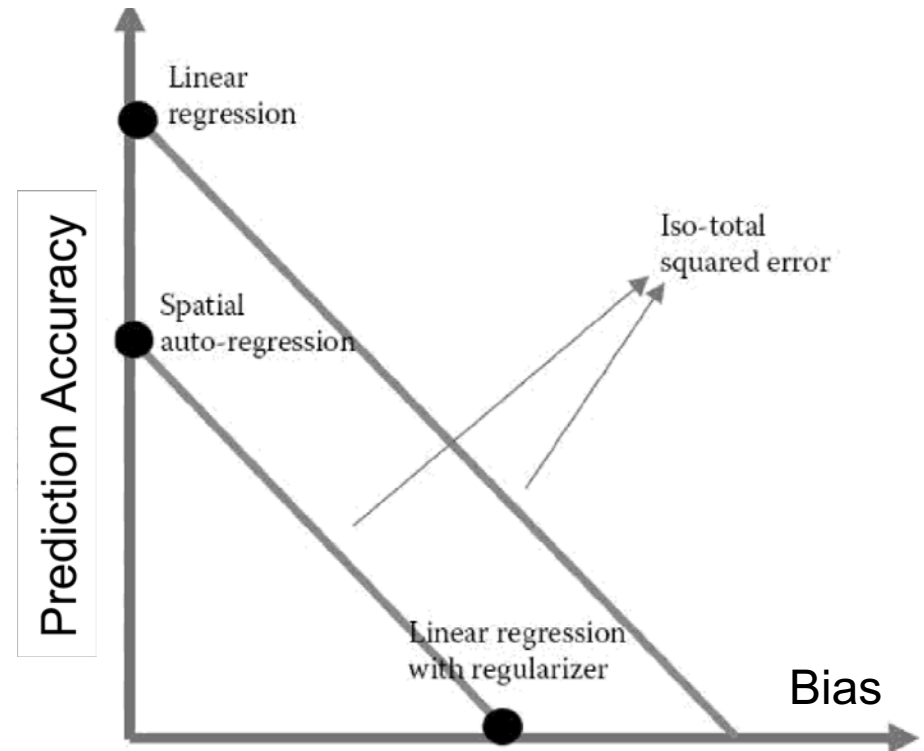
- LR with Auto-correlation Regularizer

$$y = X\beta + \varepsilon$$

$$\varepsilon = \|y - X\beta\|^2 + \|y - y_{neighbor}\|^2$$

- Spatial Auto-Regression

$$y = \rho W y + X\beta + \varepsilon$$

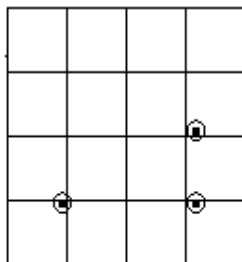


Source: Geospatial Data Science: A Transdisciplinary Approach.
In *Geospatial Data Science Techniques and Applications* (pp. 17-56). CRC Press, 2017
(E. Eftelioglu, R. Ali, X. Tang., Y. Xie, Y., Li and S. Shekhar).



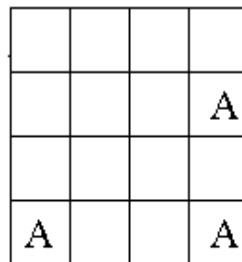
Research Needs for Location Prediction

- Spatial Auto-Regression
 - Estimate W
 - Scaling issue $\rho W y$ vs. $X\beta$
- Spatial interest measure
 - e.g., distance(actual, predicted)



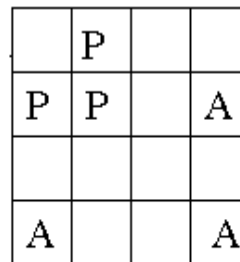
(a)

Actual Sites



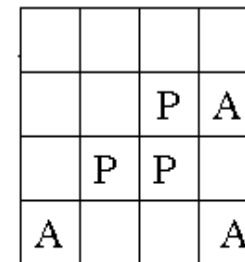
(b)

Pixels with
actual sites



(c)

Prediction 1



(d)

Prediction 2.

Spatially more interesting
than Prediction 1

Legend

- = nest location
- A = actual nest in pixel
- P = predicted nest in pixel



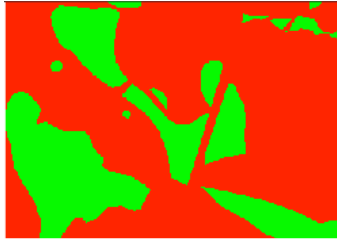
Salt n Pepper Noise

■ wetland ■ dry land

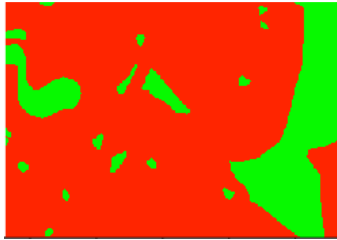
Input:

Output:

train



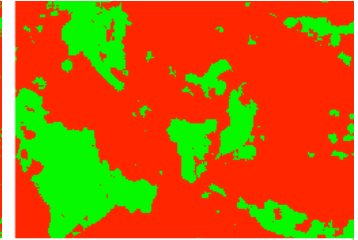
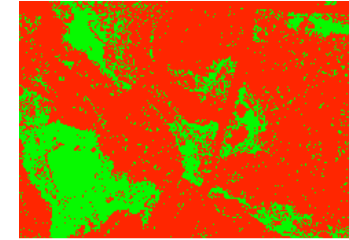
test



(a) aerial photo

(b) aerial photo

(c) true classes



(d) DT prediction
(Salt n Pepper
Noise)

(e) SDT prediction

Training samples: upper half

Test samples: lower half

Spatial neighborhood: maximum 11 pixels by 11 pixels

DT: decision tree

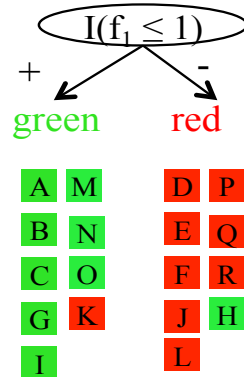
SDT: spatial decision tree

Details: Focal-Test-Based Spatial Decision Tree Learning. [IEEE Trans. Knowl. Data Eng. 27\(6\)](#): 1547-1559, 2015 (summary in Proc. IEEE Intl. Conf. on Data Mining, 2013).(w/ Z. Jiang et al.)

Spatial Decision Tree

Inputs: table of records

ID	f_1	f_2	Γ_1	class
A	1	1	1	green
B	1	1	0.3	green
C	1	3	0.3	green
G	1	1	0.3	green
I	1	3	0	green
K	1	2	-1	red
M	1	1	1	green
N	1	1	0.3	green
O	1	3	0.3	green
D	3	2	0.3	red
E	3	2	0.3	red
F	3	2	1	red
H	3	1	-1	green
J	3	2	0	red
L	3	2	0.3	red
P	3	2	0.3	red
Q	3	2	0.3	red
R	3	2	1	red



Predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R

feature test	information gain
$f_1 \leq 1$	0.50
$f_2 \leq 1$	0.46
$f_2 \leq 2$	0.19

Inputs:

- feature maps, class map
- Rook neighborhood

Feature f_1

1	1	1	3	3	3
1	3	1	3	1	3
1	1	1	3	3	3

Feature f_2

1	1	3	2	2	2
1	1	3	2	2	2
1	1	3	2	2	2

Class map

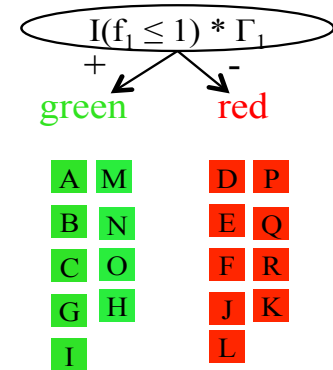
green	green	green	red	red	red
green	green	green	red	red	red
green	green	green	red	red	red

Focal function Γ_1

1	.3	.3	.3	.3	1
.3	-1	0	0	-1	.3
1	.3	.3	.3	.3	1

Predicted map

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R



Location Prediction Models

- Traditional Models, e.g., Regression (with Logit or Probit),
 - Linear Regression, Bayes Classifier, ...
- Semi-Spatial : auto-correlation regularizer $\varepsilon = \|y - \beta X\|^2 + \|\beta X - \beta X_{neighbor}\|^2$
- Spatial Models
 - Spatial autoregressive model (SAR)
 - Markov random field (MRF) based Bayesian Classifier

Traditional

$$y = X\beta + \varepsilon$$

$$\Pr(C_i | X) = \frac{\Pr(X | C_i) \Pr(C_i)}{\Pr(X)}$$

Neural Networks

Decision Trees

Spatial

$$y = \rho W y + X\beta + \varepsilon$$

$$\Pr(c_i | X, C_N) = \frac{\Pr(C_i) \Pr(X, C_N | c_i)}{\Pr(X, C_N)}$$

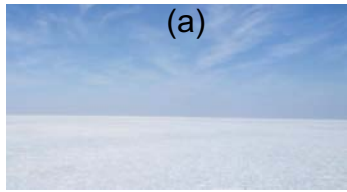
Convolutional Neural Networks

Spatial Decision Trees

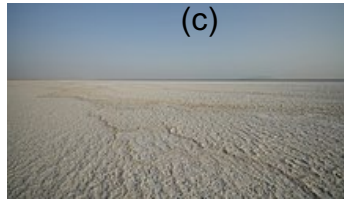
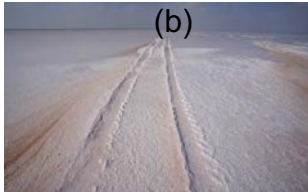


Spatial Variability Challenge: Amorphous Features

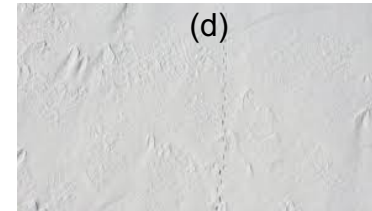
Q1. Which images show snow ?



Runn of Kutch, Gujarat, India



Lake Karum, Ethiopia



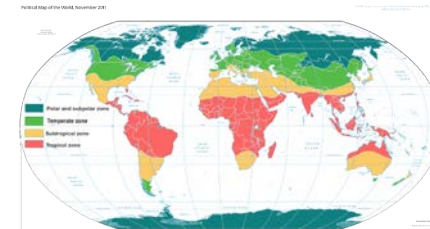
Snow



Snow

Q2. Which geo-challenges are addressed by Convolutional Neural Network (CNN) ?

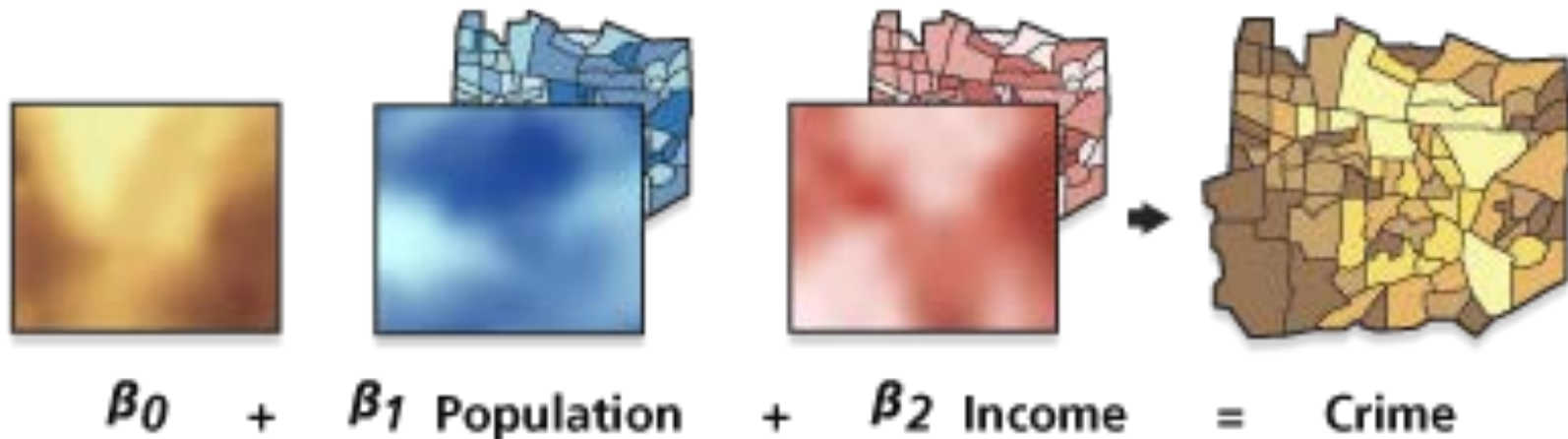
- (a) High Cost of spurious and missed patterns
- (b) Spatial Auto-correlation
- (c) Spatial Heterogeneity
- (d) Teleconnections



Details: [Towards Spatial Variability Aware Deep Neural Networks \(SVANN\): A Summary of Results](#), J. Gupta, Y. Xie, and S. Shekhar, DeepSpatial2020 (1st ACM SIGKDD Workshop on Deep Learning for Spatiotemporal Data, Applications, and Systems). **Best paper award.**

Modeling Spatial Heterogeneity: GWR

- Geographically Weighted Regression (GWR)
 - Goal: Model spatially varying relationships
 - Example: $y = X\beta' + \varepsilon'$
Where β' and ε' are location dependent

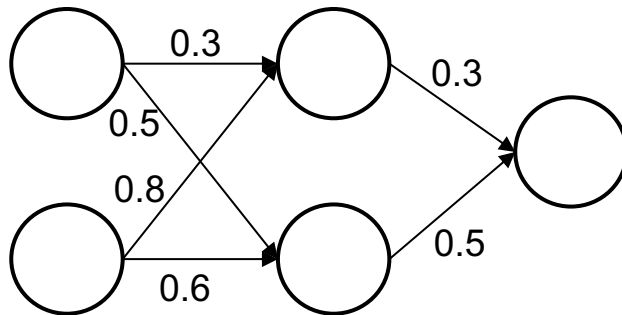


Source: resources.arcgis.com

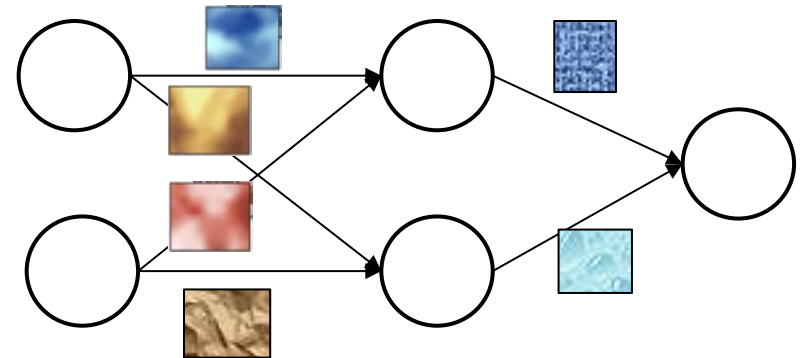


Spatial Variability Aware Neural Networks (SVANN)

A Neural Network (NN)



SVANN



- Each NN parameter is a map i.e., a function of location
 - Similar to Geographically Weighted Regression
- Evaluation Task:
 - Urban Garden Detection across Hennepin County, MN and Fulton County, GA.
 - SVANN outperformed OSFA by 14.34% on F1-scores.

Details: J. Gupta, Y. Xie and S. Shekhar,

Towards Spatial Variability Aware Deep Neural Networks (SVANN): A Summary of Results, ACM SIGKDD Workshop on Deep Learning for Spatiotemporal Data, Applications, and Systems (Deepspatial 2020), 2020. (Best Paper Award). [arXiv:2011.08992v1](https://arxiv.org/abs/2011.08992v1)

Full paper accepted for ACM Transaction on Intelligent Systems and Technology.



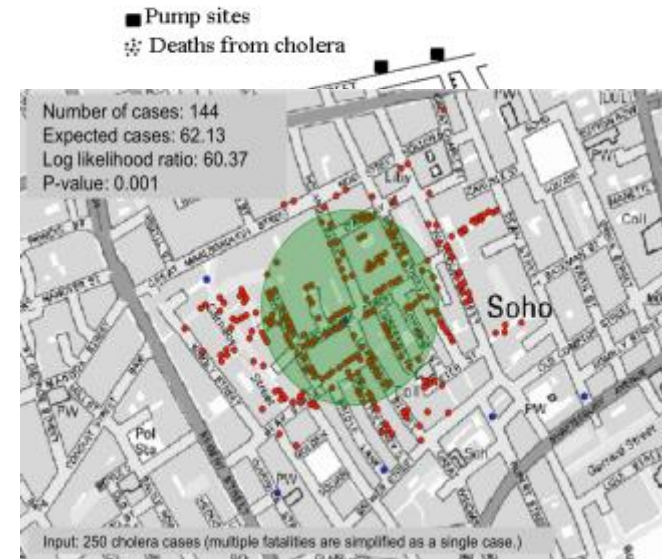
Spatial Challenges: Traditional Data Science

- Traditional methods not robust in face of
 - Challenge 1: Spatial continuity
 - Challenge 2: Auto-correlation, Heterogeneity , Edge-effect, ...
 - Challenge 3: Noise
 - High cost of spurious patterns

Details: [Data Science for Earth: The Earth Day Report](#) , E. Eftelioglu, S. Shekhar, J. Hudson, L. Joppa, C. Baru, V. Janeja, et al. ACM SIGKDD Explorations Newsletter, 22(1), May 2020

Dealing with Noise & Spurious Chance Patterns

- Statistics: Deal with Noise
 - Quantify uncertainty, confidence, ...
 - Is it (statistically) significant?
 - Is it different from a chance event or rest of dataset?
 - e.g., SaTScan finds circular hot-spots
- Spatial Statistics, Spatial Data Mining
 - Auto-correlation, Heterogeneity, Edge-effect, ...



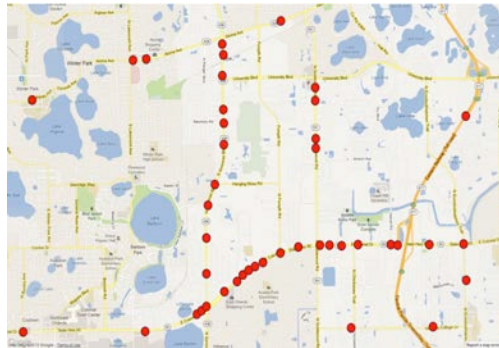
Spatial Scan Statistics (SatScan)

- Goal: Omit chance clusters
- Ideas: Likelihood Ratio, Statistical Significance
- Steps
 - Enumerate candidate zones & choose zone X with highest likelihood ratio (LR)
 - $LR(X) = p(H1|data) / p(H0|data)$
 - $H0$: points in zone X show complete spatial randomness (CSR)
 - $H1$: points in zone X are clustered
 - If $LR(Z) \gg 1$ then test statistical significance
 - Check how often is $LR(CSR) > LR(Z)$
using 1000 Monte Carlo simulations

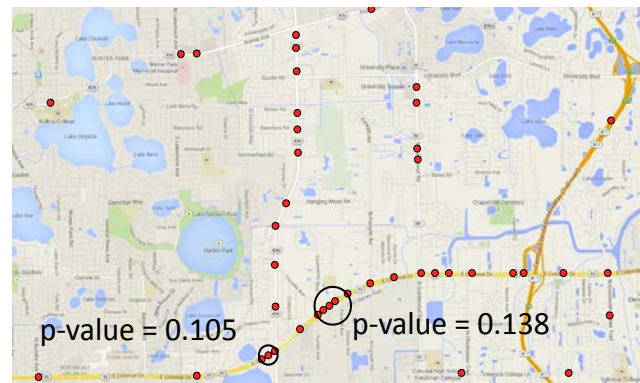


Beyond SatScan: Spatial Concept/Theory-Aware Hotspots

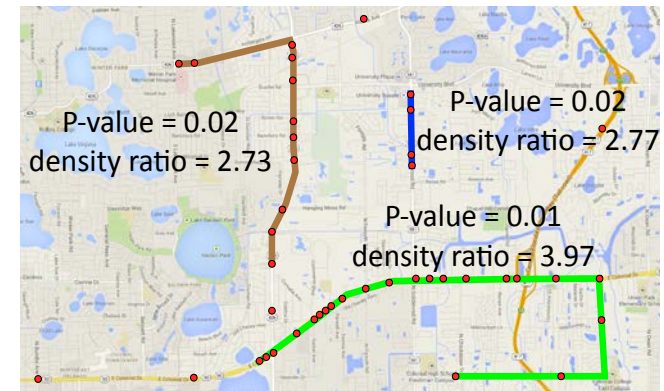
- Geographic features, e.g., rivers, streams, roads, ...
 - Hot-spots => Hot Geographic-features, e.g., **Linear Hotspots**
- Spatial Theories, e.g., environmental criminology
 - Circles → Doughnut holes



Pedestrian fatalities
Orlando, FL



Circular hotspots
by SatScan



Linear hotspots

Details: Significant Linear Hotspot Discovery, IEEE Transactions on Big Data, 3(2):140-153, 2017.
(Summary in Proc. Geographic Info. Sc., Springer LNCS 8728, pp. 284-300, 2014.)



Hotel That Enlivened the Bronx Is Now a ‘Hot Spot’ for Legionnaires’

By WINNIE HU and NOAH REMNICK AUG. 10, 2015

Contaminated Cooling Towers
Five buildings have been identified as the potential source of the Legionnaires' disease outbreak in the South Bronx.

- Possible sources of Legionnaires' outbreak
- Additional sites found with legionella bacteria
- Locations of people with Legionnaires'

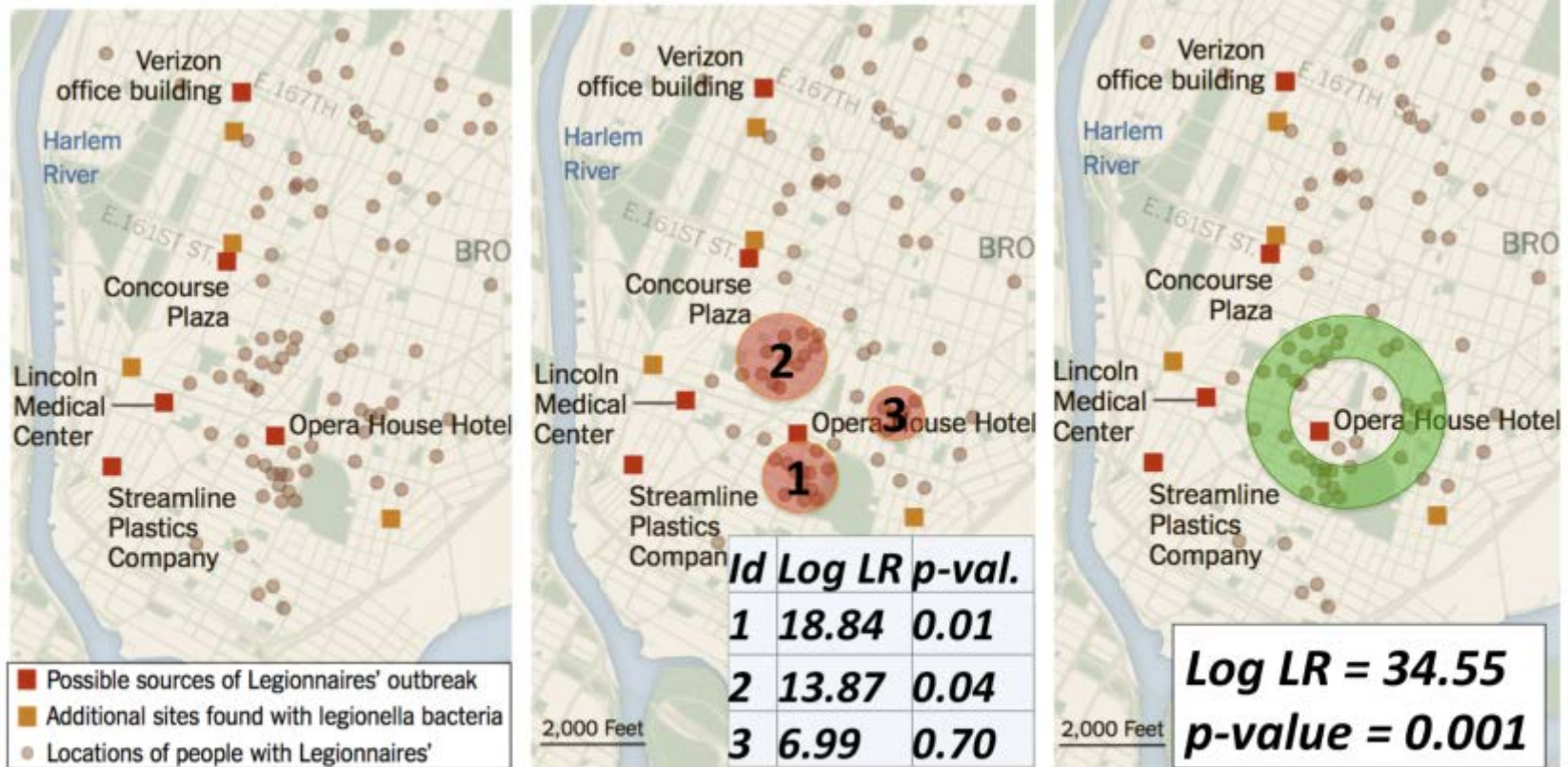


Source: New York Mayor's Office
By The New York Times



The Opera House Hotel is at the center of the outbreak. Edwin J. Torres for The New York Times

Legionnaires' Disease Outbreak in New York



(a) Legionnaire's in New York (2015) (b) Output of SaTScan (c) Output of RHD

Details: Ring-Shaped Hotspot Detection, IEEE Trans. Know. & Data Eng., 28(12), 2016.
(A Summary in Proc. IEEE ICDM 2014) (w/ E. Eftelioglu et al.)

Robust Clustering (Hotspot Detection)

- **Problem definition**

- **Inputs:** Collection of event locations, Test statistic; Significance level
- **Output:** Significant clusters (hotspots)
- **Constraints:** Avoid chance patterns despite non-trivial noise in data

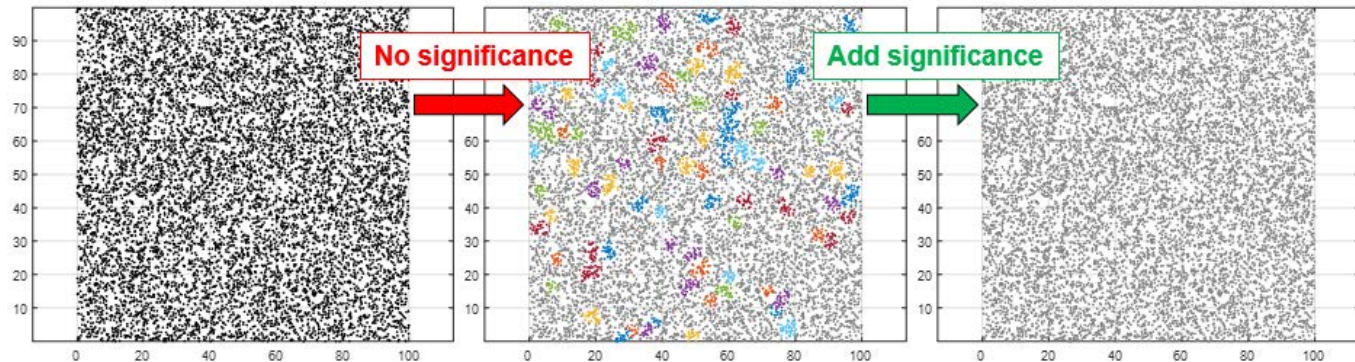
- **Limitations of Related Work**

- DBSCAN cannot avoid chance patterns
- SaTScan cannot detect clusters of arbitrary shapes

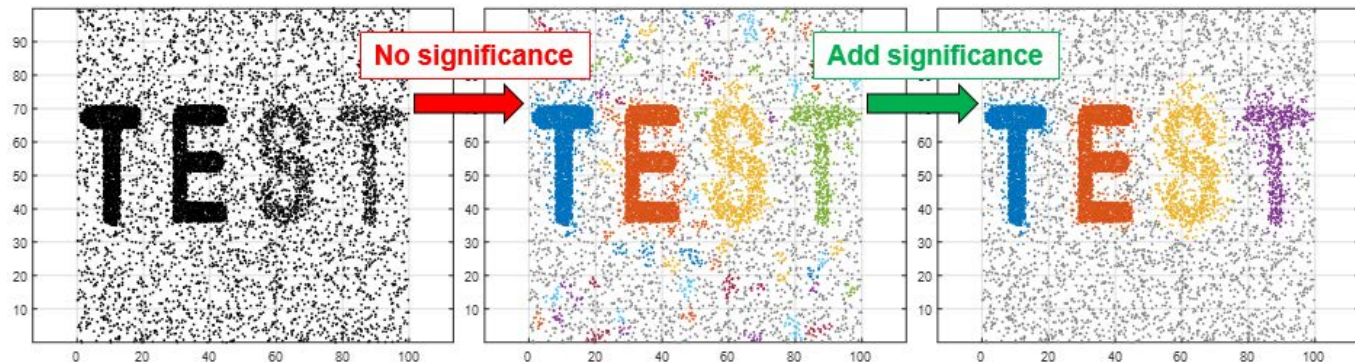
- **Contributions**

- Significance modeling in DBSCAN
- A fast dual-convergence algorithm

Complete
Spatial Random
(no significant
hotspots)



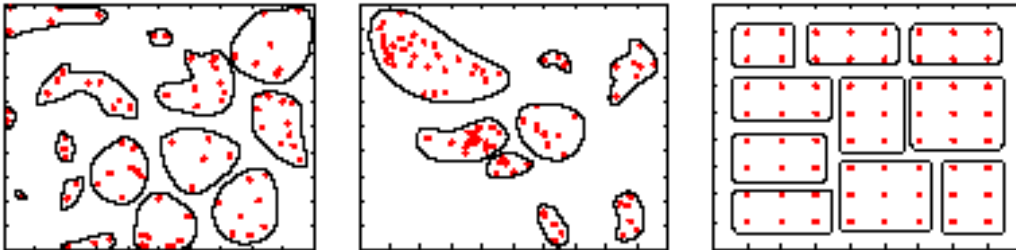
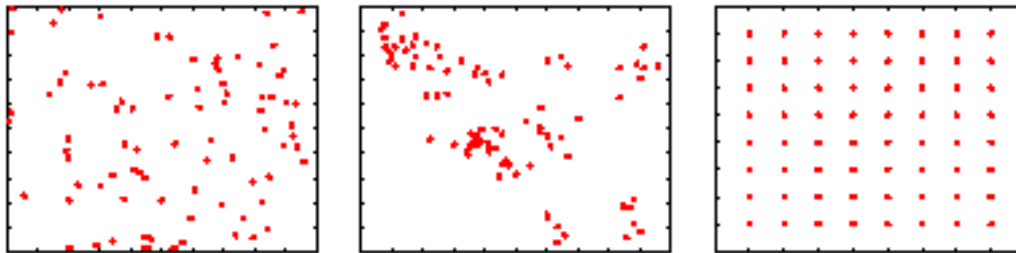
Significant
Hotspots
with Noise



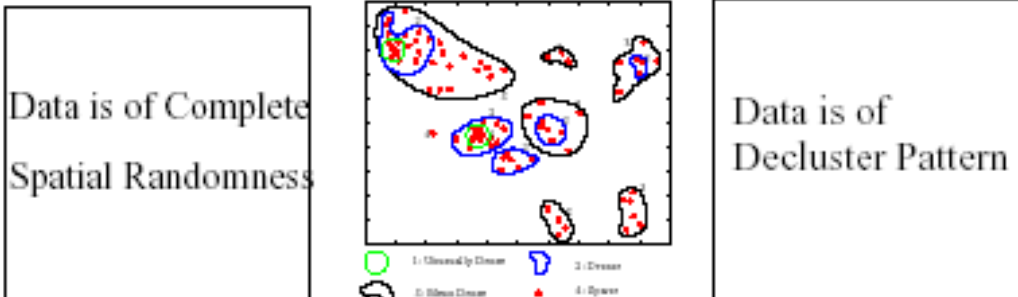
Details: Significant DBSCAN towards Statistically Robust Clustering, (w/ Yiqun Xie),
In Proc. 16th Intl. Symposium on Spatial and Temporal Databases (SSTD), 2019, ACM. **(Best Paper Award)**

Limitation of Traditional Clustering

- Challenge: **One size does not fit all**
 - Prediction error vs. model bias, Cost of false positives, ...
- Example. Clustering: Find groups of points



Traditional Clustering
(K-means always finds clusters)



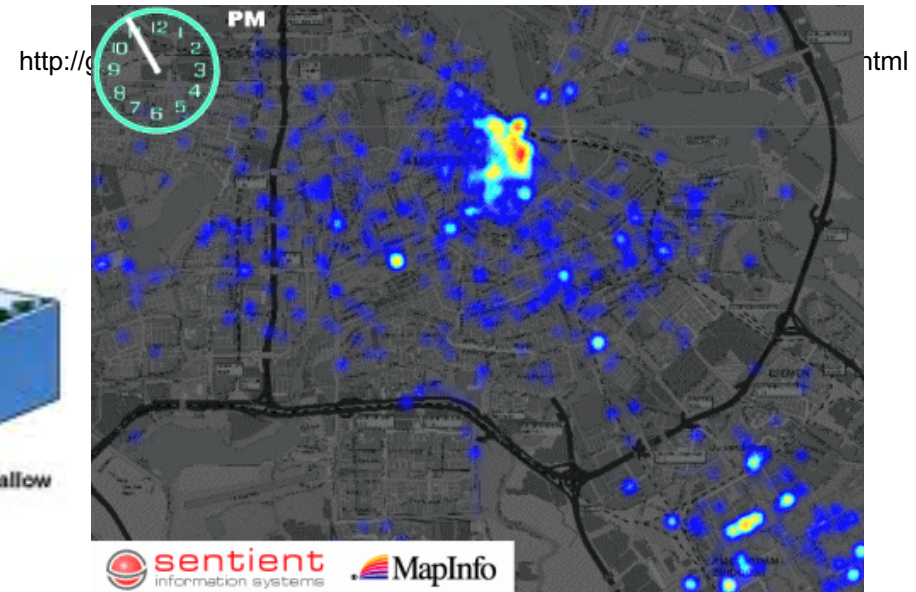
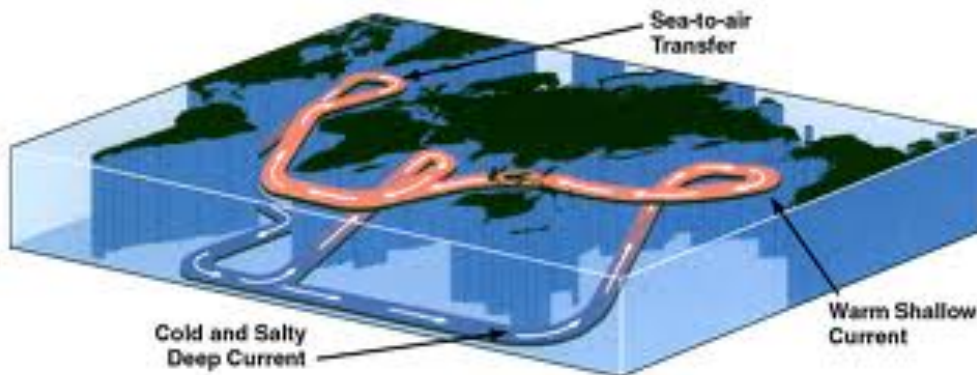
Spatial Clustering begs to differ!

What has changed? Spatial Data Revolution

Spatial	Last Century	Last Decade
Data	Few satellites and sensors	Nano-satellites, Billions of GPS enabled smartphones
Data Access	Need special hardware and network	Cloud based repositories, e.g., Earth on AWS
Spatial Platforms	ESRI Arc/Info	SQL3/OGC, e.g., Postgis, ESRI GIS Tools for Hadoop, Google Earth Engine
Spatial Data Science	Spatial Patterns, e.g., hotspots (SatScan, ESRI Geostatistics)	(a) Spatial Network Patterns, e.g., linear hotspots (b) Spatio-temporal (ST) patterns, e.g., Change time-series (Google Timelapse)
Spatial Visualization	Quilt: MS Terraserver Fly through: Google Earth	(a) Space time: Timelapse (b) There Dimensions

Towards Time-Travel and Depth in Virtual Globes

- Virtual globes are snapshots
- How to add time? depth?
 - Ex. Google Earth Engine, NASA NEX
 - Ex. Google Timelapse: 260,000 CPU core-hours for global 29-frame video
- How may one convey provenance, accuracy, age, and data semantics?
- What techniques are needed to integrate and reason about diverse available



A UCGIS Call to Action:

Bringing the Geospatial Perspective to Data Science Degrees and Curricula

Data that are geographically referenced or contain some type of location markers are both common and of high value (e.g., data subject to state-specific policies, laws and regulations; demographic data from the census; location traces of smartphones and vehicles; remotely sensed imagery from satellites, aircraft and small unmanned aerial vehicles; volunteered geographic information; geographically referenced social media postings). A 2011 McKinsey Global Institute report estimates a value of “about \$600 billion annually by 2020” from leveraging personal location data² to reduce fuel waste, improve health outcomes, and better match products to consumer needs. Spatial data are critical for societal priorities such as national security, public health & safety, food, energy, water, smart cities, transportation, climate, weather, and the environment. For example, remotely-sensed satellite imagery is used to monitor not only weather and climate but also global crops³ for early warnings and planning to avoid food shortages.



One Size Data Science Does not Fit All Data!

However, spatial data presents unique data science challenges. Recent court cases that address gerrymandering, the manipulation of geographic boundaries to favor a political party, offer a high-profile example. Instances of such exploitation of the modifiable areal unit problem (or dilemma) is not limited to elections since the MAUP affects almost all traditional data science methods in which results (e.g., correlations) change dramatically by varying geographic boundaries of spatial partitions. The fundamental geographic qualities of spatial autocorrelation, which assumes properties of geographically proximate places to be similar, and geographic heterogeneity, where no two places on Earth are exactly alike, violate assumptions of sample independence and randomness that underlie many conventional statistical methods. Other spatial challenges include how to choose between a plurality of projections and coordinate systems and how to deal with the imprecision, inaccuracy, and uncertainty of location.

A UCGIS Call to Action:

Bringing the Geospatial Perspective to Data Science Degrees and Curricula



University Consortium for
GEOGRAPHIC INFORMATION SCIENCE

Summer 2018

Spatial Data Science Tools

measurements. To deal with such challenges, practitioners in many fields including agriculture, weather forecast, mining, and environmental science incorporate *geospatial data science*⁴ methods such as spatially-explicit models, spatial statistics⁵, geo-statistics, geographic data mining⁶, spatial databases⁷, etc.

⁴ Y. Xie et al., [Transdisciplinary Foundations of Geospatial Data Science, *ISPRS Intl. Jr. of Geo-Informatics*](#), 6(12):395-418, 2017. DOI: [10.3390/ijgi6120395](#).

⁵ N. Cressie, [Statistics for Spatial Data](#), Wiley, 1993 (1st ed.), 2015 (Revised ed.).

⁶ H. Miller and J. Han, [Geographic Data Mining and Knowledge Discovery](#), CRC Press, 2009 (2nd Ed.).

⁷ S. Shekhar and S. Chawla, [Spatial Databases: A Tour](#), Prentice Hall, 2003.

A UCGIS Call to Action:

Bringing the Geospatial Perspective to Data Science Degrees and Curricula



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Summary : One size data science does not fit all

- Spatial Data are ubiquitous & important
- Traditional Data Science Tools are inadequate
 - Gerrymandering, Spatial Auto-correlation, ...
- Ask:
 - Spatial Data Science Methods
 - Spatial Statistics, Spatial Data Mining, SDBMS, ...



References :Surveys, Overviews

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- **Spatial Computing** ([html](#) , [short video](#) , [tweet](#)), Communications of the ACM, 59(1):72-81, January, 2016.
- **Transdisciplinary Foundations of Geospatial Data Science** ([html](#) , [pdf](#)), ISPRS Intl. Jr. of Geo-Informatics, 6(12):395-429, 2017. (doi:10.3390/ijgi6120395)
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- Identifying patterns in spatial information: a survey of methods ([pdf](#)), [Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery](#), 1(3):193-214, May/June 2011. (DOI: 10.1002/widm.25).
- [Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data](#), IEEE Transactions on Knowledge and Data Mining, 29(10):2318-2331, June 2017. (DOI: 10.1109/TKDE.2017.2720168).
- [Parallel Processing over Spatial-Temporal Datasets from Geo, Bio, Climate and Social Science Communities: A Research Roadmap](#). IEEE [BigData Congress 2017](#): 232-250.
- **Spatial Databases: Accomplishments and Research Needs**, IEEE Transactions on Knowledge and Data Engineering, 11(1):45-55, 1999.