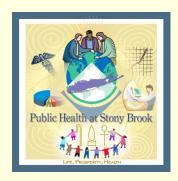
## Performance of Cancer Cluster Q-statistics for Case-Control Residential Histories

#### Jaymie R Meliker

Graduate Program in Public Health, Department of Preventive Medicine Consortium for Inter-Disciplinary Environmental Research (CIDER) Stony Brook University (SUNY)

Co-investigators: Chantel D. Sloan<sup>1</sup>, Geoffrey M. Jacquez<sup>2</sup>, Carolyn M Gallagher<sup>1</sup>, Mary H Ward<sup>3</sup>, Rikke Baastrup<sup>4</sup>, Ole Raaschou-Nielsen<sup>4</sup>

<sup>1</sup>Stony Brook University (SUNY), <sup>2</sup>BioMedware, Inc., <sup>3</sup>US National Cancer Institute, <sup>4</sup>Danish Cancer Society









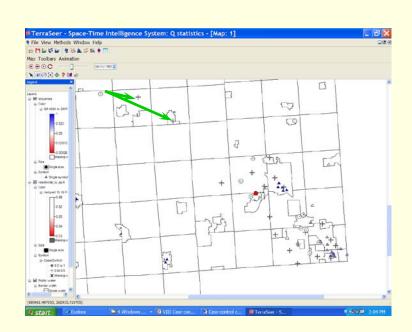


#### Statement of Problem

- Goal: Use cancer clusters to generate valuable hypotheses for diseases with largely unknown etiology
  - Most cancer cluster investigations ignore disease latency, using locations at time of diagnosis or death
  - Recent statistical advances have begun to investigate clustering in mobile populations
    - Spatial generalized additive models
    - Jacquez's Q-statistics
  - Few performance evaluations have been conducted on these new statistics
    - Multiple testing through time is a large concern

## Q-statistics for Case-Control Populations

- Rely on a matrix representation that describes how spatial nearest neighbor relationships change through time
- Space-time extension of Cuzick-Edwards' Test
- User must specify number of nearest neighbors
  - Neighbors that are cases are then counted around each case
    - Repeated every time there is a change in location





#### Q-statistics cont'd

#### Different versions:

- Q<sub>ikt</sub>: When and where is there local clustering around a case?
  - Assesses clustering around each case every time there is a change in residence
- Q<sub>kt</sub>: When is there global clustering of cases?
  - Assesses global clustering at each time slice
- Q<sub>ik</sub>: Is there clustering surrounding a case, on average, throughout his/her mobility history?
  - Assesses clustering around a person through time; Sum of Q<sub>ikt</sub>
- Q<sub>k</sub>: Is there global clustering, overall across all cases, in the residential histories?
  - Assesses whether, in general, clustering is present

Focused versions are also available



### Procedure for Evaluating Significance

- Step 1. Calculate Q-statistic (Q\*) for the observed data.
- Step 2. Reallocate the case-control identifier c<sub>i</sub> over the participants using approximate randomization, and calculate Q-statistic:
  - consistent with the desired null hypothesis
  - holding the observed number of cases fixed
  - holding the locations and attributes fixed

Case

Control

Observed

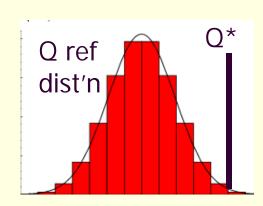
Randomization #1

Repeat many times (e.g., 999) to create a reference distribution



Randomization #2

Step 3. Compare Q\* to this reference distribution to evaluate the statistical probability of observing Q\*.



## Comments on Q-statistics and Evaluating Significance

- Must run many randomizations to resolve small p-values
  - Time-consuming → lessens likelihood of pvalue correction such as false discovery rate<sup>1</sup>
- Can we identify a p-value to use as a cut-off for significance (in light of multiple testing)?
- Can we determine which Q-statistic(s) to use to identify a cluster?

<sup>&</sup>lt;sup>1</sup>Caldas de Castro M, Singer BH. Controlling the false discovery rate: A new application to account for multiple and dependent tests in local statistics of spatial association. Geogr Anal 2005; 38: 180-208.

### Analytic Plan

- Blank slate: many approaches could be used
- Simulated clusters were created to examine Q-statistics' performance
  - Used actual mobility histories from studies of NHL in US, and testicular cancer in Denmark
- Examine whether Q-statistics identify simulated clusters, and differentiate them from false positives

#### Simulated Clusters

- Iowa
- California
- Central Denmark

 Reflected a variety of space-time cluster characteristics

Table 1.	Characteristics	of the Cluster	Regions

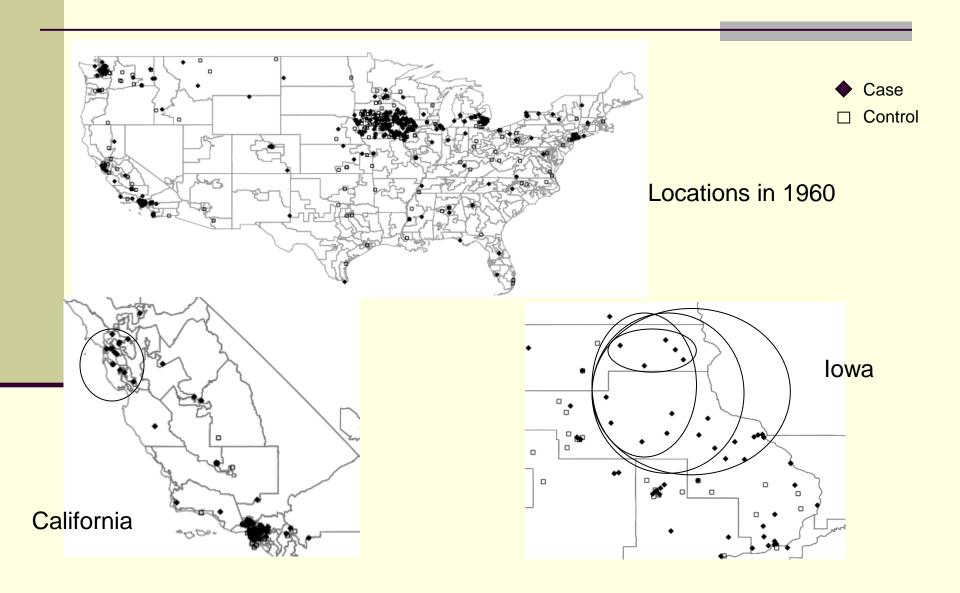
		Number of Cases	Cluster Sizeª	Cluster Density <sup>b</sup>	Case Mobility <sup>e</sup>
US Case-Control	1000 residential histories				
Dataset, Clusters		5	1.0%	100%	99%
Created in 1960	Torre	12	2.4%	100%	90%
	Iowa	18	3.6%	95%	83%
		27	5.4%	90%	84%
	California	43	8.6%	63%	47%
	2378 residential histories				
		6	0.3%	75%	87%
	Torre	14	0.6%	70 <b>%</b>	80%
	Iowa	23	1.0%	66%	84%
		33	1.4%	69%	78%
Danish Case-	6594 residential histories				
Control Dataset,		11	0.3%	89%	50%
Clusters Created		41	1.1%	84%	74%
in 1971		90	2.6%	82%	70%
		127	3.7%	81%	80%

<sup>\*</sup>Cluster Size: Percent of cases in cluster out of total number of cases in study

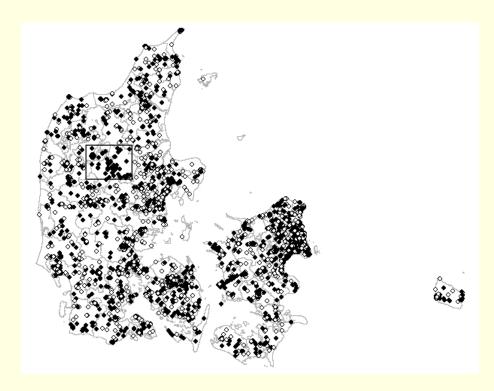
<sup>&</sup>lt;sup>b</sup>Cluster Density: Percent of cases in cluster region out of total number of cases and controls in cluster region from 1960-1975 in US dataset, 1971-1980 in Danish dataset.

Case Mobility: Percent of person-years of cases in cluster region out of maximum possible person-years from 1960-1975 in US dataset, 1971-1980 in Danish dataset

## US Cluster Regions



## Danish Cluster Region



Locations in 1971

### Results - Summary

- Using k=5, 10, 15 (and 20)
- Global Q<sub>k</sub>: significant (p=0.05) for only 1 of the 31 analyses of simulated clusters
- Local Q<sub>ikt</sub>: significant (p=0.01 or smaller) even for very small clusters, but unable to differentiate true clusters from false positives
- Global Q<sub>kt</sub>: time-slice global; also conservative like Q<sub>k</sub>
- Local Q<sub>ik</sub>: best able to identify true clusters and differentiate them from false positives.
- Combining Q<sub>ik</sub> and Q<sub>ikt</sub> showed best performance

# Local Clusters Significant for both $Q_{ik}$ (p=0.001) and $Q_{ikt}$ (p=0.05)

	Cluster Region	Number of Cases in Cluster	No. of Nearest Neighbors	True Positivesª	False Positives <sup>b</sup>	Max. Size of False Positive Cluster
US Case- Control Dataset	Iowa, 500 cases, 500 controls	N=0 (purely random)	k=5 k=10 k=15	N/A N/A N/A	0 1 0	0 1 0
		N=5	k=5 k=10 k=15	0 0 0	2 1 1	1 1 1
Cal	if almatar.	N=12	k=5 k=10 k=15	0 0 0	0 1 0	0 1 0
Calif cluster: Greater size, lower density,		N=18	k=5 k=10 k=15	1 5 2	0 0 0	0 0 0
lower mobility	rer mobility	N=27	k=5 k=10 k=15 K=20	11 16 11 0	0 0 1 0	0 0 1 0
	California, 500 cases, 500 controls	N=43	k=5 k=10 k=15	0 2 0	0 1 0	0 1 0
	California + Iowa, 500 cases, 500 controls	N=43 in Cal. N=27 in Iowa	k=10	6, in both Iowa and Cal. cluster regions	0	0

Each row presents results of one suite of Q-statistic analyses.

# Local Clusters Significant for both $Q_{ik}$ (p=0.001) and $Q_{ikt}$ (p=0.05) Cont'd

	_				
Cluster Region	Number of Cases in Cluster	No. of Nearest Neighbors	True Positivesª	False Positives <sup>b</sup>	Max. Size of False Positive Cluster
Iowa, 1189 cases, 1189 controls	N=0 (purely random)	k=5 k=10 k=15	N/A N/A N/A	2 1 0	1 1 0
	N=5	k=5 k=10 k=15	0 0 0	3 4 4	2 2 1
	N=12	k=5 k=10 k=15	0 0 0	2 2 3	1 1 2
	N=18	k=5 k=10 k=15	3 2 1	2 2 3	2 2 2
	N=27	k=5 k=10 k=15	3 3 2	2 3 3	2 2 2

Did not perform as well differentiating clusters of smaller density from false positives.

Fairly consistent across choice of k-nearest neighbors.

Maximum size of false cluster never exceeds 2 individuals.

# Local Clusters Significant for both $Q_{ik}$ (p=0.001) and $Q_{ikt}$ (p=0.05) Cont'd

	Cluster Region	Number of Cases in Cluster	No. of Nearest Neighbors	True Positivesª	False Positives <sup>b</sup>	Max. Size of False Positive Cluster⁴
Danish Case- Control dataset	Viborg, Denmark, 3297 cases, 3297 controls	N=0 (purely random)	k=5 k=10 k=15 k=20	N/A N/A N/A N/A	0 0 1 2	0 0 1 1
		N=11	k=5 k=10 k=15 k=20	0 0 0 0	0 0 0 0	0 0 0 0
		N=41	k=5 k=10 k=15 k=20	0 2 3 5	0 0 0 2	0 0 0 1
		N=90	k=5 k=10 k=15 k=20	1 2 10 11	0 1 0 3	0 1 0 1
		N=127	k=5 k=10 k=15 k=20	5 6 22 32	0 0 1 4	0 0 1 1

Performs better for larger clusters (but still not that large: size ~2-4%!). Some differences across choice of k-nearest neighbors.

### Supplementary Analyses

We ran FDR p-value adjustment on two of the simulated clusters (only 2 because timeconsuming), using 9999 randomizations to create reference distribution

Cluster Region	Number of Cases in Cluster	No. of Nearest Neighbors	True Positives*	False Positives <sup>b</sup>	Max. Size of False Positive Cluster <sup>c</sup>
Iowa, 500	N=18	k=10	5	0	0
cases, 500	FDR results		0	0	0
controls	N=27	k=10	16	0	0
	FDR results		5	0	0

Suggests FDR is more conservative than combined Q<sub>ik</sub>, Q<sub>ikt</sub> approach.

#### Conclusions

- These are the first simulation analyses of Q-statistics and provide several insights into their performance:
  - Ability to detect cluster is sensitive to # of cases, cluster size, density, and population mobility
  - Global Q<sub>k</sub> is conservative, unable to detect localized clusters
  - Local Q<sub>ik</sub> and Q<sub>ikt</sub> were able to identify strong true clusters, occasionally without false positives, using a critical value for Q<sub>ik</sub> of p=0.001 and examining Q<sub>ikt</sub> (p≤0.05) only among those individual cases significant for Q<sub>ik</sub>.
  - Choice of k not critical for these ranges of cluster characteristics

#### Conclusions cont'd

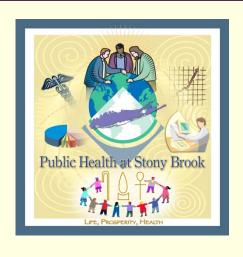
- Recommendation from these limited simulations:
  - Begin analyses using k=10 or k=15 neighbors
  - A cluster of three significant (Q<sub>ik</sub>, Q<sub>ikt</sub>) individuals or larger can be called a true positive and is a good starting point for follow-up studies
    - Only useful for distinguishing dense, large, low mobility clusters
    - Misses smaller, lower density, less persistent clusters
    - At this stage in development of Q-statistics, we feel this is an acceptable compromise since it limits inquiry into false positives, thereby conserving limited resources for more thorough investigations of true clusters
    - Are implementing this rule set with these (nonsimulated) datasets

#### Future Work

- Generalizability uncertain: differences such as edge effects, population density, mobility patterns, case-control ratio, and cluster shape, size, and density
- At this juncture, we recommend user conducts similar sets of simulation analyses on each dataset to determine the best criteria (p-values, number of k nearest neighbors) for identifying true positive clusters
  - In time we hope a consistent rule set will emerge
  - Alternatively, could explore wide library of potential clusters, datasets, and geographies to derive more empirical ruleset(s) and sensitivity to cluster characteristics; this would take a very long time.
- Comparing results of Q-statistics with other recently developed methods for mobile populations (Sabel et al., 2009; Webster et al., 2006) is also important

### Thank you!

## Contact details: jrmeliker@gmail.com





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