Incorporating data on residential history for disease mapping

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I. Motivation

Background

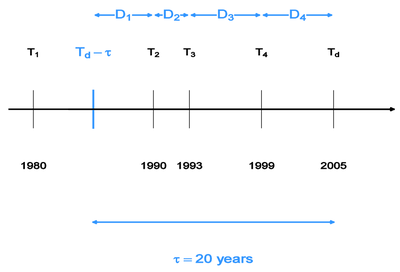
- Based on case location, disease mapping estimates a risk of disease across a geographic region
- Location at diagnosis does not necessarily correspond to location at exposure
- Some disease have long latency periods (e.g. leukemia, mesothelioma)
- Time, duration and location of exposure are unknown
- Residential history has already been incorporated in tests for cluster detection [1,3]

Questions

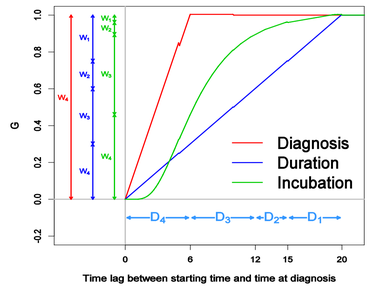
- How can residential history be incorporated in disease mapping?
- Can location at exposure be identified more accurately?

II. Methods

a. Example of data (4 locations)



b. Creating Weights: $W_k = G(D_k)$



c. Adapt distance-based mapping (DBM) [2]

- **Disease mapping**: compares an observed CDF F to an expected F_0 across a 2-dimensional study region
- **DBM** consists of four steps:
  1. Project the data to one dimension: Observed distribution of distances to one chosen fixed point (F_i)
  2. Compare the observed distribution to that expected under the null (F_{0i})
  3. Repeat 1 and 2 for a selection of fixed points (i =1,...,N)
  4. Average the measure across projections to compute a risk-like score at each point in the region
- **DBM adapted to residential history**: replace F_i and F_{0i} by averaged sums $\Sigma W_k F_{ik}$ and $\Sigma W_{0k} F_{0ik}$ respectively

d. Simulations

- Expected spatial distribution (F_0) : Uniform in unit square
- Observed spatial distribution (F): Increased risk in small circle
- Strength: q% cases have one location in circle (Multinomial, incubation weights)

e. Evaluation

- Estimate DBM scores across region
- Resolution = 50x50 grid points
- Dichotomize scores according to threshold *

(*) Threshold: we draw 100 sample of size 100 including a randomly located cluster of 10 points. Cluster radius is uniformly selected from (0.05,0.3). For each sample and a range of threholds, we select the one that minimizes the distance between the points (1,0) and (sensitivity,1-specificity). The median threshold across all 100 simulations is then selected for all remaining simulations.

Number of grid points	With a high score	With a low score
In cluster region	a	b
Not in cluster region	c	d

Sensitivity = a/(a+b) Specificity = d/(c+d)

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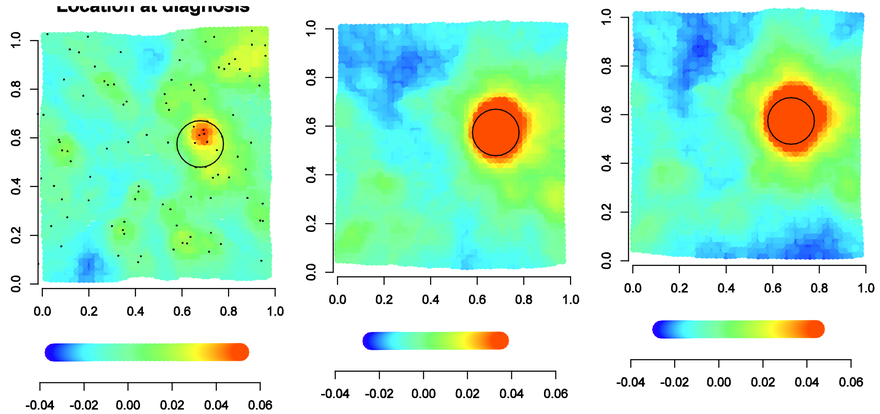
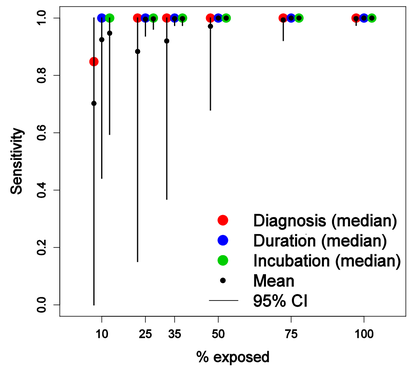
III. Results

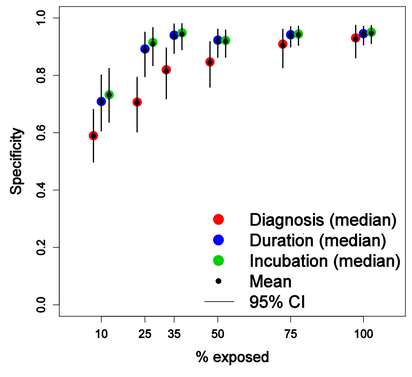
a. Illustration with 1 simulation (q=50%)



- The higher risk circle is identified more accurately by mapping using duration or incubation weights, rather than by mapping using only location at diagnosis
- The color cutoffs are determined by resampling from the reference population F_0

b. Evaluation of 1000 simulations





- Mapping using duration weights rather than only location at diagnosis improves sensitivity and specificity
- Mapping using incubation rather than duration weights improves sensitivity and specificity mostly when less than 50% cases are exposed
- Sensitivity and specificity tend to increase as the percentage of exposed cases increases

IV. Conclusion

- Disease mapping can incorporate residential history of cases by using a weighting scheme
- The accuracy at locating an increased risk improves by mapping with duration or incubation weights rather than mapping with location at diagnosis only
- There are other choices for the function G:
  - Step function
  - Weight all locations of a case equally
  - Include (time varying) covariates
- A similar method can be developed when cases are available with multiple daily locations (home/work/school) along with the proportion of the day spent at each location
- In future work, we can relax some limitations in the methods (missing spatial information) and simulations (non-uniform population, atemporal dichotomized risk)

References

1. Jacquez GM, Kaufmann A , Meliker , Goovaerts P , AvRuskin G , and Nriagu J. “Global, local and focused geographic clustering for case-control data with residential histories.” *Environmental Health: A Global Access Science Source* (BioMed Central Ltd) 4, no. 1 (2005): 4.
2. Jeffery C, Ozonoff A, White LF, and Pagano M. “Locating spatial clusters in a surveillance setting.” *Submitted.*
3. Manjourides J, and Pagano M. “Improving the power of chronic disease surveillance by incorporating residential history.” *Submitted.*