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Advances in spatial and space-time modelling: Example of bladder cancer in Utah

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Background

Disease mapping is used to investigate the geographical distribution of disease and uncover sources of heterogeneity that may identify underlying environmental risk factors. A traditional approach to disease mapping is to use the standardised mortality/morbidity rate (SMR). For rare diseases and/or small areas (and hence small population at risk) the SMR may be very unstable (high variability). To overcome this excess variability it is common practice to stabilise the relative risk estimates using a Bayesian hierarchical model (BHM), to give relative risk estimates which are smoothed i.e. towards a combination of local and global means, compared to the SMRs.

The data are usually aggregated over time. Recent methodological advances in space-time analyses have investigated the persistence of patterns over time. Unusual space-time patterns may highlight localised clusters that could be linked to underlying environmental risk factors.

Case study: Spatio-temporal analysis of bladder cancer in Utah, 1973-2004

To illustrate the use of BHM spatial and space-time models, we carried out a spatio-temporal analysis of the variation of bladder cancer incidence in Utah for the period 1973-2004, at the census tract level. This project is a part of a collaboration with the Centers for Disease Control and Prevention (CDC) in the US, within a framework of the US Environmental Public Health Tracking Program (EPHTP).

Methods

Pure spatial models

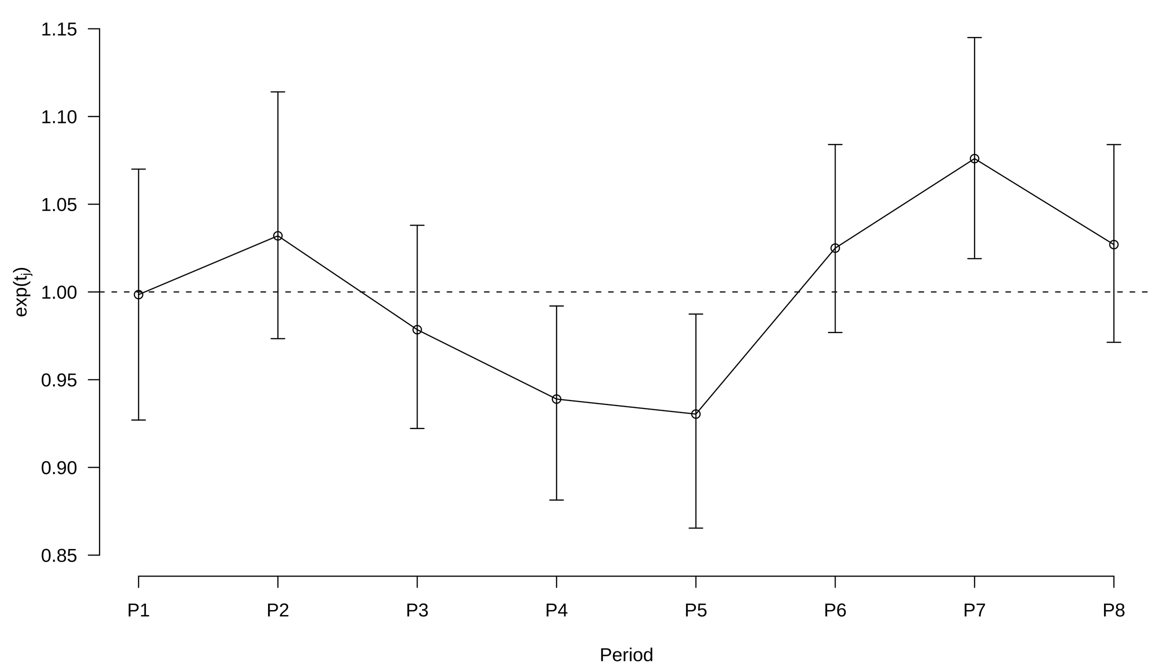
At the first stage of the BHM, a Poisson distribution is used to allow for the variability due to rare events: $O_i \sim \text{Poisson}(E_i \rho_i)$, where O_i is the observed number of cases for area i, E_i is the expected number of cases and ρ_i is the unknown relative risk in area i to be estimated.

At the next stage of the model, the variability of the log relative risks, $\log(\rho_i)$ is modelled using a spatially structured (conditional autoregressive) model and, additionally, including unstructured heterogeneity (Besag et al, 1991), which allows the necessary borrowing of information between areas to stabilise the relative risk estimates (Best et al, 2005).

Spatio-temporal models

We propose a new model that uses spatial and temporal autoregressive structures together with a 2-component mixture model for possible space-time interactions (Abellán et al, 2008). The first component is designed to shrink idiosyncratic noise whereas the second component captures important departures from the space and time main effects, thus highlighting possible space-time clusters.

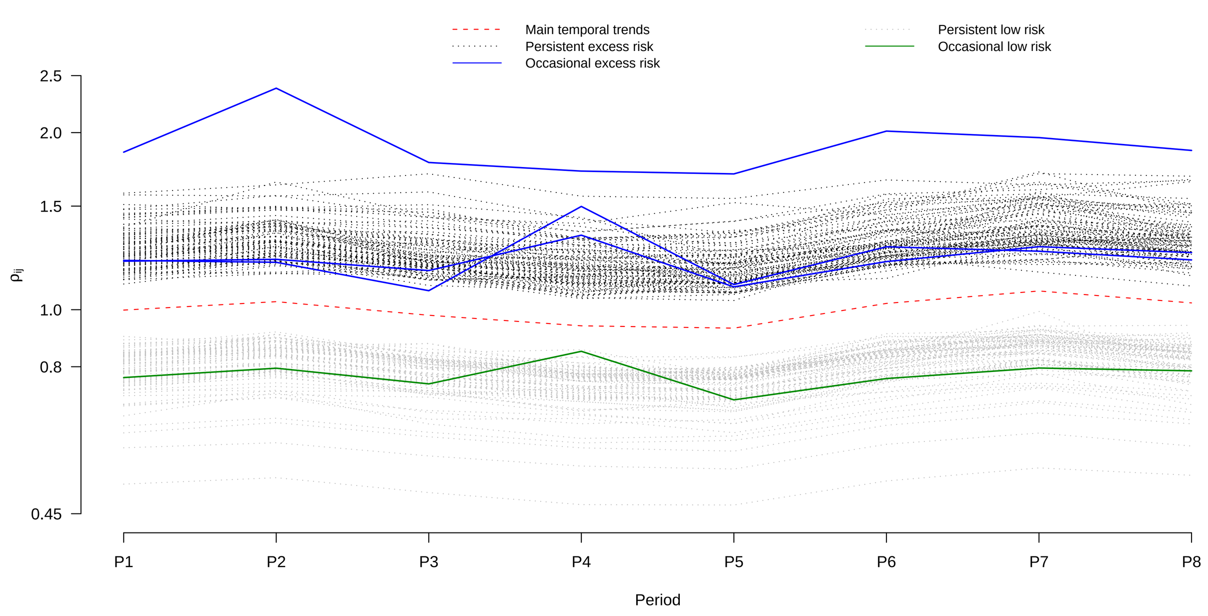
Smoothed temporal trends by period



We observe a slow but continuous decrease of risk of bladder cancer between the periods 1977-80 (P2) and 1989-92 (P5), followed by a steep increase in the period 1997-2000 (P7).

Stable versus unusual patterns

Thirteen areas were detected as having an "unusual" temporal trend that could warrant further investigation. We found 93 areas with sustained increased risk (black lines in the figure) and 81 with sustained low risk (grey lines); the temporal trend for Utah as a whole is shown by the red line. Additionally, three high risk areas (blue) and one low risk area (green) had unusual temporal patterns.

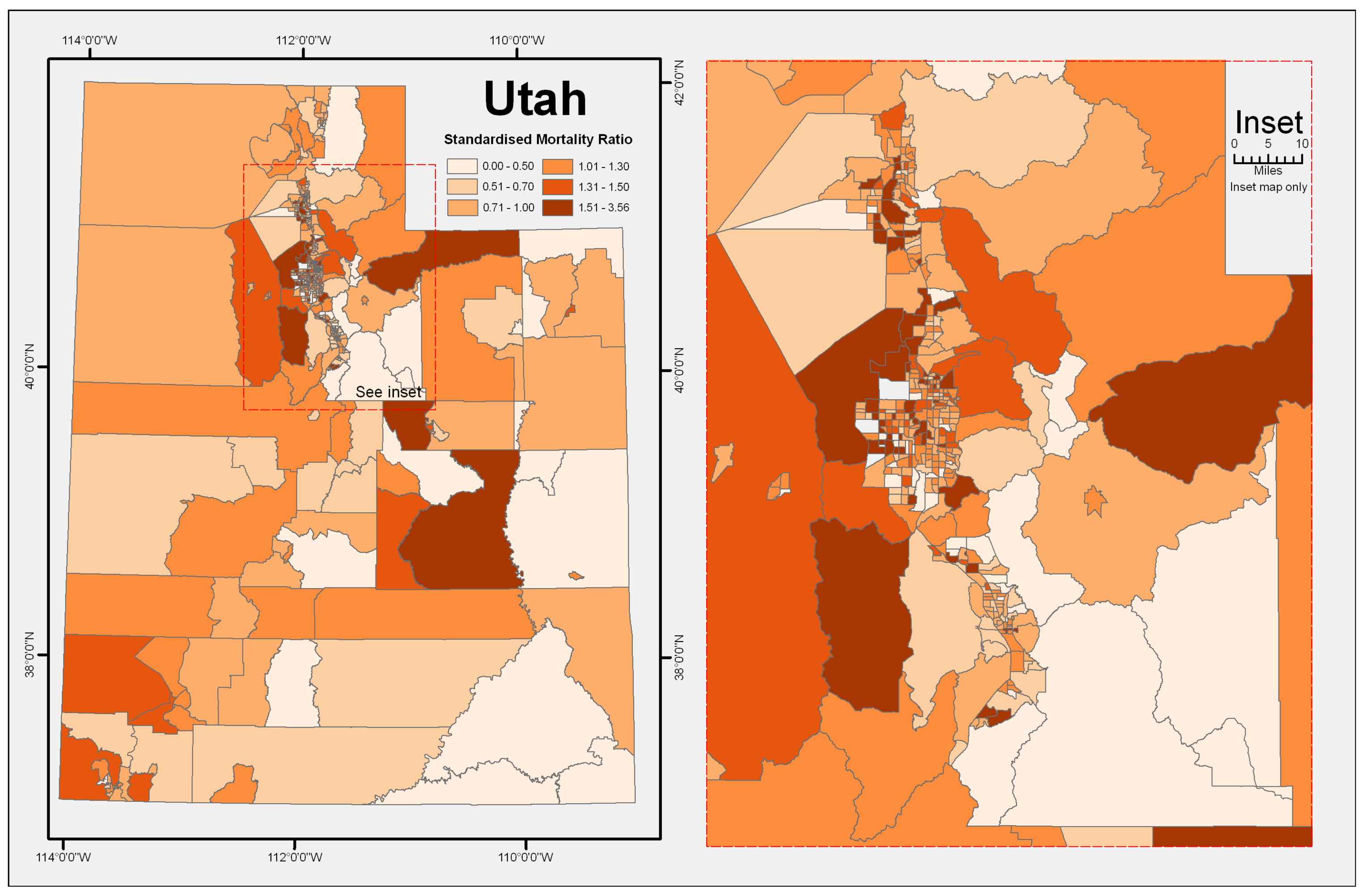


Environmental exposures

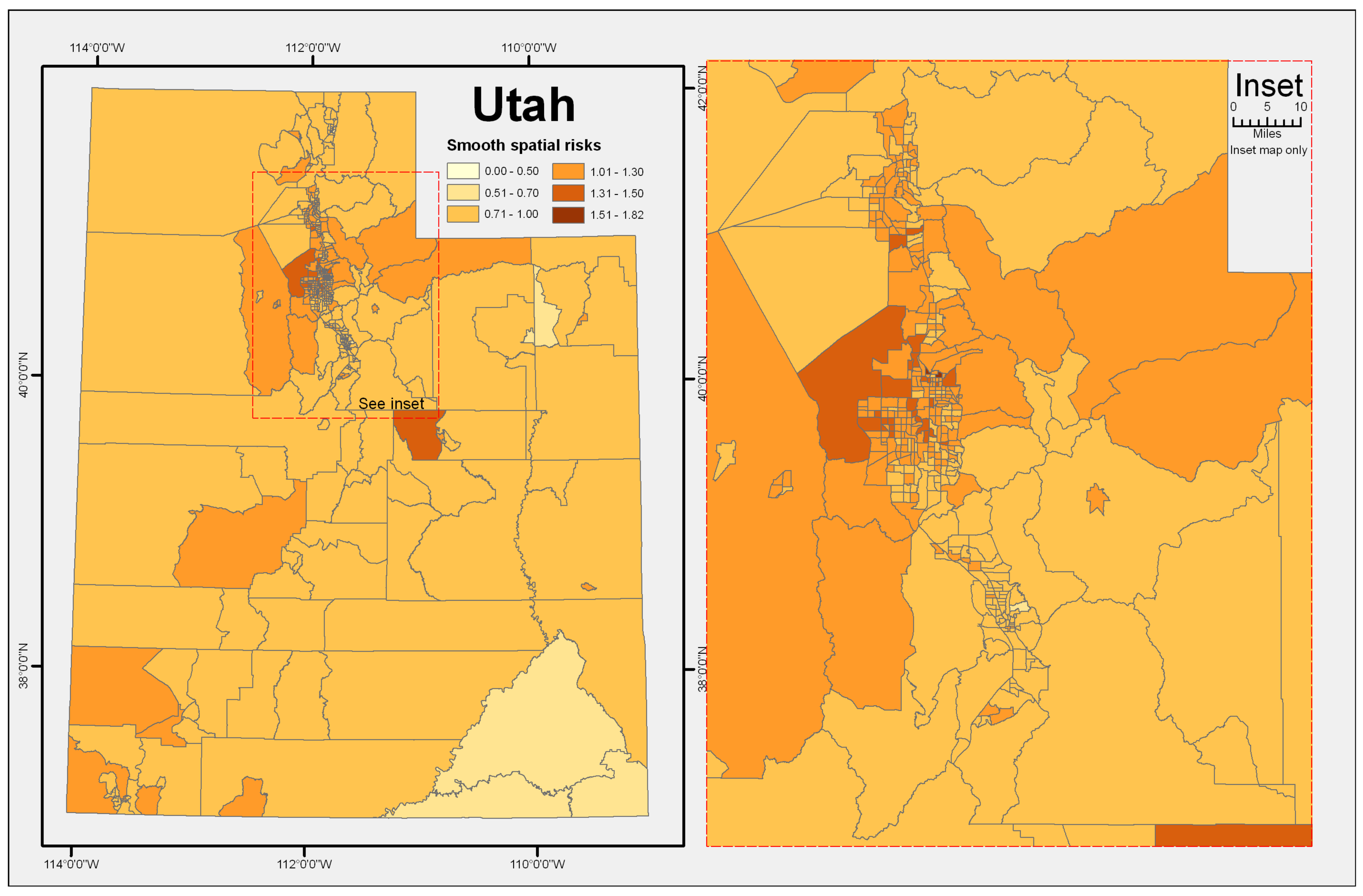
Areas with a high/low stable spatial risk were used to perform a "geographical" case-control study in order to assess the relationship between bladder cancer risk and the presence of Toxic Release Inventory (TRI) sites in Utah. The odds ratio was 7.46 (p-value=0.038), suggesting possible environmental effects of TRI sites, requiring further investigation.

	TRI sites		
	Absence	Presence	Total
Stable census tracts			
Low spatial risk	80	1	81
High spatial risk	85	8	93
Total	165	9	174

Crude SMR by census tract

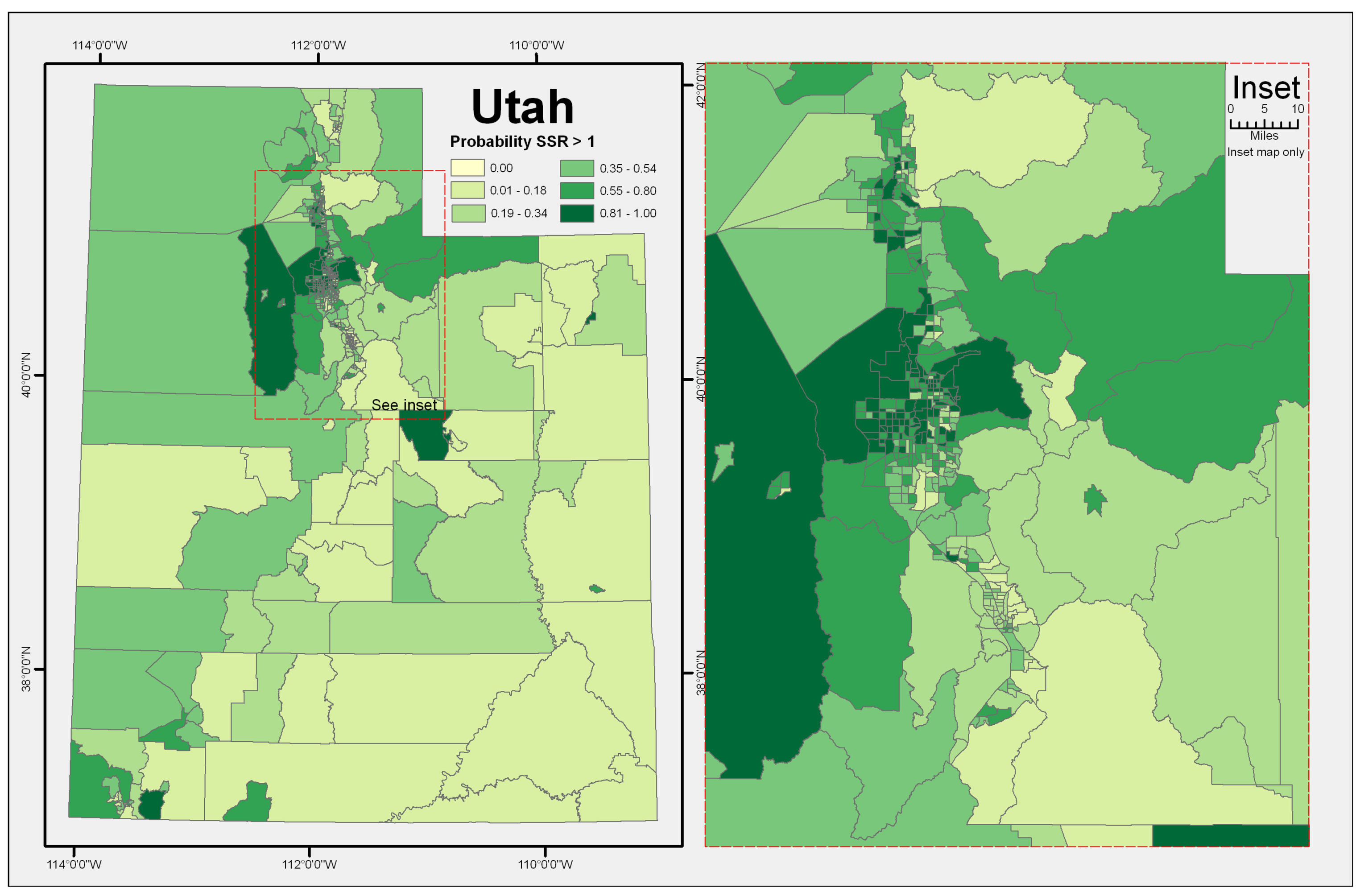


Smoothed spatial risks by census tract



The map of the estimated spatial risks (main effects of the space-time model), shows evidence of spatial heterogeneity with higher risks in central areas around Salt Lake city.

Probability that the smoothed spatial risks exceed 1.0



96 out of the 496 areas have high probability (i.e. above 0.8) that the spatial risk is above 1 (Richardson et al, 2004).

Conclusion

Recent advances in Bayesian hierarchical analyses have been used to investigated the spatial and spatio-temporal variations in disease. When accompanied with suitable decision rules focussed on highlighting specific patterns (e.g. high/low risk, space time clusters), these models provide a powerful new approach for investigation of risks of diseases associated with environmental exposure.

References

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