Modelling spatial dependence in grizzly bear health and environmental data in the Alberta Rocky Foothills.

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1. Introduction

The Rocky Mountain Foothills in Alberta, Canada, form part of the eastern fringe of the grizzly bear (*ursus arctos)* range in North America (McLellan 1998). A recent study of the grizzly bear population in Alberta estimates that fewer than 500 remain (Henton 2007). With increasing land use change, there is concern that this long-term stress will lead to the extirpation of the Alberta population.

In response, the Foothills Research Institute (FRI) was initiated in 1999 to provide scientific knowledge and planning tools to ensure the preservation of grizzly bears in Alberta (FRI n.d.). To support this goal, data has been collected regarding their location and health, as well as environmental conditions. One aim of the FRI is to use this data to increase understanding of how health is affected by environmental conditions and stress (FRI n.d.). However, the development of statistical models is challenging due to observation dependence caused by the spatial proximity and overlap of grizzly bear home ranges.

1.1 Research Objective

This paper investigates spatial dependence caused by the proximity and overlap of grizzly bear home ranges. Spatial dependence is the occurrence of similar attribute values in locations “close” to each other, which effectively reduces the number of independent samples (Anselin and Bera 1998). Ignoring this in statistical tests and estimation can reduce the reliability of inference (Anselin and Bera 1998). A model of spatial dependence can be used to improve inferences and indicate processes that cause the observed spatial dependence (Miron 1984).

In modelling spatial dependence, it is necessary to define which pairs of observations are 'nearby' or neighbours. This research thus develops a variety of spatial neighbourhoods to use for testing spatial dependence. Once the structure of spatial dependence is modelled it can be used as a spatial weights matrix in a spatial model of grizzly bear health.

2. Data and Methods

2.1 Grizzly bear location and home range

Grizzly bear locations were acquired using GPS radio collars which were attached to bears annually from 1999. Collars provide locations every 4 hours or less.

GPS locations are used to compute an annual home range for each bear. The home range is "… that area traversed by the individual in its normal activities of food gathering, mating, and caring for young," (Burt 1943).

Abode v.4 (Laver 2005), is used to compute home ranges based on a working definition of home range given by Worton (1995), "the probability of an animal occurring in the area." A kernel density estimator (Silverman 1986) estimates a density-of-use surface based on the observed locations within a moving window. The width of the window is selected using Least Squares Cross Validation as proposed by Bowman (1984).

In this research the core areas of the home ranges are used as the units of analysis. Core areas can highlight patches of high resource concentration (Powell 2000) and differences in resource use within the home range (Harris et al. 1990). Also, while home ranges can overlap considerably, core areas tend to overlap less or not at all. The core area is delineated using a method suggested by Powell (2000) which essentially identifies clusters of high density-of-use within the home range.

2.2 Indicators of health

The FRI provided 9 variables of grizzly bear health as well as reproductive class, date of capture and capture method. Individually, these variables do not indicate good health, rather health is dependent on the level of biological functioning with respect to stress, growth, reproduction, immunity and movement (Cattet, Vijayan and Janz 2007). This study focuses on growth, immunity and stress.

To relate individual health variables to an overall score for Growth, Immunity and Stress it is first necessary to map each variable to a value between 1 (good) and 0 (poor) based on subjective expert knowledge. A sinusoidal function is used to transform original values to a score between 0 and 1 which indicates the degree of membership to the group, "good", and accounts for uncertainty in membership criteria and measurement precision. This approach is based on Fuzzy Sets where membership to a set can fall on a continuum between 0 and 1 as determined by a membership function (Zadeh 1965).

The normalized variables are then conflated into a single value for Growth, Immunity and Stress by weighted summation. The weights are obtained from expert opinion through the application of the Analytical Hierarchical Process (Saaty 2005). The same process is used to conflate Growth, Immunity and Stress into a single score for Health.

2.3 Environmental variables

Environmental datasets relating to vegetation, land cover, land use, topography, water, and human features are used. Each environmental variable is summarized within the core areas either as a weighted average or weighted proportion of the core area. Weights are obtained from the home range kernel density surface.

2.4 Spatial neighbourhoods and dependence

Once the variables are computed for each core area, spatial neighbourhoods are developed. For N observations, there are N^2 possible interactions, which can be represented in an N x N matrix. Each element represents the strength of covariance between a pair of observations.

In this research, neighbourhoods explored include those defined by distance relationships, topological relationships and overlapping core areas.

When constructing distance and topological neighbourhoods, a central point of the analysis unit must be defined. In this research various centre points are investigated, including geometric, harmonic, and centre-of-minimum-distance centroids, as well as the point of maximum density-of-use.

For distance neighbours, covariance between neighbours is a function of the distance between them. Distance neighbourhoods can be defined in a binary fashion or by a distance decay function. The covariogram, Moran's I correlogram and a marked correlation function based on Ripley's K (Ripley 1976) are used to explore the relationship between covariance and distance (Haining 2003, Fortin and Dale 2005).

Typically distance is measured as Euclidean distance; however, this does not reflect how bears traverse across the landscape. Thus distance is also measured as the route a grizzly bear is likely to follow, taken as the least cost path between two points. In some cases, observations which were previously considered neighbours will become separated by high-cost (impassable) features such as mountainous ridges.

Neighbours can also be defined topologically using connectivity network algorithms. Fortin and Dale (2005) describe methods to create a hierarchical set of graphs. In a graph, edges connect pairs of observations based on topological rules. The simplest graph consists of mutual nearest neighbours while the highest level graph with the most connections is a Delaunay network.

The last neighbourhood structure to be explored is one where the strength of covariance is measured by the proportion of overlap between core areas. However, this prevents the inclusion of nearby but non-overlapping core areas; hence a combined distance decay and proportion overlap neighbourhood is also defined.

The neighbourhood structures described above are shown conceptually in fig. 1 below.

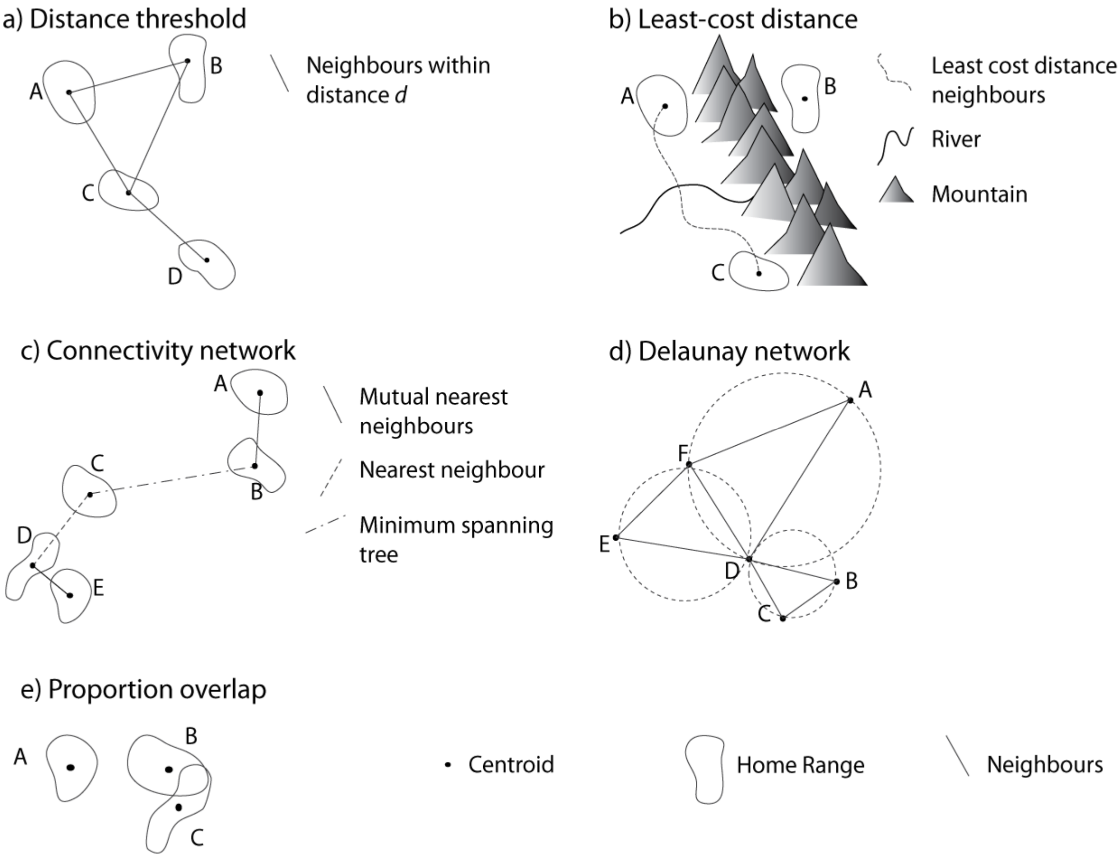

Figure 1. Neighbourhood configurations.

Once various neighbourhood matrixes are constructed, variables are tested for global spatial autocorrelation using Moran's I (Moran, 1950), Geary's C (Geary, 1954) and general Getis-Ord G (Getis and Ord 1992).

Local spatial autocorrelation is also tested using local Moran's I (Anselin 1995) and local Getis-Ord G_i^* (Ord and Getis 1995).

3. Results and Discussion

It can be assumed that the environmental characteristics of nearby or overlapping home ranges will be similar. In this dataset many home ranges are in close proximity of each other or overlapping, thus it is reasonable to anticipate that spatial autocorrelation will be found in the explanatory environmental variables. It is expected that neighbourhoods defined by a least-cost distance decay function and proportion overlap of home ranges will be most effective in detecting and modelling spatial autocorrelation as these are the most meaningful neighbourhood descriptions. It remains to be seen whether correlation in the explanatory variables will cause dependence in the health variable. If the hypothesis that environmental factors have a significant effect on grizzly bear health is true, then we would also expect to see spatial dependence in health, assuming that relevant variables have been measured at an appropriate scale. Also, if genetics has an influence on the health status of bears and, if related bears tend to occupy home ranges close to each other, this may also induce spatial dependence in the health variable. Thus discovered spatial structures may be an indicator of genetic dependencies.

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