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Spatial-Temporal Analysis of Marine Wildlife

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ABSTRACT

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The growth of marine monitoring programs and improved ease of spatial data collection has increased the availability of fine-scale marine data sets which can be combined with advanced spatial analysis and GIS to address innovative research questions. Analysis of both space and time is often required, but few spatial-temporal analysis methods are available. Here we demonstrate combining an advanced spatial analysis approach, kernel density estimation, with a novel temporal analysis method, the space time string, to quantify spatial-temporal patterns in marine wildlife. Using a data set on gray whale (*Eschrichtius robustus*) foraging from Clayoquot Sound, British Columbia, Canada, we identify spatial-temporal trends in foraging and relate them to prey population dynamics. Results suggest two types of between year spatial-temporal patterns: prey in equilibrium and severe disturbance. By demonstrating the theory, implementation, and interpretation of advanced methods, we provide marine researchers with approaches applicable to a variety of research questions.

ADITIONAL INDEX WORDS: *gray whale, spatial-temporal patterns, spatial analysis*

INTRODUCTION

Spatially and temporally extensive wildlife data sets are becoming increasingly common due to developments in global positioning systems (GPS), remote sensing, and geographic information systems (GIS). In response to these large data sets, and aided by advancing technology, spatial analysts and geographic information scientists have developed local and exploratory spatial analysis techniques.

The interest in applying geographically local methods to large spatial data sets is growing. Local methods can be conceptualized in contrast to traditional global measures, which assume stationarity, or that the nature of a spatial process is independent of location (Bailey and Gatrell, 1995). However, when data sets are large the assumption of stationarity is typically invalid. Local methods are necessary to identify spatial variation in pattern and provide a mechanism for identifying locations, within a region, where the pattern is anomalous (Boots, 2002). While the development of local approaches has been a fundamental response to the increasing spatial extents of data sets, few spatial-temporal methods currently exist, regardless of whether they are local or global.

A second response to large data sets has been the development of exploratory data analysis methods. The term exploratory data analysis is used here to refer to techniques that enable an analyst to describe data, develop hypotheses, and identify outliers (Bailey and Gatrell, 1995). Visualization is a particularly powerful approach to exploratory analysis (Fotheringham, 1999; Gahegan, 2000), but few multivariate visualization tools produce results that are mappable (*e.g.*, Fotheringham et al., 2000; Meliker et al., 2005). There is a need to marry improvements in local spatial analysis with developments in multivariate visualization in order to address spatial-temporal questions using data sets that are extensive in both space and time.

Spatial analysis has permeated terrestrial studies of wildlife and ecology (Fortin and Dale, 2005) However, application of spatial analysis to marine mammal studies has been more limited (Nelson et al, 2008). This is likely related to the fact that large spatial marine mammal data sets have only recently become available, yet technological improvements are likely to lead to an increase in the spatial and temporal extents of marine mammal data. The analysis of spatial-temporal data should provide new insights into fine spatial-scale marine processes such as predator-prey dynamics.

In gray whale (*Eschrichtius robustus*) research there has been an implicit assumption that prey and predator densities function in a dynamic equilibrium, or balanced system. Whales feed until prey are below some threshold, and move to a new area while prey replenish, with the whales returning once prey populations have increased beyond some threshold. The underlying processes of predator-prey interaction should therefore be reflected in the

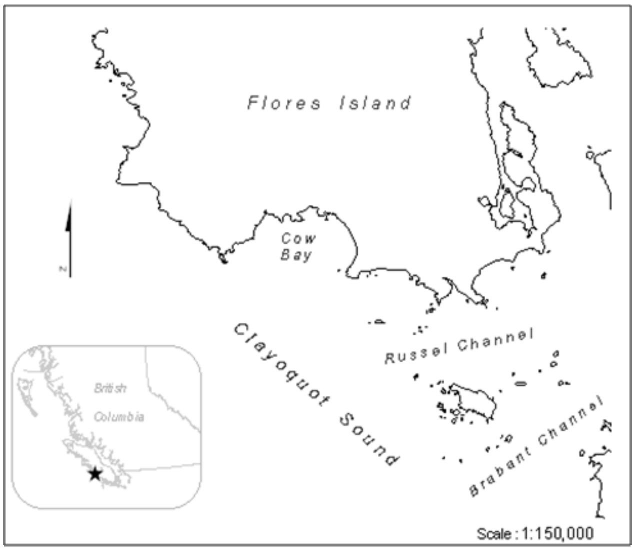

Figure 1. Study area: Flores Island, Clayoquot Sound, British Columbia, Canada.

spatial-temporal patterns of foraging (DUNHAM and DUFFUS, 2001; 2002).

Our goal is to demonstrate an approach to characterizing the temporal persistence or variability in spatial pattern of marine mammal presence and absence and gain a better understanding of gray whale population dynamics. Our approach is applied to nine years of data on the location of foraging gray whales off the west coast of Vancouver Island, British Columbia. We hypothesize that within the study area there are differing spatial-temporal patterns. To explore this hypothesis we define annual foraging ranges from 1997 to 2005 using kernel density estimation. Next, we apply a method, which we call the Space Time String (STS), to quantify temporal trends in the spatial pattern of foraging at each location (grid cell) within our study region. Space time patterns are then explored for regions within the study area.

STUDY AREA AND DATA

Data were collected off the southwest coast of Flores Island, Clayoquot Sound, British Columbia (Figure 1), and for this study included three regions. The region we refer to as the entire study area included locations where foraging was observed in at least one year and is 30 km^2 (defined by the foraging range described below). Over the 9 years of whale foraging surveys, 53.13% of whales have been observed within 250m of the 10m bathymetric contour. To determine if there was spatial variation in the temporal variability of foraging range persistence, we applied a 250m radius buffer to the 10m bathymetric contour. The area within the buffer was designated as the core foraging area (8.3km^2). Locations outside the core that were observed as foraging range in at least one time period were considered the periphery (21.7km^2).

Whale foraging surveys were conducted between May 24th and September 8th, 1997 to 2005. Surveys were visual and were typically completed every four to five days in order to create a representative sample of annual summer foraging whale locations.

METHODS

Identifying Home Range

The definition of foraging range is based on the concept of animal home range, defined as the smallest sub-region which accounts for a specified portion of the total area used by an animal (JENNRICH and TURNER, 1969). In our study, data points indicate the location of foraging whales, and therefore by applying home range methods we are actually detecting foraging range.

Kernel density estimates were used to define annual foraging ranges as they are commonly used to characterize wildlife home ranges (e.g., WORTON, 1989; WORTON, 1995; SEAMAN and POWELL, 1996; POTVIN et al., 2003; RIGHTON and MILLS, 2006; SHI et al., 2006). When wildlife locations are identified as points, kernel density estimation can be used to convert data to a continuous intensity surface. Kernel density estimators provide a quantitative description of the amount of time animals spend at a particular location (SEAMAN and POWELL, 1996).

Conceptually, the intensity $\lambda(z)$ at a particular location z in a study area can be estimated by the naïve kernel estimator

$$\hat{\lambda}(z) = \frac{\text{number of events in a disk centered on } z}{\text{area of the disk}} \qquad (1)$$

The amount of smoothing controlled the radius disk (KELSALL and DIGGLE, 1995). The disk radius was determined using the least-squares cross-validation method. Disk radii selected via the least-squares cross-validation method are appropriate when using the 95th percentile of a kernel density estimated surface for identifying animal home range (WORTON, 1995; SEAMAN and POWELL, 1996; RIGHTON and MILLS, 2006; SHI et al., 2006). Suggested annual disk values ranged from 180 m to 330 m. When comparing multiple kernel surfaces, there is benefit to using a consistent disk radius; therefore, the median value, 230 m, was used for all kernel density estimation. Kernel density estimates were stored in grid cells of 25 m by 25 m.

Quantifying Spatial-Temporal Trends

The STS method was used to characterize temporal trends in the presence of foraging (range) for each grid cell. Grid cells were given a value of 1 if they were part of an annual foraging range and a value of zero if they were not. For each grid cell a one-dimensional string may be used to record the foraging pattern state through time. Given we have nine time periods (years) of whale foraging observations, a STS has nine digits of 1s and 0s. The first digit in the string represents the state of the spatial pattern signal in 1997 and the last digit denotes the state in 2005. For instance, a STS of 100001001 indicates that a location was part of the gray whale foraging range in 1997, 2002, and 2005.

STS properties provide a mechanism for quantifying the temporal variability or persistence of a spatial pattern over many time periods. The STS properties we found most useful for understanding the temporal persistence and variability in the inter-annual spatial distribution of foraging gray whales from 1997 to 2005 included: the total number of years a cell was part of the foraging range; the maximum number of consecutive foraging range years; and the maximum number of consecutive non-foraging range years. STS properties were computed and explored through mapping and by comparing relative frequency distributions of STS properties over the entire study, in the core, and in the periphery. We were then able to consider the resulting STS properties in the context of what is known, or theorized, concerning gray whale prey-predator interactions.

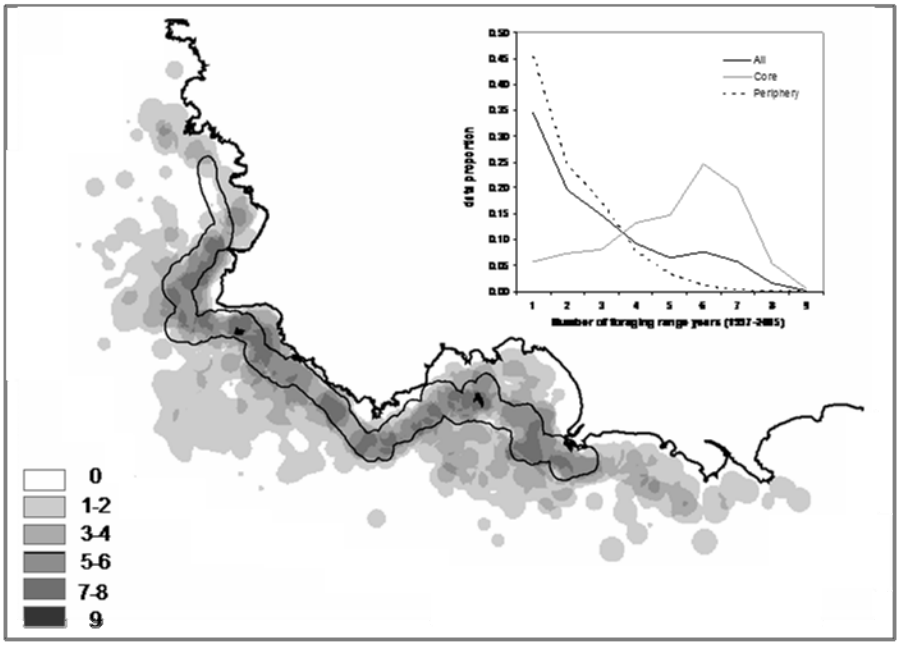

Figure 2. The number of foraging range years.

RESULTS

The number of foraging range years and relative frequency distributions for the entire area, the core, and the periphery are shown in Figure 2. The map of the number of foraging range years indicates that there are few locations that temporally persist as part of the foraging range. In contrast, a large portion of the study area is part of a foraging range over few time periods. The frequency distributions (Figure 2) clearly indicate that the temporal persistence in foraging range locations varies between the core and periphery. In the periphery, the likelihood of a location being a foraging range only once is high (45.6%) while in the core this is uncommon (5.6%). In contrast, the core has a high proportion

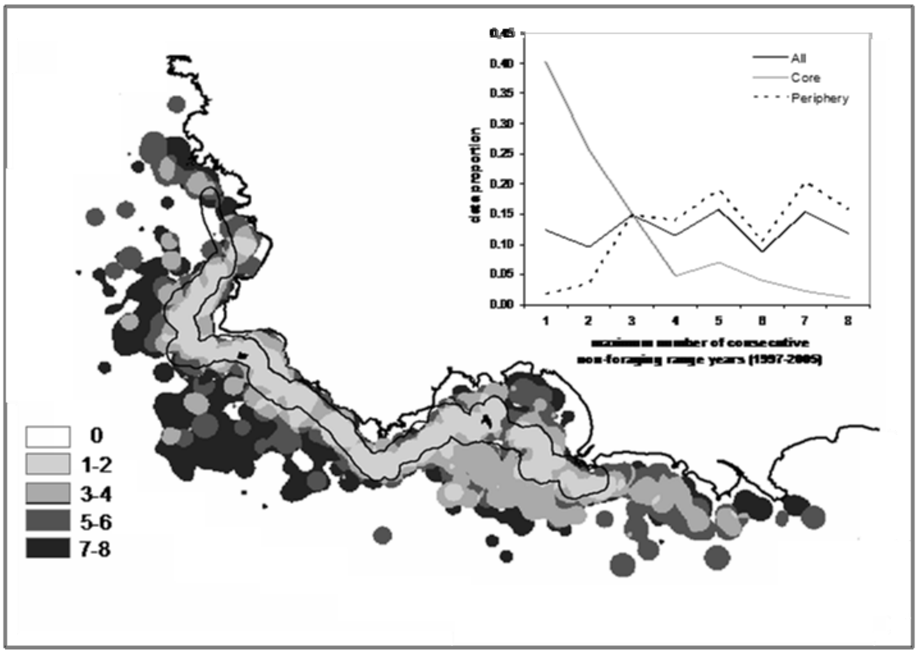

Figure 3. The maximum number of consecutive non-foraging range years.

(50.6%) of locations that are part of foraging range in six or more years, while this is uncommon in the periphery (1.7%).

The maximum number of consecutive non-foraging range years has a strong spatial pattern (Figure 3). Almost all locations with a maximum number of consecutive non-forging range years of one or two are found in the core area, and locations where many years were not part of a foraging range are almost exclusive to the periphery. There is also a core/periphery pattern to the number of temporal switches between foraging range and non-foraging range states, or STS bumpiness (Figure 4). There is more temporal persistence in the periphery, where non-foraging conditions dominate, and more variability in the core where foraging activity is greater.

DISCUSSION AND CONCLUSION

Spatially explicit population analysis using the STS method allows us to view what is essentially habitat quality from a prey perspective reflected through the temporal pattern of whale foraging A dynamic equilibrium approach, wherein whales remove prey biomass, prey replenish themselves, and whales return is supported by STSs that have many foraging range years, and few maximum consecutive non-foraging range years. The spatial-temporal pattern reflected in the core is indicative of a dynamic equilibrium hypothesis for prey-predator interactions. Here it is believed that the whales interact with the prey on a cycle, feeding continually for up to four years, followed by a prey recovery period of between one and three (although usually one) years, known as bottom up forcing. The quality of habitat in the core areas, particularly for prey reproduction, which may involve over-wintering prey populations, is likely the key element holding gray whales in this small core area.

In the periphery, the pattern reflects an intermediate disturbance process. The intermediate disturbance approach (*i.e.*, as observed in COYLE et al., in press) predicts that whales will forage heavily in a location and prey may not recover in an observed time interval, or at all, and is linked to STSs that have few foraging range years and a high value in the maximum consecutive non-foraging range years. In other words, the whales ate everything in one year and the prey did not recover within the temporal extent of our study (top down forcing).

Highly variable sites are possibly a reflection of overall prey density. The years when foraging occurs in variable locations are coincident with high levels of whale foraging activity. Whales may be moving to exploit these temporally variable patches as they become available, causing the dispersal equivalent to a temporary local extinction as peripheral sites are not recolonized until core populations rebound.

The STS method is an approach to space-time analysis and has several qualities that make it ideal for analysis of large, multi-temporal data sets and we have demonstrated its applicability to studies of marine mammals. The local nature of the STS method enabled different temporal trends in the spatial pattern to be identified in the core and in the periphery. Had a spatially global approach been used, it is likely that the patterns associated with the dynamic equilibrium processes would have been masked.

Secondly, the STS approach provides a quantitative, two-dimensional visualization of multi-dimensional data. Using STS properties, we characterize the state of a spatial pattern through many time periods. The STS approach enables the nature of a spatial process through time to be summarized, and spatial variability in temporal trends to be mapped. Visualizing STS results was an important component in teasing apart core/periphery trends in the space-time patterns of foraging gray whales.

In conclusion, this study has demonstrated the effective use of novel spatial temporal analysis techniques on a large marine data set. With the increase in spatially and temporally extensive data sets, these techniques have tremendous potential for many other marine environment studies.

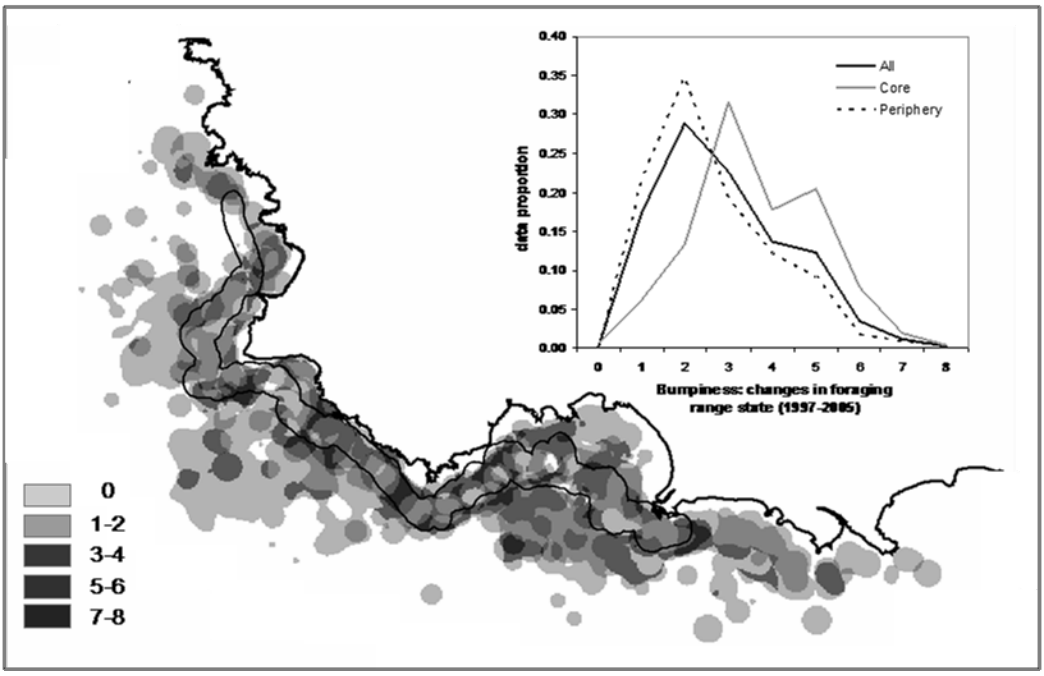

Figure 4. Bumpiness, or the number of changes between foraging and non-foraging range states.

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