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A geospatial analysis of shark attack rates for the east coast of Florida: 1994–2009

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Shark attacks have historically been studied from a viewpoint of encounter number per region and so limited to the areas in which the attacks occurred. In this exploratory modeling study, the goal was to examine whether an area-specific cluster analysis algorithm undertaken with a modern cluster analysis tool (SaTScan™ 9.1.0) could enhance our spatial and spatio-temporal understanding of attack patterns. The data used were from Florida's east coast between 1994 and 2009. The program suggests several high- and low-risk areas for shark attacks. The results are discussed from a quantitative rather than qualitative perspective.

Keywords: shark attack; Florida; geospatial; cluster analysis; SaTScan™

Introduction

Since the time humans started to enter the sea for recreational or professional purposes, the fear of attack by a shark has preyed upon their minds (Ritter et al. 2008). So it is not surprising that early scholars around the world started to collect attack information to understand the nature of attacks better (Burton 1935; Coppleson 1951; Davis 1963) and to look for potential repellents (Fogelberg 1944; Gilbert and Springer 1963; Tester 1963). From the beginning, it was evident that shark attacks are primarily recorded where environmental circumstances are most favorable for people to swim (Coppleson 1951; Baldridge 1959; Gilbert et al. 1959). Because of this, attack prone regions and commonly involved species became the foundation for attack statistics around the world (Caldicott et al. 2001; Woolgar et al. 2001). One of the shortcomings of analyzing shark attacks is that data are loosely descriptive and not consistent. Among other pieces of information, they record where an attack occurred, species involved (Ritter and Levine 2004; Ihama et al. 2009), the size (Ritter and Levine 2005; Lowry et al. 2009; West 2011), what appeared to cause the attack (Tricas and McCosker 1984; Ritter 2004), and whether the presence of the sharks was seasonal or a year-round occurrence (Davis 1963; Levine 1996; Hazin et al. 2008; West 2011).

The aim of this investigation was to test whether spatial and spatio-temporal cluster analysis could add to our understanding of attack patterns. To do this, we

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postulated two hypotheses: (1) that shark attacks are proportionate to human beach activities and (2) that no space–time interaction for shark attacks exists with respect to area and time. The most suitable program to test such hypotheses is the spatial scan statistic program SaTScan™, developed by Martin Kulldorf (Kulldorff 2001; Kulldorff et al. 2006; Kulldorff et al. 2009), which has already been applied in a variety of fields including environmental studies (Sudakin et al. 2002; Vadrevu 2008), botanical and forestry research (Coulston and Riitters 2003; Bayon et al. 2007; Tuia et al. 2008), and cancer investigations (Fang et al. 2004; Sheehan and DeChello 2005; Amin et al. 2010).

Methods

Data sources

Because of incomplete beach population data for the Florida east coast counties prior to 1994, the study was limited to 16 years from 1994 to 2009. Since shark attacks are proportional to the number of people visiting and entering the ocean, we used shark attack rate rather than shark attack count for this study. A shark attack rate was defined as the ratio of annual reported shark attacks in a given region to the annual estimated beach attendance for a given region. The ideal population to use would be the annual number of people who enter the water at the given location, but such data do not exist. The closest available population data come from the United States Lifesaving Association (USLA), a non-profit professional association of beach lifeguards. The USLA keeps intermittent annual attendance data for the beaches at which its lifeguards are present. Even though the population data from the USLA are a strict beach attendance, meaning an annual count of people going to the beach, the data served as a sufficient population proxy given the assumption that the same proportion of people attending a beach will enter the water for all beaches. While serving as a good proxy for the required populations entering the water, it contained two deficiencies that required correction: some population data were not specific enough with respect to location, or were completely absent for some locations. To make the analysis more spatially specific, large counties, such as Volusia and Palm Beach County, were broken up into smaller units that increased the number of locations from 12 counties to 25 coastal regions. Since beach populations in the smaller units were not likely to be the same for every unit, we weighed the population with respect to the coastal populations. For counties with large sections of population data missing, adjacent beaches, with known populations, were used to approximate the population. Upon acquisition of shark attack and population data, each attack was classified and assigned to a specific unit within a county (Figure 1). The shark attack data for the study were made available from the Global Shark Attack File (GSAF) of the Shark Research Institute. An attack was defined as any shark–human interaction where the lowest level of contact was a hit or brush that could not be classified as accidental. No difference was made for the severity of an incident. An incident was excluded if the person provoked the shark, e.g., fishing for sharks. During the chosen time period 345 shark attack reports were filed, of which 210 and 114 incidents were categorized as surfing and non-surfing shark attacks (swimming, bathing), respectively. Twenty-one filed incidents with the GSAF did not fit the chosen criteria and were excluded.

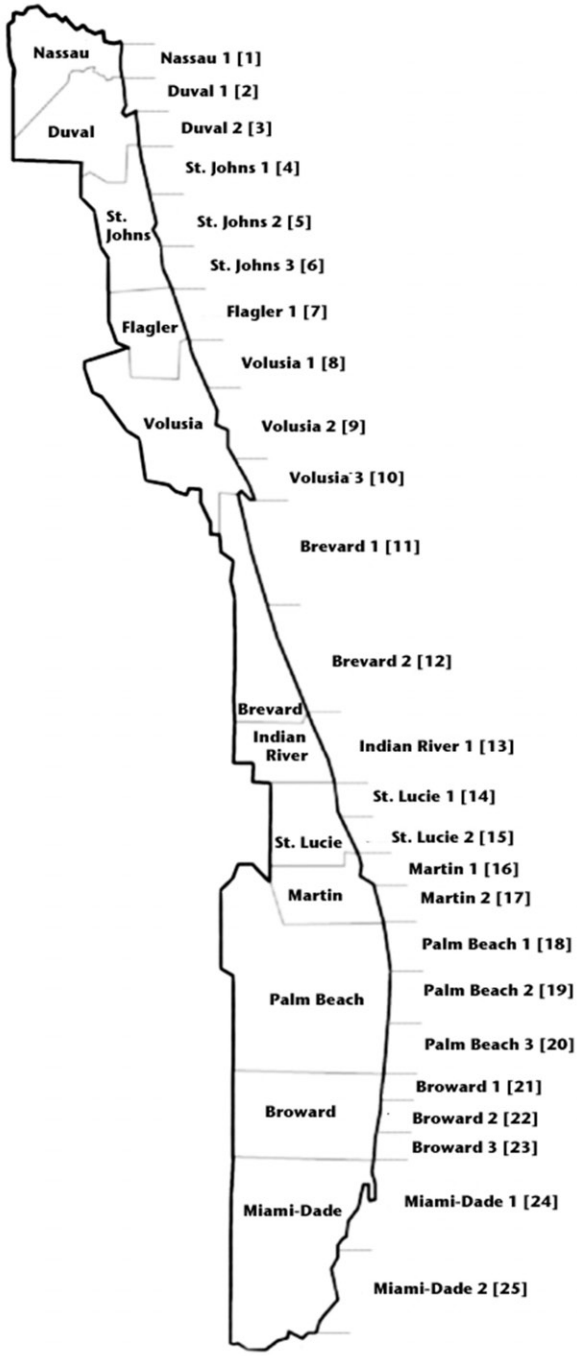

Figure 1. Division of the eastern Florida shore into 25 coastal regions for the purpose of the analysis.

Data analysis

The software SaTScan^{TM} version 9.1.0, which uses the scan statistic to identify and test for the significance of clusters, was applied to evaluate the shark attack data for the east coast of Florida. The counts of shark attacks in each coastal region were used in two ways, a spatial analysis in two dimensions and a three-dimensional setting for a space–time analysis with the additional dimension of time. The clustering algorithm deals with the relation of two spatial and one temporal dimensions by evaluating all combinations of spatial sizes and temporal lengths, such as, e.g., a "pizza shape" (large spatial area, short time interval), a "pencil" (small geographical area, long time interval), a "dot" (small spatial area and short time interval), and a "barrel" (large geographical area and long time interval), as well as everything in between. The multiple testing inherent in the many options evaluated is adjusted. It was assumed that the incidence of a shark attack in each coastal region was distributed according to a Poisson distribution. This method tested the null hypothesis that the shark attack risk was the same for all coastal regions. Shark attacks were separated by being either surfing or non-surfing attacks. For SaTScan^{TM}'s model to work, each coastal region needed to be defined through a centroid. ArcGIS was used to calculate the geographical centroid of each coastal region. SaTScan^{TM}'s spatial scan statistics creates a "spatio-temporal window" that moves spatially over a map, and includes a variety of sets of adjacent regions represented by their corresponding centroids. If a centroid of a specific coastal region is included in the moving window, then this region is added to the window, as well. The center of the window was only positioned at the 25 coastal region centroids. The radius of the window for each grid point varied continuously in size between zero and a specific upper limit. This allowed the window to be flexible for both its location and size. A large number of distinct geographical circles were then created with different sets of close data locations within the circles, where each circle represented a possible shark attack cluster for the data. We used the coordinates to be sure that each data location was a potential cluster in itself. For each window, the spatial scan statistic tested the null hypothesis of equal risk of a shark attack for all coastal regions against the alternative hypothesis that there exists an elevated shark attack risk or a high risk within the scan window, as compared with areas outside the window. SaTScan^{TM} also allowed the option of testing against the alternative hypothesis that there exists a depressed shark attack risk or a low risk. The likelihood function for the Poisson model can be shown to be proportional to

$$\left(\frac{n}{E}\right)^n \left(\frac{N-n}{N-E}\right)^{N-n} I(n > E)$$

where n is the number of shark attack incidents within the scan window, N the total number of incidents in Florida, and E the expected number of shark attack incidents under the null hypothesis. Since a one-tailed test was used that rejected the null hypothesis if there existed an elevated shark attack risk, an indicator function I was applied such that $I = 1$ when the scan window had a larger number of shark attack incidents than expected if the null hypothesis were true, and zero otherwise. It can be shown that for given values of N and E, the likelihood increases as the number of shark attack incidents n increases in the scan window. SaTScan^{TM} generated 999 random replications of the data set by a Monte Carlo simulation in order to obtain the p-value for the likelihood ratio for the identified shark attack clusters.

The identified shark attack clusters were listed by SaTScan^{TM} in order of the value of the likelihood ratio test statistic. A cluster was considered a "significant cluster" when the *p*-value for each cluster was smaller than the set significance level. In this study, a significance level of 0.05 was set. SaTScan^{TM} uses a likelihood ratio test to identify the cluster with the highest probability of existing. This cluster is called "the most likely cluster." All other clusters are arranged in order according to the values of the likelihood ratio test. These clusters are called "secondary clusters." We decided not to include any clusters that were not significant at the significance level 0.05. It was possible to use circular or elliptical windows for the purpose of identifying circular shark attack clusters and elliptically shaped clusters, respectively. In this study, we used circular windows to identify clusters. The spatial scan statistic chosen for this study requires specification of the underlying distribution of the data used in SaTScan^{TM}, making it a parametric statistical method. To ensure adequate statistical power, all shark attack incidents for the period between 1994 and 2009 were used to perform a purely spatial analysis. The space–time analysis is a temporal extension of the spatial analysis, where the algorithm searched within the period from 1994 to 2009 for time periods in which shark attack clusters appear. For convenience, high and low shark attack risks were further labeled "high risk" and "low risk", respectively.

Results

Analysis of shark attack rates

All shark attacks analyzed were initially combined without dividing them into activity-related subcategories. Spatial analysis revealed two high-risk areas along the eastern Florida coast, regions [9–13] and [18], respectively, and two significant low-risk clusters for the regions [2–6] and [20–25], respectively (Figure 2). Table 1 presents the number of true and expected attacks, percentage of risk increase and decrease, relative risk, as well as the attack rates, and the probabilities that the respective clusters were due to random causes. Since the purely spatial analysis for the period 1994–2009 did not indicate when the shark attack cluster appeared, a space–time analysis was performed. Assessing these clusters using the Poisson model within SaTScan^{TM} showed few differences (Figure 3). Regions [9–13] reappeared as the most likely temporal cluster with elevated risk for the time period between 2001 and 2008, whereas the secondary high cluster spread around region [18], from [14] to [19], between 1998 and 2008 (Table 2). Similarly, regions [2–7] and [20–25] appeared between 1994 and 2001, and 2008 and 2009, as primary and secondary low-risk areas, respectively. To verify whether the high-risk clusters shifted over time, the study period was partitioned into two periods, 1994–2000 and 2001–2009. During 1994–2000, the most likely cluster spread between regions [7] and [17] with 111 shark attacks, a relative rate (RR) of 16.14, and a *p*-value of 0.001, whereas for the second time period between 2001 and 2009, the most likely cluster consisted of the regions [9–18], with 172 attacks, $RR = 12$, and a *p*-value of 0.001.

Determination of surfing and non-surfing attack rates

Based on the available information, the total shark attack numbers were partitioned into surfing attacks and non-surfing attacks. A purely spatial analysis for the high

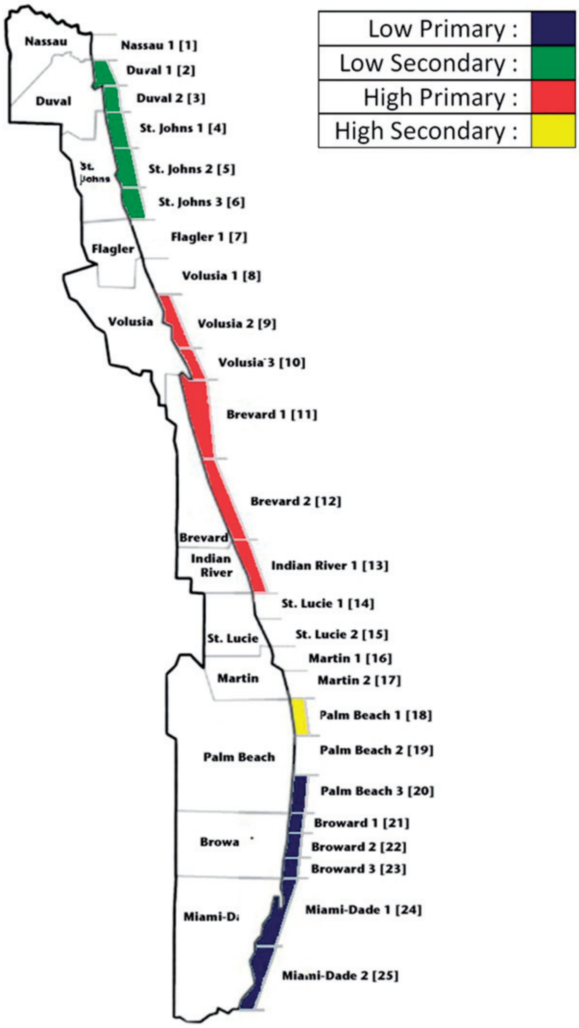

Figure 2. Spatial analysis of low and high primary and secondary attack clusters between 1994 and 2009.

Table 1. Spatial data for the high- and low-risk cluster areas in Florida between 1994 and 2009 for all attacks.

Area	R_{rel}	N_{true}	RR	N_{exp}	R_{att}	p
[9–13]	Primary high	213	9.38	50.64	2/1,000,000	0.0001
[18]	Secondary high	16	4.01	4.13	2/1,000,000	0.0003
[20–25]	Primary low	17	0.053	169.85	0.05/1,000,000	0.0001
[2–6]	Secondary low	19	0.40	43.5	0.002/1,000,000	0.0008

Notes: R_{rel}, relative risk; N_{true}, true number of attacks; RR, relative risk; N_{exp}, expected number of attacks; R_{att}, attack rate; P_{rand}, probability that cluster is due to random causes (Monte Carlo rank); and p, p-value of log likelihood ratio test.

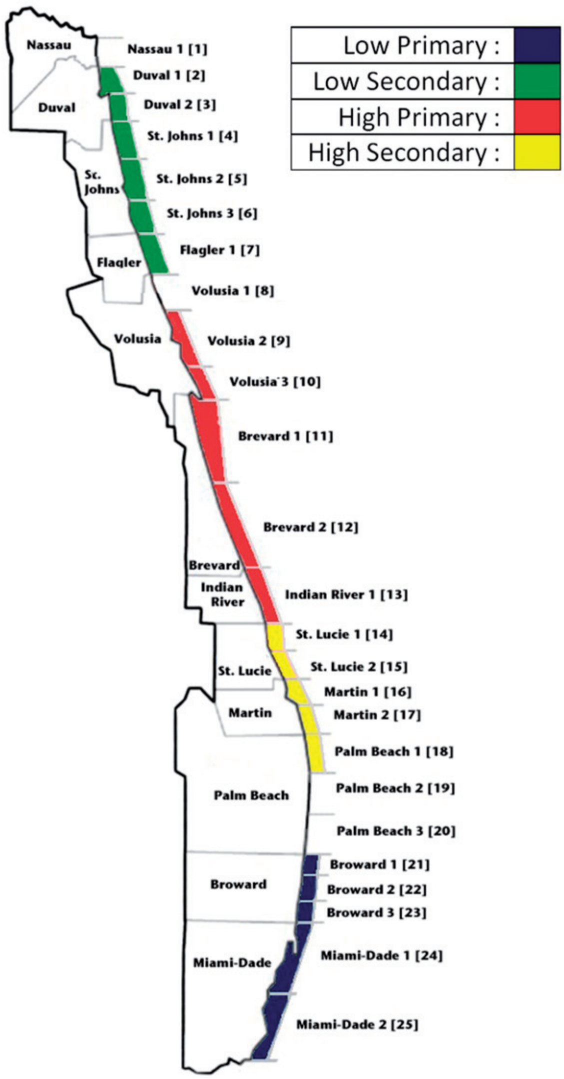

Figure 3. Space–time analysis of low and high primary and secondary attack clusters between 1994 and 2009.

Table 2. Time spatial data for the high- and low-risk cluster areas in Florida between 1994 and 2009 for all attacks.

Area	R_{rel}	N_{true}	RR	N_{exp}	Period	p
[9–13]	Primary high	137	7.79	26.91	2001–2008	0.0001
[14–19]	Secondary high	29	3.25	9.48	1998–2003	0.0009
[20–25]	Primary low	8	0.005	92.55	1994–2001	0.0001
[2–7]	Secondary low	0	0	9.59	2008–2009	0.0162

Notes: R_{rel}, relative risk; N_{true}, true number of attacks; RR, relative Risk; N_{exp}, expected number of attacks; Period, years during which cluster remained; and p, p-value of log likelihood ratio test.

Table 3. High- and low-risk cluster areas for surfing and non-surfing attacks in Florida.

Area	Activity	R_{rel}	N_{true}	RR	N_{exp}	Pop_{est}	p
[9–13]	Surfing	Primary high	158	15.8	35.67	6,983,401	0.001
[18]	Surfing	Secondary high	11	4.56	2.52	492,773	0.008
[20–25]	Surfing	Primary low	1	0.0049	103.39	20,242,710	0.001
[2–8]	Surfing	Secondary low	28	0.46	52.75	10,328,264	0.003
[8–16]	Non-surfing	Primary high	85	6.31	36.15	13,396,605	0.001
[20–25]	Non-surfing	Primary low	16	0.17	56.12	20,242,710	0.001

Notes: R_{rel}, relative risk; N_{true}, true number of attacks; RR, relative Risk; N_{exp}, expected number of attacks; Pop_{est}, estimated beach going population; and p, p-value of log likelihood ratio test.

and low surfing and non-surfing attack rates, respectively, is given in Table 3. By adding the time factor, the space–time analysis for surfing attacks showed the years between 2001 and 2008 as the time period for the high-risk cluster (Figure 4), whereas the low-risk areas appeared between 1994 and 2001, with a second low-risk cluster between 2002 and 2008 (Table 4). Similarly, the space–time analysis for the non-surfing high attack rates fell between 2000 and 2007 as the period for the high-risk cluster, with a corresponding low-risk period between 1995 and 2000 (Figure 5). The chi-squared test for independence between type of attack (surfing and non-surfing) and type of region (high and low attack rates) was significant ($p = 0.0006$). A significant association exists between type of attack and type of region. The coastal areas falling into the high attack rate cluster have a proportion of surfer attacks of 46% while this percentage is only 21% in the low attack rate cluster.

Discussion

This project focused on the quantitative analysis of shark attack data from a spatial and spatio-temporal point of view using cluster analysis. Based on the results, the two hypotheses that shark attacks are proportionate to beach attendance, and that there exists no space–time interaction of shark attacks over time and area on the Florida east coast can be rejected. If the shark attack rates are identical in all coastal regions in Florida, then we would expect to find the number of shark attacks in each coastal region to be proportional to the number of people attending the beaches in the corresponding coastal region. However, the data analysis showed several areas along the east coast with either a significant increase of attack rates, or areas with significantly lower rates than expected. A significant space–time cluster signifies that the rate of shark attacks are not just ''purely spatial'' or just ''purely temporal.'' Instead, specific years exist during which shark attack rates increased (or decreased, when scanning for low shark attack rates). Such information could be useful in future studies in which it is desired to identify causal factors that may have led to the change in shark attack rates in certain years. Historically, the most prominent area for shark attacks in Florida is within Volusia County. It has commonly been labeled as the ''shark attack capitol of the world,'' and understandably so when considering attack numbers alone (Burgess et al. 2010; Shark Research Institute 2010). However,

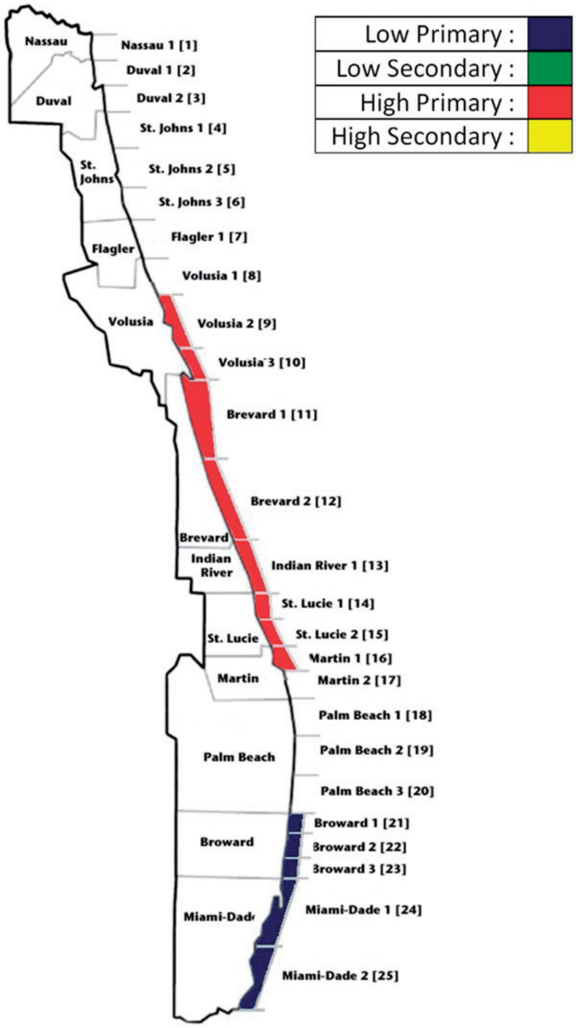

Figure 4. Space–time analysis of low and high primary and secondary surf attack clusters between 1994 and 2009.

Table 4. Time spatial data for the high- and low-risk cluster areas in Florida between 1994 and 2009 for surfing and non-surfing.

Area	Activity	R_{rel}	N_{true}	RR	N_{exp}	Period	p
[9–16]	Surfing	Primary high	118	11.08	18.96	2000–2008	0.001
[20–25]	Surfing	Primary low	1	0.013	0.018	1994–2001	0.001
[8–15]	Non-surfing	Primary high	51	4.80	16.47	2000–2007	0.001
[21–25]	Non-surfing	Primary low	1	0.036	22.55	1995–2000	0.001

Notes: R_{rel}, relative risk; N_{true}, true number of attacks; RR, relative risk; N_{ex}, expected number of attacks; Period, years during which cluster remained, p, p-value of log likelihood ratio test.

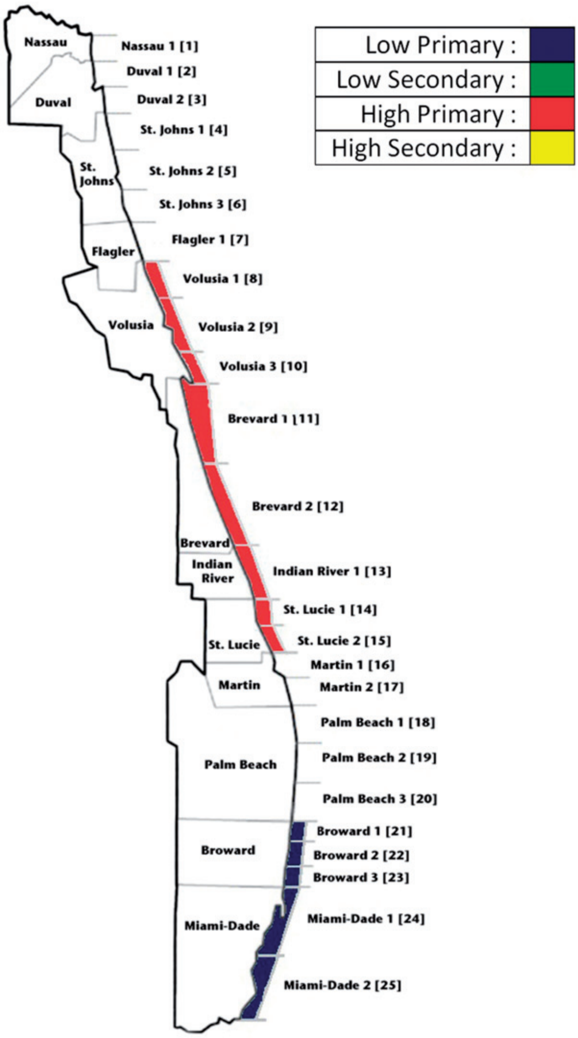

Figure 5. Space–time analysis of low and high primary and secondary non-surfing attack clusters between 1994 and 2009.

when using attack rates instead of encounter numbers, several additional coastal regions can be identified as showing a significantly high shark attack rate.

Activity specific attraction

The fact that there is a person in the water affects the likelihood of a shark attack (Cliff 1991; Woolgar et al. 2001; Ritter and Levine 2004) but beyond this, comparison of absolute numbers alone from different water activities or the appearance of wound patterns do not permit valid analysis in the absence of further baseline data. Since waves are not favorable to swimmers and generally non-surfers alike, it could be assumed that low and high attack risks for surfers in Florida would occur in different areas, but the surfing- and the non-surfing-related shark attacks overlap for high- and low-risk areas. Such a result indicates that either both activities are limited to the same beaches, which is not the case for the Florida east coast, or that surfing is indeed a more incident-prone activity. The latter could be assumed for Florida's east coast, should the number of surfers and non-surfers be directly proportional to each other, which is not a known statistic at this point. Nevertheless, the naturally greater distance of surfers from shore, the prolonged duration of their activities as well as the likely increase of shark density toward the open water makes surfing a more incident-prone activity than swimming. Even if contact time is probably enhanced, it can still only partly explain the difference between high- and low-risk areas. Since the ratio between surfer-and non-surfer-related attacks remains significant along the coast, although less prominent in low-risk areas. This implies non-activity-related factors that might function as widespread triggers rather than the potential effect of the activity itself.

Species specific impacts and likelihood of encounters

Although it is possible that shark nursery areas along the east Florida coast (Castro 1993; Aubrey and Snelson 2007; Reyier et al. 2008), inshore spawning or migration of preferred food sources (Trent et al. 1997) or migration patterns of some shark species (Castro 1996) contribute to the overall numbers of attacks in specific regions of the study area, such time-limited events are not likely to be entirely responsible for the space–time high attack rate clusters revealed in this analysis. But, even if the periodic increase of a species attests to a higher attack rate, the likelihood is still slim that the lack of such biological phenomena elsewhere along its coast could explain the space–time low shark attack clusters. It is rather probable that the presence of these clusters for the space–time analyses suggest continuous or seasonal critical conditions along stretches of coast that increase the likelihood of shark attack incidents. Unfortunately, and not just for Florida, species identification of attacking sharks is poor and often based on non-expert eye witness reports, the victims' guesses, the probability of common species in the area or previously identified species of earlier incidents (Cliff 1991; Woolgar et al. 2001; West 2011). A better knowledge and understanding of all species involved would greatly improve the prospects of such an analysis.

Attack triggering factors

Identifying factors that attract sharks or keep them away from a person or an area is paramount to the understanding of shark attacks. Although the research literature is far away from comprehending what attracts sharks in the first place, the opposite is even less understood, as the history of finding a functioning shark repellent reveals (reviewed in Sisneros and Nelson 2001). This project did not aim to reveal causal links for shark attack but to identify potential high- and low-risk clusters along the Florida east coast. The ability to identify high- and low-risk areas for shark attack along a very large and heavily populated coastline opens the possibility of searching for causal links, such as environmental pollution and other anthropogenic triggers (Adams and McMichael 1999). Large-scale changes in physical parameters, such as water temperature, could also be examined for their potential to facilitate shark migration and aggregation (Heupel and Simpfendorfer 2005) or meteorological phenomena like short-term air pressure changes, which have been known to affect the swim patterns of sharks (Heupel et al. 2003). Being able to identify low-risk areas may also provide an invaluable baseline from which causal factors could be extracted.

Value of cluster analysis for analyzing shark attacks

Spatial statistics methodology has been well established in recent years (e.g., Roddick and Spiliopoulou 1999; Kalnis et al. 2005; Chi et al. 2007; Rosswog and Ghose 2008). The methodology has been applied in many fields (Sudakin et al. 2002; Coulston and Riitters 2003; Amin et al. 2010). This project is the first to use it to analyze shark attack data and to compare surfing and non-surfing attack rate data on a heavily populated coast. The methodology does not identify specific links between immediate risk and encounter outcomes but does permit comparisons across large territories to reveal previously hidden correlations. The outcomes provide baseline data and methodology to generate and test new hypotheses.

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References

Adams DH, McMichael RH. 1999. Mercury levels in four species of sharks from the Atlantic coast of Florida. Fish Bull. 97(2):372–379.

Amin R, Bohnert A, Holmes L, Rajasekaran A, Assanasen C. 2010. Childhood clustering in Florida: weighing the evidence. Pediatr Blood Cancer. 54(4):511–518.

Aubrey C, Snelson F. 2007. Life history in spinner sharks in Florida waters. In: McCandless C, Kohler N, Pratt H, editors. Shark nursery grounds of the Gulf of Mexico and the east coast waters of the Unites States. Bethesda (MD): American Fisheries Society. p. 175–189.

Baldridge HD. 1959. Shark attack: a definitive analysis of the world's best information on attacks by sharks against men including excerpts from over 200 case histories. Anderson (SC): Droke House/Hallux.

Bayon C, Pei MH, Ruiz C, Hunter T. 2007. Genetic structure and spatial distribution of the mycoparasite *Sphaerellopsis filum* on *Melampsora larici–epitea* in a short–rotation coppice willow planting. Plant Pathol. 56:616–623.

Burgess G, Buch RH, Carvalho F, Garner BA, Walker CJ. 2010. Factors contributing to shark attacks on humans: a Volusia county, Florida, case study. In: Carrier JC, Musick JA, Heithaus MR, editors. Sharks and their relatives II. Boca Raton (FL): CRC Press. p. 541–566.

Burton M. 1935. Shark attack along the South Carolina coast. Sci Mon. 40:279–283.

Caldicott DG, Mahajani R, Kuhn M. 2001. The anatomy of a shark attack: a case report and review of the literature. Injury. 32(6):445–453.

Castro JI. 1993. The shark nursery of Bulls Bay, South Carolina, with a review of the shark nurseries of the southeastern coast of the United States. Environ Biol Fish. 38(1–3):37–48.

Castro JI. 1996. Biology of the blacktip shark, *Carcharhinus limbatus*, off the southeastern United States. Bull Mar Sci. 15:508–522.

Chi Y, Song X, Zhou D, Hino K, Tseng BL. 2007. Evolutionary spectral clustering by incorporating temporal smoothness. Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery Data Mining; 2007 August 12–15; San Jose (CA), USA.

Cliff G. 1991. Shark Attacks on the South African coast between 1960 and 1990. S Afr J Sci. 87:513–518.

Coppleson V. 1951. A review of shark attacks in Australian water since 1919. Med J Aust. 1:633–635.

Coulston JW, Riitters KH. 2003. Geographic analysis of forest health indicators using spatial scan statistics. Environ Manage. 31:764–773.

Davis D. 1963. Shark attack and its relationship to temperature, beach patronage and the seasonal abundance. Investigational Report, No. 6. Durban (South Africa): Oceanographic Research Institute.

Fang Z, Kulldorff M, Gregorio DI. 2004. Brain cancer in the United States, 1986–95: a geographic analysis. Neuro Oncol. 6:179–187.

Fogelberg J. 1944. The use of chemical material as shark repellants. Washington (DC): Naval Research Lab. p. 32.

Gilbert PWS, Leonard P, Springer S. 1959. Shark attacks during 1959. Science. 132(3423):323–326.

Gilbert P, Springer S. 1963. Testing shark repellents. In: Gilbert PW, editor. Sharks and survival. Lexington (MA): Heath and Co. p. 477–494.

Hazin F, Burgess G, Carvalho F. 2008. A shark attack outbreak off Recife, Pernambuco, Brazil, 1992–2006. Bull Mar Sci. 82(2):199–212.

Heupel MR, Simpfendorfer CA. 2005. Quantitative analysis of aggregation behavior in juvenile blacktip sharks. Mar Biol. 147:1239–1249.

Heupel MR, Simpfendorfer CA, Hueter RE. 2003. Running before the storm: blacktip sharks respond to falling barometric pressure associated with tropical storm Gabrielle. J Fish Biol. 63:1357–1363.

Ihama Y, Ninomuya K, Noguchi M, Fuke C, Miyazaki T. 2009. Characteristic features of injuries due to shark attacks: a review of 112 cases. Leg Med. 11(5):219–225.

Kalnis P, Mamoulis N, Bakiras S. 2005. On discovering moving clusters in spatio-temporal data. Lect Notes Comput Sci. 3633:364–381.

Kulldorff M. 2001. Prospective time-periodic geographical disease surveillance using a scan statistic. J Roy Stat Soc A. 164:61–72.

Kulldorff M, Huang L, Konty K. 2009. A scan statistic for continuous data based on the normal probability model. Int J Health Geogr. 8:58.

Kulldorff M, Huang L, Pickle L, Duczmal L. 2006. An elliptic spatial scan statistic. Stat Med. 25:3929–3943.

Levine M. 1996. Unprovoked attacks by white sharks off the South African coast. In: Klimely AP, Ainley DG, editors. Great White Sharks: the biology of Carcharodon carcharias. San Diego (CA): Academic Press. p. 435–448.

Lowry D, Fagundas de Castro AL, Mara K, Whitenack LB, Delius B, Burgess GH, Motta P. 2009. Determining shark size from forensic analysis of wound damage. Mar Biol. 156(12):1432–1793.

Reyier EA, Adams DH, Lowers RH. 2008. First evidence of a high density nursery ground for the lemon shark, Negaprion brevirostris, near Cape Canaveral, Florida. Fla Sci. 71(2):134–148.

Ritter E. 2004. Sharks–Mistaken identity? In: Bekoff M, editor. Encyclopedia of animal behavior. Westport (CT): Greenwood Press. p. 963–964.

Ritter EK, Levine M. 2004. Use of forensic analysis to better understand shark attack behaviour. J Forensic Odontostomatol. 22(2):40–46.

Ritter EK, Levine M. 2005. Bite motivation of sharks reflected by the wound structure on humans. Am J Forensic Med Pathol. 26(2):136–140.

Ritter E, Lutz K, Levine M. 2008. When humans and sharks meet. In: Olsson F, editor. New developments in the psychology of motivation. New York: Nova Biomedical Books. p. 45–52.

Roddick JF, Spiliopoulou M. 1999. A bibliography of temporal, spatial and spatiotemporal data mining research. SIGKDD Explor. 1:34–38.

Rosswog J, Ghose K. 2008. Detecting and tracking spatio-temporal clusters with adaptive history filtering. Proceedings of the 8th IEEE International Conference on Data Mining Workshops; 2008 December 15–19; Pisa, Italy.

Shark Research Institute. 2010. Incident log; [cited 2010 Jun 23]. Available from: http://www.sharkattackfile.net/incidentlog.htm

Sheehan TJ, DeChello LM. 2005. A space–time analysis of the proportion of late stage breast cancer in Massachusetts, 1988 to 1997. Int J Health Geogr. 4:15.

Sisneros JA, Nelson DR. 2001. Surfactants as chemical shark repellants: past, present, and future. Environ Biol Fish. 60:117–130.

Sudakin DL, Horowitz Z, Giffin S. 2002. Regional variation in the incidence of symptomatic pesticide exposures: applications of geographic information systems. J Toxicol Clin Toxicol. 40:767–773.

Tester A. 1963. The role of olfaction in shark predation. Pac Sci. 17(2):145–170.

Trent L, Parshley DE, Carlson JK. 1997. Catch and bycatch in the shark drift gillnet fishery off Georgia and East Florida. Mar Fish Rev. 59(1):19–28.

Tricas TC, McCosker JE. 1984. Predatory behavior of the white shark (*Carcharodon carcharias*), with notes on its biology. Proc Calif Acad Sci. 43:221–238.

Tuia D, Ratle F, Lasaponara R, Telesca L, Kanevski M. 2008. Scan statistics analysis of forest fire clusters. Commun Nonlinear Sci Numer Simul. 13:1689–1694.

Vadrevu KP. 2008. Analysis of fire events and controlling factors in eastern India using spatial scan and multivariate statistics. Geogr Ann. 90A:315–328.

West J. 2011. Changing patterns of shark attacks in Australian waters. Mar Freshwat Res. 62:744–754.

Woolgar J, Cliff G, Nair R, Hafez H. 2001. Shark attack: review of 86 consecutive cases. J Trauma. 50(5):887–891.