

Spatio-temporal analysis of wildfire ignitions in the St Johns River Water Management District, Florida

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Abstract. We analyse the spatio-temporal structure of wildfire ignitions in the St Johns River Water Management District in north-eastern Florida. We show, using tools to analyse point patterns (e.g. the L -function), that wildfire events occur in clusters. Clustering of these events correlates with irregular distribution of fire ignitions, including lightning and human sources, and fuels on the landscape. In addition, we define a relative clustering index that summarizes the amount of clustering over various spatial scales. We carry our analysis in three steps: purely temporal, purely spatial, and spatio-temporal. Our results show that arson and lightning are the leading causes of wildfires in this region and that ignitions by railroad, lightning, and arson are spatially more clustered than ignitions by other accidental causes.

Additional keywords: clustering; confidence envelope; fire occurrence; L -function; point process.

Introduction

Optimal allocation of fire suppression resources depends on the spatial and temporal nature of fire ignitions. Information about clustering can be used by managers and law enforcement to manage wildfires. Analyses of ignition sources show spatial clustering (e.g. lightning, human populations) (Rorig and Ferguson 1999; Hammer *et al.* 2004). Rorig and Ferguson (1999) report that lightning fire ignitions are consistent with the collocation of fuels and high lightning frequencies. Temporal clustering of wildfires, whether deriving from multiple-ignition lightning events, arson (Prestemon and Butry 2005), or other sources, combined with favorable fuel and weather conditions, can force suppression resource rationing across space. Spatial clustering of fires, if not accompanied by temporal clustering, would imply that firefighting resources could be optimally prepositioned to reduce response times. Spatial clustering can also indicate the presence of risk factors (e.g. a local arsonist, high fuel loads); property crimes display spatio-temporal clustering (e.g. Surette 2002; Jacob and Lefgren 2003; Townsley *et al.* 2003) and Butry and Prestemon (2005) described spatial concentrations of wildland arson in addition to temporal clustering. Suppression resource allocation would therefore be improved by better information on the extent of clustering.

The objectives of this research are to (1) demonstrate a method for quantifying spatial clustering and (2) evaluate

how the extent of clustering in wildfires differs across years and among ignition sources. The method demonstrated is the calculation of the L -function, a descriptor of the degree of departure from complete spatial randomness in a point process. The subject of our empirical analysis is wildfire incidence over 21 years in the St Johns River Water Management District (SJRWMD) of Florida. Our empirical application begins by evaluating the long-run temporal variations in wildfire ignitions in the district over the period of analysis. We continue by quantifying the extent of spatial clustering over the 21-year period. This includes evaluating wildfire clusters in the temporal aggregate and then quantifying their changes over time. We separately model departure from randomness using the L -function for arson, railroad, lightning, and other accidental ignition sources. Departure from randomness for each ignition source is evaluated against a 95% confidence interval that is constructed by simulation. Our results demonstrate that all ignition sources are spatially clustered; that this clustering varies over time within ignition sources; and that railroad, lightning, and wildland arson ignitions are the most spatially clustered.

Methods

Spatio-temporal point processes

A spatio-temporal point process is a random collection of points, where each point represents the time and location in

space of an event. The realization of a spatio-temporal point process is called a spatio-temporal point pattern. For example, an event could be the occurrence of a fire, a lightning strike, a volcanic eruption, an earthquake, the incidence of a disease, or the sighting of a certain species. In our study, the point pattern under investigation consists of wildfire ignitions in the SJRWMD in Florida; that is, 31 693 wildfires during the period 1981–2001.

Dissing and Verbyla (2003) analysed spatial patterns of lightning strikes in Alaska, but they did not use tools from spatio-temporal point processes. Podur *et al.* (2003) examined a spatial point pattern of wildfires caused by lightning in Ontario, Canada, where lightning fires account for 35% of ignitions and 85% of the area burned. Not surprisingly, they rejected the hypothesis that lightning ignitions are randomly distributed across space. They found that lightning fires ‘arrive in spatial and temporal clusters that can strain the fire organization’. They also discussed reasons why lightning fires might be clustered. We extend this type of analysis by investigating whether all wildfire ignitions (by cause) occur randomly, in clusters, or in some regular pattern. In addition, we examine whether the spatial point pattern varies among the causes of the wildfire (lightning, arson, accidents, railroad), over time, or depends on wildfire size. In other words, we perform a spatio-temporal analysis of wildfire ignitions. To this aim, we define a simple relative clustering index (which is described below).

A typical data analysis sequence begins with a test for complete spatial randomness (CSR), followed by an attempt to model any lack of spatial randomness. Nearest-neighbor distances provide an objective method for looking at small-scale interactions between wildfires. The empirical distribution function of the point-to-point nearest-neighbor distances can be used for a comparison to a CSR process. If there is clustering in the data, then we would expect to see an excess of short-distance neighbors. If there is regularity in the data, then there will be an excess of long-distance neighbors. In our case, the empirical distribution function of the point-to-point nearest neighbor distances reveals an excess of short-distance neighbors (mostly between 0 and 1 km), thus indicating clustering of the fire locations.

An alternative approach to the one above consists in overlaying a grid on the spatial region, then comparing the distance from the resulting grid nodes to their nearest neighbors (wildfires). The empirical distribution function of these node-to-point nearest-neighbor distances has an interpretation that is opposite to that above. An excess of long-distance values is interpreted as clustering. In our case, the empirical distribution function of the node-to-point nearest-neighbor distances reveals an excess of long distances (mostly between 1 and 120 km), thus again indicating clustering of the fire locations.

Two popular tools to describe departures from CSR are the K -function proposed by Ripley (1976) and the L -function.

They are both used to describe how the interaction or spatial dependence between events varies through space (or time). The K -function $K(h)$ at distance h is defined by:

$$K(h) = E(\text{Number of events within distance } h \text{ of an arbitrary event})/\lambda,$$

where h is positive and E denotes the mathematical expectation. The quantity λ is the intensity of the point process (the mean number of events per unit area). Intuitively, the K -function describes the expected number of events, relative to λ , in a disc of radius h centered at an arbitrary event. One advantage of the K -function is that its theoretical values are known for several useful models of spatial point processes. In particular, for a CSR process (i.e. a process with no spatial dependence), the K -function is simply $K(h) = \pi h^2$, the area of a disc of radius h . Ripley’s K -function estimator, which includes an adjustment for edge effects, can be compared to the one expected for a CSR process. If the CSR hypothesis is rejected, then there must be a tendency towards either clustering or regularity, or the intensity of the process λ , i.e. the number of events per unit area, must not be constant across the region.

The L -function is defined as:

$$L(h) = \sqrt{K(h)/\pi}.$$

Under CSR, $L(h)$ is equal to h . Thus it is particularly simple to detect clustering by graphing $L(h)$ against the distance h . When the events are clustered, $L(h)$ lies above the 45 degree line at short distances. As an example of how to interpret the L -function, consider a case where the value of the L -function at $h = 10$ m is $L(10) = 15$. This says that, starting at an arbitrary fire, the number of fires within 10 m is equal to the number that would be expected within 15 m if the fires were spatially random and if the frequency of wildfires were constant in all areas of the region under study. We used the statistical software *R* (R Development Core Team 2004) and functions in the spatial point processes library *spatstat* (Baddeley and Turner 2005) to compute the empirical L -function. Note that most software can compute the K - and L -functions only for rectangular regions, which if used improperly gives very misleading results. The spatial point processes package *spatstat* allows the user to provide the actual boundaries for an irregularly shaped window of observation and computes the L -function over that window. We also make use of the special command *Kest.fft* in order to compute the K -function for our large datasets based on the Fast Fourier Transform.

One feature of the L -function is that it depends on the distance h , and therefore tells us the spatial scales at which clustering occurs. In addition to this information, a unique summary value that represents the information contained in the L -function across spatial scales is desirable. We therefore define a clustering index (CI) by the area located between

the estimated L -function from data and the one expected for a CSR process (i.e. the sum of $L(h)-h$ over the possible distances h). Because our interest lies in understanding how this clustering index changes over time, we further define a relative clustering index, RCI , as the clustering index minus its average over time, which is then normalized by the average clustering index over time. In other words, RCI will represent departures (positive or negative) from the average clustering index over time. The normalization makes RCI easier to compare in various settings, for example, if we want to study the clustering of wildfire ignitions resulting from different causes.

It seems reasonable to assume that fuel (in aggregate—land cover) and heat (ignition source) are not homogeneous across a landscape; thus we expect to find a non-CSR spatial point process for wildfire ignitions. Fuel and heat sources may vary over time as well as spatially, so we perform three analyses: purely temporal, purely spatial, and spatio-temporal.

Data sources and background information

The SJRWMD comprises all or portions of 18 north-eastern Florida counties and its size is $\sim 31\,681\text{ km}^2$. Figure 1 depicts a map of the SJRWMD with rivers, lakes, county boundary lines, and five major cities: Jacksonville, St Augustine, Gainesville, Daytona Beach, and Orlando. The St Johns River runs north–south from Jacksonville to about half-way down the center of the SJRWMD. In the middle of the SJRWMD is Ocala National Forest (federal lands are excluded from this analysis due to data constraints). Each year the SJRWMD experiences on average 340 lightning wildfires, 445 arson (incendiary) wildfires, and 724 accidental wildfires. Accidental ignitions include those wildfires caused from campfires, cigarettes, debris burning, equipment, railroad, and children (children-caused fires deemed non-incendiary). It also includes 139 miscellaneous wildfires and 158 cause-unknown wildfires. These 1509 ignitions constitute 50 857 acres of wildfire each year on average (from 1981 to 2001). Understanding the spatio-temporal structure of wildfire incidence is important because of the potentially large economic impacts; see Butry *et al.* (2001) for an analysis of the cost of catastrophic wildfires.

The datasets used include (1) wildfire records from 1981 to 2001 and (2) an Arc/Info geographical information system (GIS) coverage of the Public Land Survey (depicting the location and boundaries of all cadastral sections within Florida). Note that the spatial scale is at the section level (1 section = $2.59\text{ km}^2 = 1\text{ mile}^2$), whereas previous studies have used data at a broader, county level scale (e.g. Prestemon *et al.* 2002).

The Florida Division of Forestry provided data concerning all wildfires generated on private and state-owned lands over the calendar year period of 1981–2001. The wildfire data used for this analysis consists of wildfire ignition date, location of ignition (township, range, and cadastral

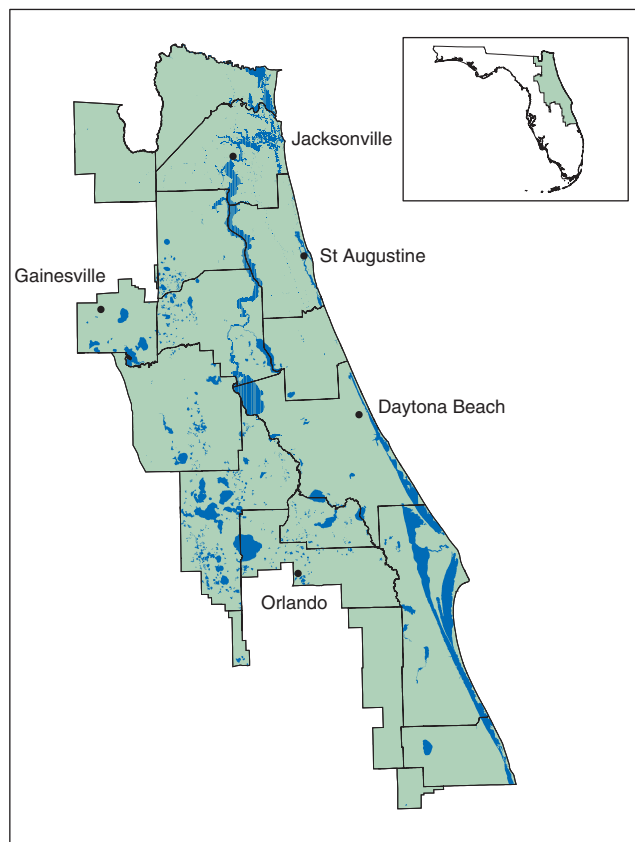


Fig. 1. Map of the St Johns River Water Management District with rivers, lakes, county boundary lines, and five major cities.

section), and size (in acres), fuel type (palmetto–gallberry, pine, swamp, hardwood, grass, muck, other), and cause (lightning, arson, campfire, equipment, railroad, children, miscellaneous, unknown, debris burning, cigarettes). For the SJRWMD, there were 31 693 ignition points located by township, range, and cadastral section. The county of Volusia, which contains Daytona Beach, experienced 4250 fire ignitions and a total of 249 838 acres of land burned, the largest numbers among all counties in SJRWMD during 1981–2001. The county of Duval, which contains Jacksonville, experienced 2905 ignitions, the next largest number. The county of Brevard, in the south of SJRWMD, reported 173 789 acres of land burned, the next largest after Volusia. Figure 2 presents a histogram of the logarithm (in base 10) of wildfire sizes (area burned in acres) in SJRWMD during 1981–2001. The logarithm transformation was used because the distribution of wildfire sizes is very skewed. Indeed, note the large number of very small fires, as well as a few very large fires.

The Florida Division of Forestry also provided a GIS coverage of the Public Land Survey, which maps all township, range, and cadastral sections in Florida. However, upon further inspection, the coverage was found to be missing sections listed in the wildfire record. These missing sections contain a relatively small number of the wildfire ignitions, but are the

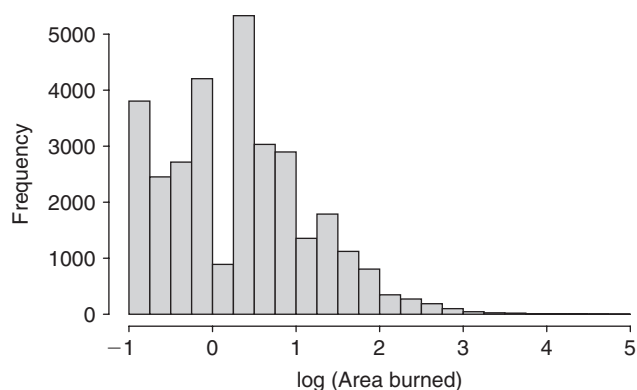


Fig. 2. Histogram of the logarithm (in base 10) of wildfire sizes (area burned in acres) in St Johns River Water Management District during 1981–2001. Note the large number of very small fires, as well as a few very large fires.

location of roughly 37% of the wildfire area burned. A new Arc/Info GIS coverage was created to identify and include these missing sections (a Florida-wide Public Land Survey System coverage was created from county level data compiled by the Florida Geographic Data Library). The new coverage is able to account (correctly locate) for 98% of the wildfire ignitions and acres burned, meaning that 98% of the wildfires (those recorded by the Florida Division of Forestry) have a location that can be identified in the GIS. It also happens that these wildfire ignitions account for 98% of the total area burned.

In the present study we analyse the spatio-temporal structure of wildfire ignitions in the SJRWMD. In particular, we show that wildfire events occur in clusters using tools to analyse point patterns, e.g. the *L*-function. The occurrence of clustering indicates spatial dependence or interaction, which can be exploited to develop better models of fire size and incidence; see, for example, Butry *et al.* (2004). Models for wildfire incidence and size used by researchers and resource managers can take quite different forms, depending on the spatial and temporal scales of the data (Reinhardt *et al.* 2001). We analyse wildfire ignitions at a fairly fine spatial scale, the cadastral section of ignition, and on a continuous temporal scale, the actual date. This allows us to investigate the distances at which clustering of fires is evident or not evident. In the next section, we carry our analysis in three steps: purely temporal, purely spatial, and spatio-temporal. Our results show that arson and lightning are the leading causes of wildfires in this region, and that ignitions by railroad, lightning, and arson are spatially more clustered than ignitions by other accidental causes.

Analysis and results

Long-run temporal analysis

In this section we analyse wildfire ignitions in a purely temporal context over the time period 1981–2001. Arson and

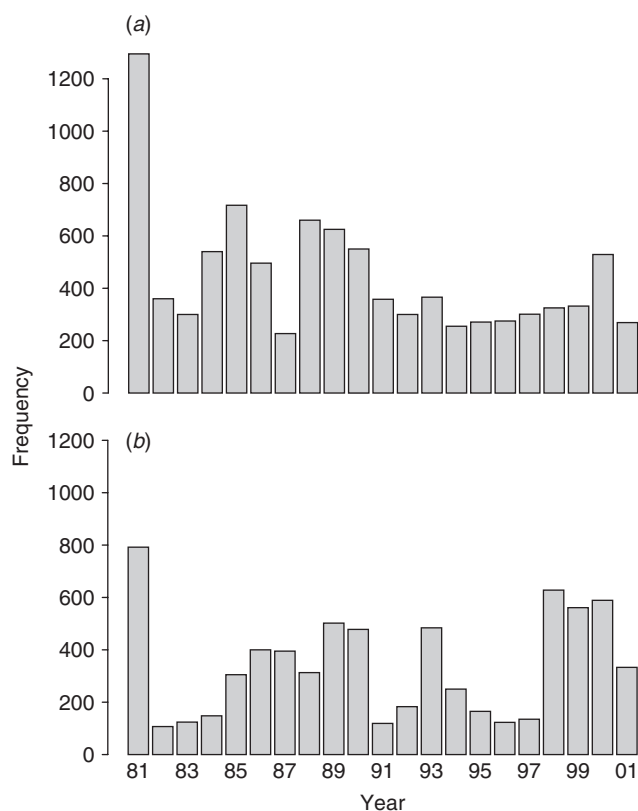


Fig. 3. Temporal evolution of the number of wildfire ignitions for arson causes (a) and for lightning causes (b) during the period 1981–2001 in the St Johns River Water Management District.

lightning ignitions are the leading causes of wildfire over this period, so for this reason we investigate in detail the temporal structure of wildfires caused by arson and lightning. Graphing ignitions as a function of time in the SJRWMD for arson causes (Fig. 3a) and for lightning causes (Fig. 3b), we observe that 1981 had the largest number of wildfires (around 1250 fires due to arson, 800 due to lightning, and around 4000 total). The SJRWMD averages a total of ~1500 wildfires annually. It is worth noting that many of these wildfires are small (less than 1000 acres) (Fig. 2) and that the temporal pattern of large wildfires (more than 1000 acres) is often different; see Butry *et al.* (2004) for details. We also find recent years exhibiting elevated number of lightning ignitions. In both cases, there seems to be an irregular pattern. But we notice that years with a small number of fires are followed by years with a large number of fires (Fig. 3).

A study of the temporal evolution of the area burned by wildfires (in acres) during 1981–2001 caused by arson and by lightning reveals that the largest individual arson fires are ~11 000 acres, whereas the largest individual lightning caused fires are ~60 000 acres. It is also interesting to note that 1998 was a very exceptional year during which lightning caused several very large wildfires (over a 6-week period in

the summer of 1998, ~500 000 acres burned in the SJRWMD, primarily from lightning-caused fires). We get some further insight about the temporal distribution of the area burned by wildfires by computing the mean area burned of the wildfires, as well as the median and the 90% quantile of area burned, as a function of time (years). Because the median curve is below the mean curve over time, we conclude that the annual distribution is skewed to the right and that there are many more small fires than large fires.

Spatial analysis

In this section, we analyse the wildfires in a purely spatial context. If we draw a map of the locations of all the wildfires in SJRWMD during 1981–2001, each point may represent several fires because the data are collected at the section level. A more informative map is obtained by hexagonal binning. It is a grouping and reduction method typically employed on large datasets to clarify the spatial structure. It can be thought of as partitioning a scatter plot into larger units to reduce dimensionality, while maintaining a measure of data density. The groups or bins are used to make hexagon mosaic maps colored or sized according to density. Rectangular or square grids are often used in this context for image-processing applications, but hexagons are preferable for visual appeal and representation accuracy. Figure 4 describes a map of wildfire counts for the period 1981–2001, obtained by hexagonal binning. The size of a hexagon is proportional to the number of wildfires that occurred in a region of ~6 km in diameter. Note the higher concentrations of wildfires along the eastern coast and in the north-western region of the map. Also, we can detect higher concentrations of wildfires around the major cities depicted in Fig. 1, with the exception of Orlando. The causes of these wildfires are investigated below.

Next, we investigate the spatial locations of wildfire ignitions for different years. Figure 5 depicts a map of wildfire counts for 1981, 1985, 1988, and 1997, obtained by hexagonal binning. Those 4 years are representative of different amounts of clustering. For instance, 1981 and 1988 exhibit important clustering, whereas 1997 seems much weaker. Note that high amounts of clustering occur in different spatial regions across those 4 years. Because the maps in Fig. 5 are also influenced by the total number of fires during a given year, we also compute the L -function for each of these years (Fig. 6). The solid line represents the theoretical L -function under CSR with dashed-line 95% confidence envelopes, whereas the dotted line represents the empirical L -function. As we can see, there is a clear departure from CSR towards clustering, the strongest being in 1988. Note that the amount of clustering for a given year changes also as a function of distance. The cadastral sections are about 1 mile across (1.6 km). Even at this scale clustering is evident. This means that, taking any fire as a starting point, there are more fires within any specified distance than expected under complete spatial randomness. The

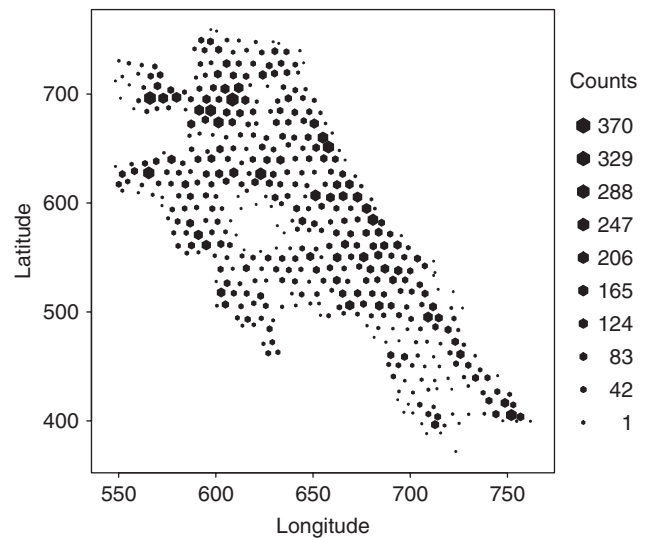


Fig. 4. Map of wildfire counts for the period 1981–2001 in the St Johns River Water Management District, obtained by hexagonal binning. The size of a hexagon is proportional to the number of wildfires that occurred in a region of about 6 km in diameter.

degree of clustering seems to increase with radius. The overall amount of clustering across the various distances for each year can be summarized by means of the clustering index. The corresponding relative clustering index is computed in the next section.

We also investigate the spatial locations of wildfire ignitions for different causes during the period 1981–2001. Figure 7 depicts a map of wildfire occurrence by cause: arson, lightning, accident, and railroad, obtained by hexagonal binning. All four wildfire causes indicate clustering in various amounts. High numbers of wildfires are caused by arson and by lightning, the latter occurring close to the sea coast. Evidently, there are more wildfires caused by accidents than by arson or lightning, because accident causes are pooled from several different causes. In particular, the railroad cause exhibits very strong clustering. This is to be expected as those fires have to occur in the neighborhood of railroad tracks in the SJRWMD. Fires caused by arson tend to be more clustered around major cities. The clustering of fires due to railroad and arson causes can be explained by the fact that human activities are clustered in space – that is, railroads are linear, multiple rail-sparking events may have a common cause, and arson fires may have a common firesetter with a limited spatial domain (Butry and Prestemon 2005; Prestemon and Butry 2005).

Note again that high amounts of clustering occur in different spatial regions across those four causes. The maps in Fig. 7 are also influenced by the total number of fires for a given cause, and thus we compute the L -function for each of them (Fig. 8). As we can see, there is a clear departure

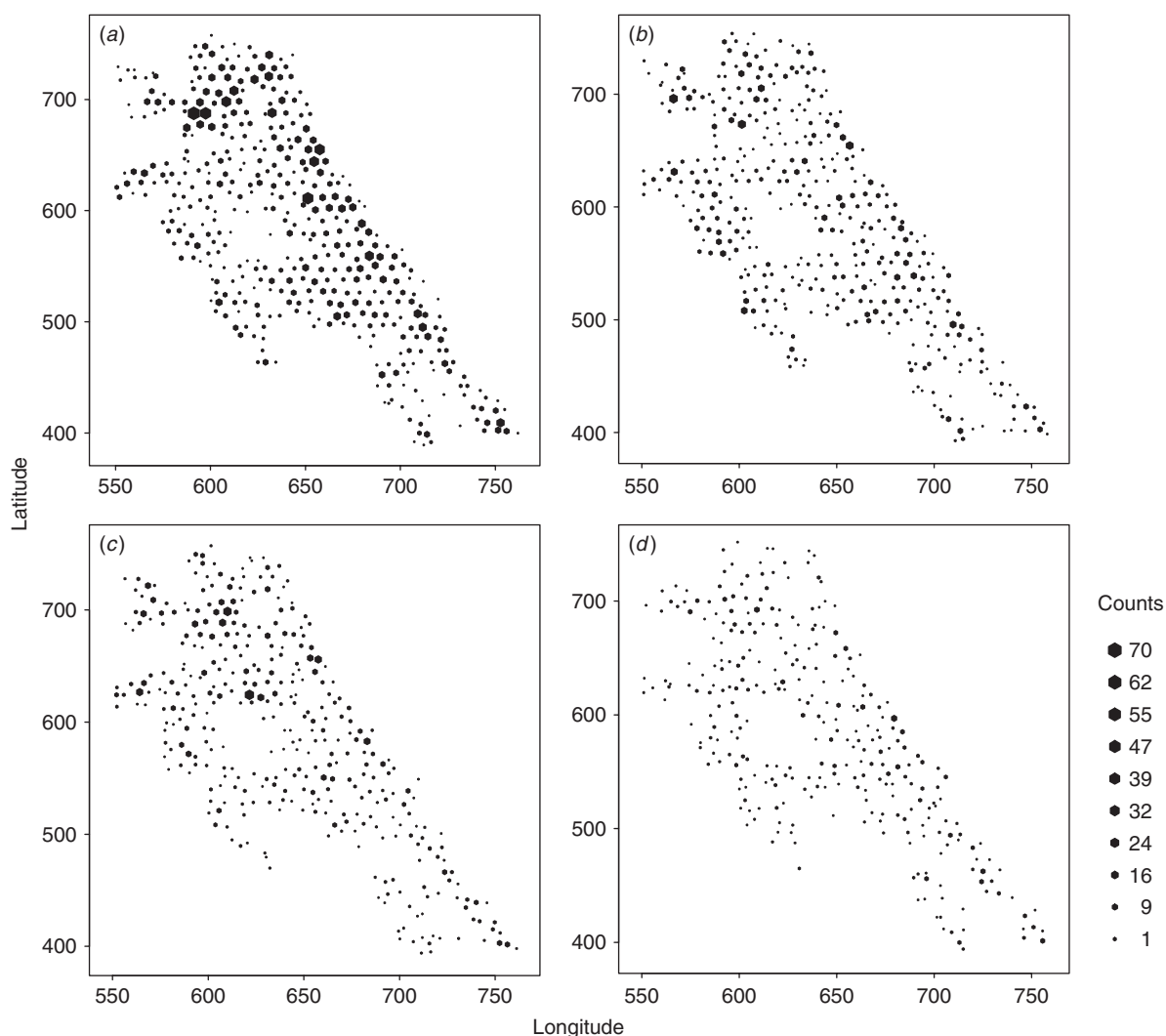


Fig. 5. Map of wildfire counts for the period 1981–2001 in the St Johns River Water Management District, obtained by hexagonal binning for different years: (a) 1981, (b) 1985, (c) 1988, and (d) 1997. The size of a hexagon is proportional to the number of wildfires that occurred in a region of about 6 km in diameter.

from CSR towards clustering, the strongest being for railroad causes. Here again, the amount of clustering for a given cause changes as a function of distance. The overall amount of clustering across the various distances for each cause can be summarized by means of the clustering index. The clustering indices for each fire cause are, in decreasing order of clustering: $CI = 855$ for railroad; $CI = 363$ for lightning; $CI = 292$ for arson; and $CI = 98$ for accident. The computations of those clustering indices are based on distances ranging from 0 to 50 km. The relative clustering index for arson, lightning, and accident (railroad belongs to this category) are computed and visualized in Fig. 9. We see that arson and lightning exhibit positive RCI , whereas accidental causes have a negative RCI . This means that, compared with the overall average amount of clustering, the ones for

arson and lightning causes are above the mean, whereas the one for accidental causes is below. Arson fires could occur in spatial and temporal clusters due to exogenous factors such as the presence of an arsonist and their serial behavior or a copycat response by a number of arsonists in the vicinity of other arson-ignited fires (Butry and Prestemon 2005). The north-western part of the SJRWMD experiences far more than its share of arson fires, and there are clusters of arson fires near St Augustine and Gainesville.

Lightning-caused fires may be clustered in space because lightning strikes are themselves clustered. In order to check this hypothesis, we consider data about wildfire ignitions caused by lightning in the SJRWMD region during June–July 1998, as well as data about strong lightning (defined here as lightning with high positive polarity) strike locations

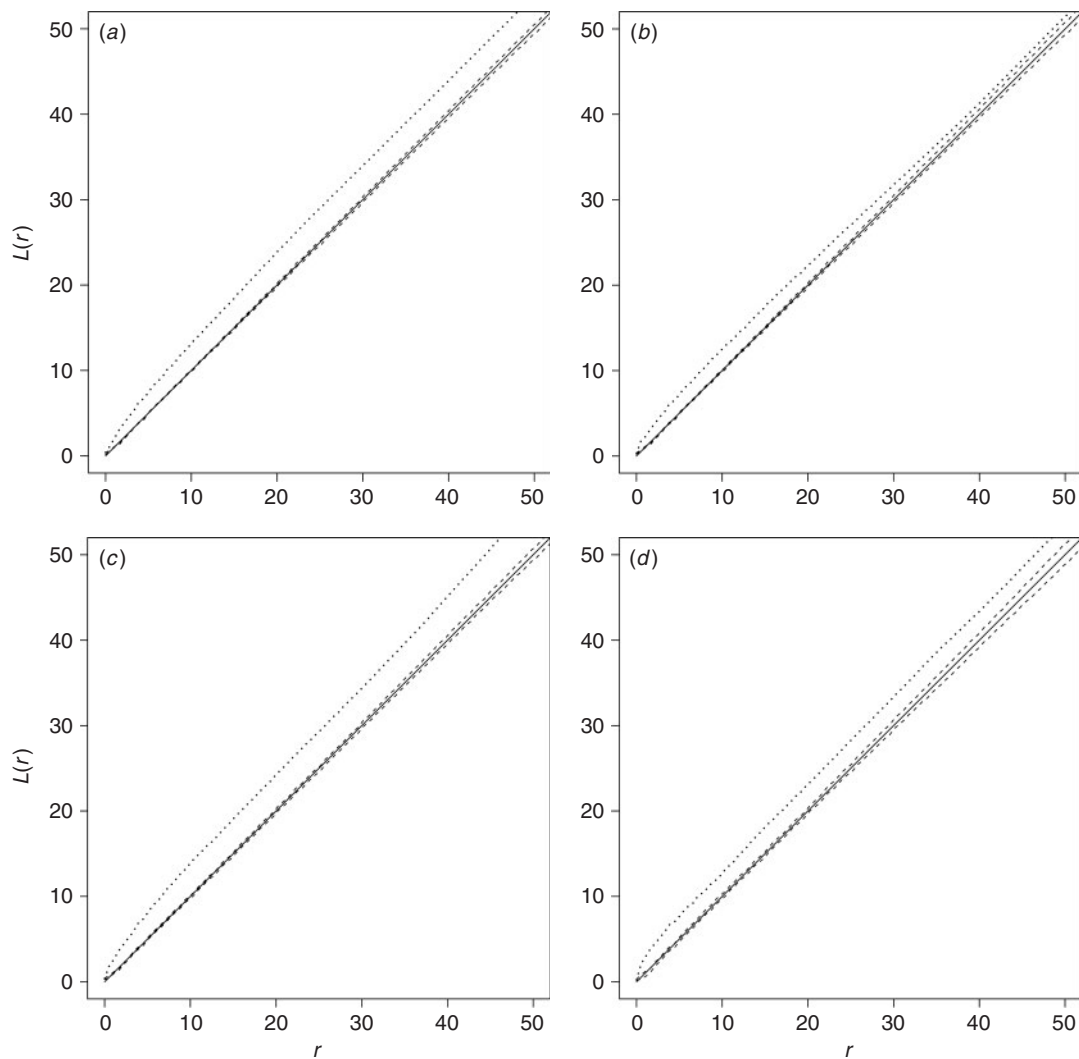


Fig. 6. The empirical L -function (dotted line) and theoretical L -function under CSR (solid line) as a function of distance (in km) for wildfire ignitions in the St Johns River Water Management District, computed for four different years: (a) 1981, (b) 1985, (c) 1988, and (d) 1997. Confidence envelopes (95%) for the theoretical L -function under complete spatial randomness (CSR) are shown with dashed lines. All four plots indicate a clear departure from CSR towards clustering.

in that region during the same period. The lightning strike data were obtained from WeatherBank (Edmond, OK, USA) and were collected through the National Lightning Detection Network. It is believed that high positive polarity and wildfire ignitions are related; see, for example, Fuquay (1980, 1982). A map of these data is presented in Fig. 10. The corresponding empirical L -function (dotted line) and theoretical L -function under CSR (solid line) as a function of distance (in km) are depicted in Fig. 10 as well. In these figures it appears that the strong lightning strikes are actually more highly clustered than the wildfire ignitions. Indeed, the clustering indices (computed within a range of 50 km) are $CI = 544$ for strong lightning strike locations and $CI = 323$ for wildfire ignitions caused by lightning. Particularly in the

southern region of the SJRWMD there are areas with dramatic clusters of lightning strikes. Some of the cluster areas in the south-western part of the region did not have many lightning-caused wildfires. This may not be unreasonable as the fuel and landscape conditions must be right in order for a lightning strike to result in an ignition. For instance, Rorig and Ferguson (1999) report that lightning occurring outside the area of precipitation (also called 'dry' lightning) is the most common contributor to ignition. More puzzling are places in the northern and coastal areas of the SJRWMD that had lightning-caused wildfires but no strong lightning strikes. This may be an indication that the relationship between strong lightning and wildfire ignitions is weaker than suggested by Fuquay (1980, 1982), at least in some spatial regions.

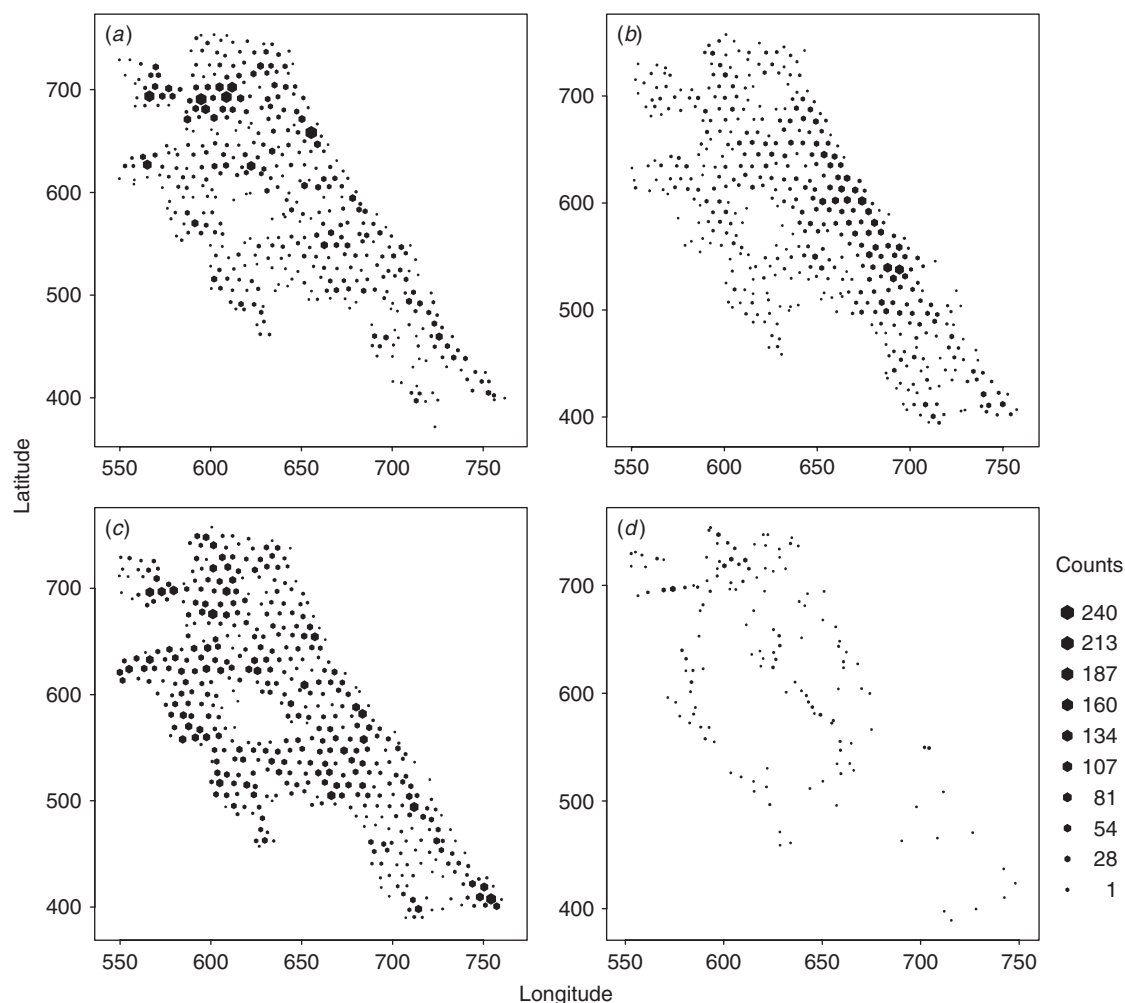


Fig. 7. Map of wildfire counts for the period 1981–2001 in the St Johns River Water Management District, obtained by hexagonal binning for different causes of wildfire ignitions: (a) arson, (b) lightning, (c) accident, and (d) railroad. The size of a hexagon is proportional to the number of wildfires that occurred in a region of about 6 km in diameter.

Spatio-temporal analysis

In this section, we analyse wildfire ignitions in a spatio-temporal context; that is, we want to see how spatial features/clusters of the locations of the wildfires in SJRWMD evolved over time from 1981 to 2001. Figure 4 depicted the hexagonal binning of the locations of all wildfires during 1981–2001. Figure 5, on the other hand, depicts the hexagonal binning of the locations of wildfires for 4 years separately. We see that 1981 has a lot of large clusters of wildfires, and that the spatial structure of those clusters changed over time. In particular, notice the higher concentrations of wildfires along the eastern coast and in the north-western region of the map. These remarks are also supported by plots of the evolution of the L -function over time in Fig. 6, again indicating clustering.

In order to better understand the evolution of the spatial clustering of wildfires due to different causes over time, we compute the relative clustering index for each year of the period 1981–2001, and for the ignitions caused by arson, lightning, and accidents separately. We plot the time series of RCI values for: arson cause (Fig. 11a), lightning cause (Fig. 11b), accident cause (Fig. 11c), and for all causes together (Fig. 11d). It is interesting to note that positive RCI values seem to be followed by negative RCI values. This means that, after a series of years where the clustering of wildfires ignitions is above average, there is typically a series of years where the clustering is below average. This pattern is especially visible for lightning causes. Also interesting is the fact that, for accident causes of fire, it appears that the RCI values are positive in recent years.

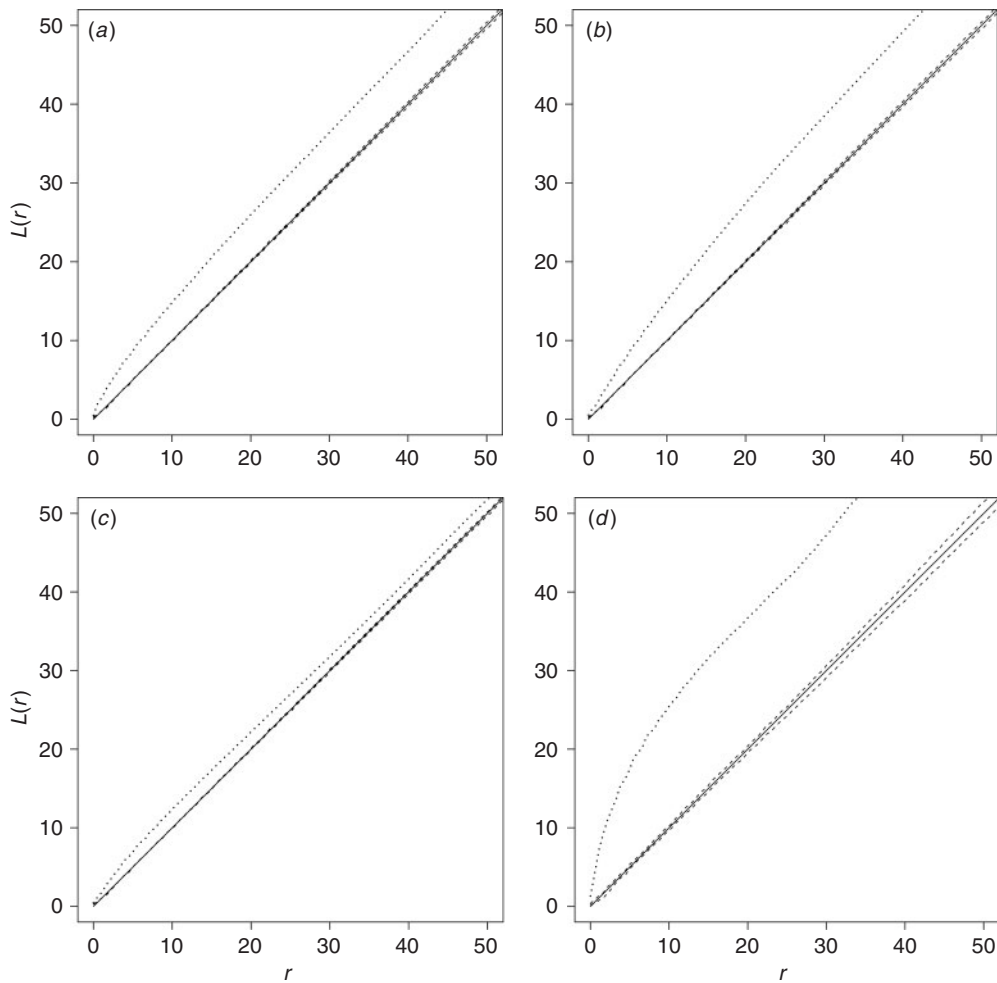


Fig. 8. The empirical L -function (dotted line) and theoretical L -function under CSR (solid line) as a function of distance (in km) for wildfire ignitions in the St Johns River Water Management District, computed for the period 1981–2001 for different causes of ignitions: (a) arson, (b) lightning, (c) accident, and (d) railroad; 95% confidence envelopes are shown as dashed lines. All four plots indicate a clear departure from complete spatial randomness towards clustering.

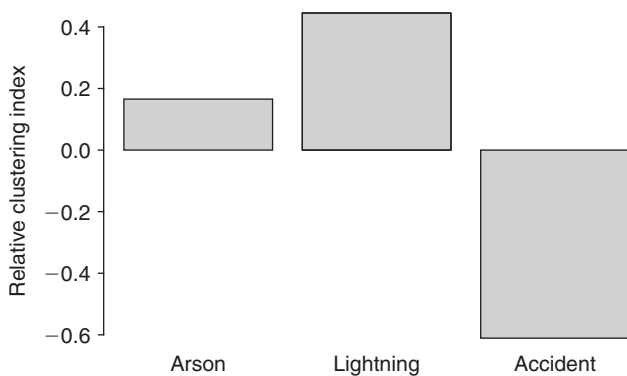


Fig. 9. Relative clustering index for wildfire ignitions during the period 1981–2001 in the St Johns River Water Management District for three different causes: arson, lightning, and accident.

Summary

In this paper, we have analysed the spatio-temporal structure of wildfire ignitions in the St Johns River Water Management District in Florida. We have used the L -function, a popular tool for the analysis of point patterns, and defined a relative clustering index that summarizes the amount of clustering over various spatial scales. We found that wildfire events tend to occur in clusters, at all spatial scales examined, and have analysed the structure of the clustering from purely temporal or spatial points of view, as well as in a spatio-temporal context.

If the intensity λ of the point process varies over the region, e.g. if there is some sort of spatial trend in the frequency of events, the point pattern is called ‘inhomogeneous’. An L -function that deviates from CSR can indicate that events

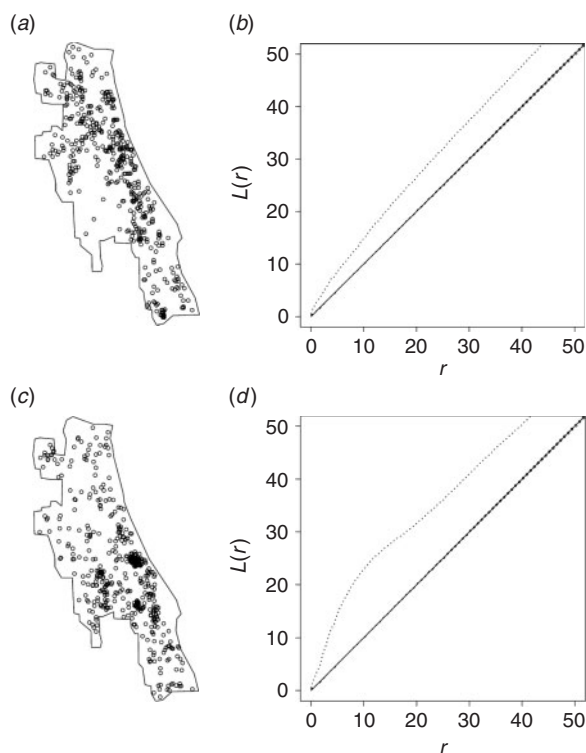


Fig. 10. Map of wildfire ignitions caused by lightning (a) and map of strong lightning strike locations (c) in the St Johns River Water Management District during the period June–July 1998. The respective empirical L -function (dotted line) and theoretical L -function under CSR (solid line) as a function of distance (in km) are depicted in parts (b) and (d). In both cases, there is evidence of significant spatial clustering.

interact or have some effect on each other, but it can also indicate that there is a trend in the pattern of wildfire ignitions, say from east to west, or it can indicate that some covariates underlie the spatial patterns. If spatial interaction is present, inclusion of information about the fire history of nearby areas will be beneficial in statistical models of fire incidence and improve the predictive ability of such models. Since the clustering is evident at all spatial scales from ~ 2 km on up, this result should hold for fire data aggregated over various spatial scales.

In addition, our study contains practical information for managers, law enforcement, and fire agencies. Our results have shown that arson and lightning are the leading causes of wildfires in the SJRWMD region and that ignitions by arson and railroad are spatially more clustered than ignitions by lightning or other accidental causes. Arson fires clustered mainly in the north-western corner of the SJRWMD and near some of the major cities. Catastrophically large wildfires are relatively rare, but those that occurred were caused by lightning. Lightning fires occurred most frequently in the eastern part of the SJRWMD near the central coast.

Acknowledgements

We thank the editor, associate editor, and two referees for valuable comments that greatly improved this manuscript. This research was supported by a cooperative agreement No. 03-CA-11330143-080 from the Southern Research Station of the USDA Forest Service.

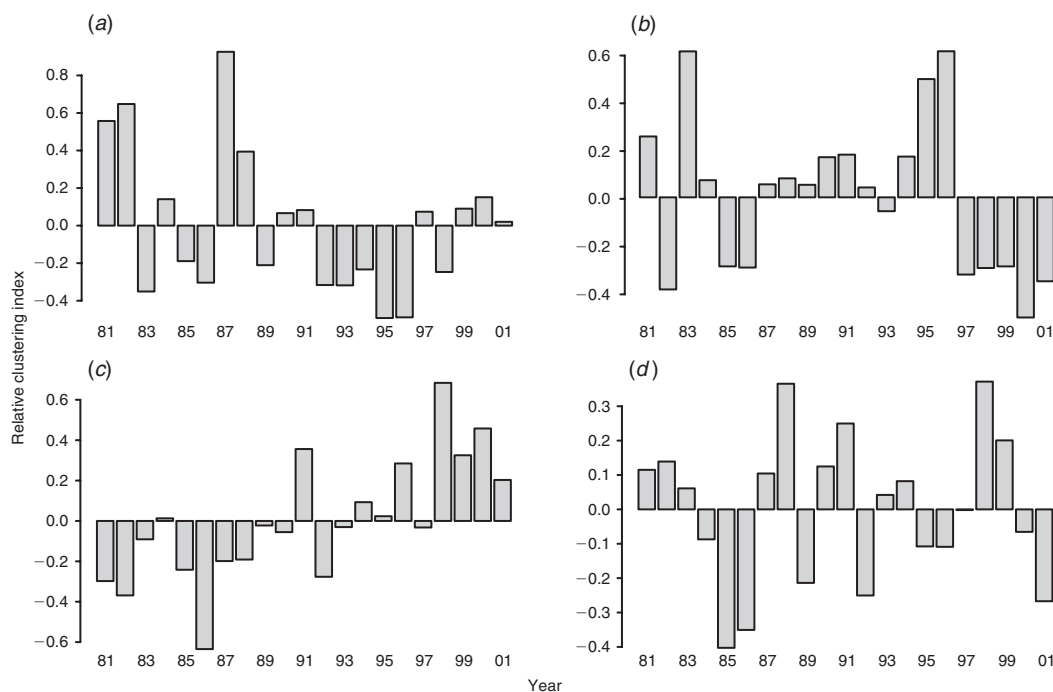


Fig. 11. Time series of relative clustering index values during the period 1981–2001 for wildfire ignitions in the St Johns River Water Management District for: (a) arson cause, (b) lightning cause, (c) accident cause, and (d) for all causes together.

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