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Geovisualization and harmonic analysis for the exploratory search of  
localized cyclic recurrences in spatio-temporal event data.

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# Abstract.

Many geovisualization environments integrate graphical representations of time. Some of them include representation of both linear and cyclic aspects of time, providing an exploratory analysis of spatio-temporal data through several temporal cyclic scales. However, few of them provide an exploratory analysis of localized cyclic recurrences in spatio-temporal data. *Ad hoc* temporal diagrams, representing both linear and cyclic aspects of time, provides a visual search for cyclic recurrences in temporal data when the possibility is left to the user to perform a gradual modification of the represented cyclic scale's duration. The combination of these graphic representations of time, with cartographic representations, displaying the spatial distribution of such cyclic recurrences, could provide an exploratory analysis of localized cyclic recurrences in spatio-temporal data. Mathematical tools coming from other scientific fields, such as the harmonic analysis, offer another way to identify cyclic behaviors in temporal data. Combining the visual approach offered by specifically designed geovisualization environments, with a harmonic analysis that suggests searching paths to the user during its exploratory analysis, can then improve the visual search for localized cyclic recurrences. We propose a geovisualization environment, which combines, on one hand, a visual analysis of localized cyclic recurrences in spatio-temporal data, using *ad hoc* temporal diagrams, cartographic representations, and specific semi-logic rules, and on the other hand mathematical tools, such as harmonic analysis and spatial clustering, that provide searching paths to the user for its visual analysis. This approach is supported by a geovisualization environment, GrAPHiST, which provides an exploratory analysis of spatio-temporal event data.

**Keywords:** Geovisualization; Exploratory analysis; Localized cyclic recurrences; Visual analysis; Harmonic analysis.

# 1 Introduction.

The representation of the cyclic aspect of time has been a research subject in visualization for a long time (Carlis and Konstan, 1998; Müller and Schumann, 2003; Aigner et al., 2011), and graphical representations allowing visual analysis of the cyclic component of spatio-temporal phenomena are used in many geovisualization environments (Andrienko and Andrienko, 2006), such as *eSTIME* (Menin et al., 2019), or *PerSE* (Swedberg and Peuquet, 2017).

A lot of these environments (Bak et al., 2009; Li, 2010; Andrienko et al., 2011; Swedberg and Peuquet, 2017; Menin et al., 2019) are calibrated to visualize spatio-temporal data through cyclic representations of time, using a limited set of usual cyclic scales corresponding to the rhythms of nature or human activities (Hornsby and Egenhofer, 2002). For this reason, few of them allow us to perform an exploratory search of unsuspected cyclic recurrences, of which the period of reappearance may have any duration, and the possibility to observe the spatiality of such recurrences.

We call “cyclic recurrences” a regular reappearance of a phenomenon or a regular evolution of its intensity, which follows a certain period of reappearance. A “localized cyclic recurrence” refers then to a cyclic recurrence contained in a specific spatial area, or presenting different periods of reappearance according to different spatial areas. For instance, a localized cyclic recurrence can correspond to the reappearance of flooding events every twenty years at a location *A*, and every fifty years at a location *B*.

The identification of cyclic behaviors in spatio-temporal data, and the analysis of their spatial component, represent a great interest for the analysis of several spatio-temporal phenomena, notably natural phenomena such as sea-level variation (Galassi and Spada, 2015) or flooding (Sabino et al., 1999; Yao, 1982). Proposing graphic representations, which would allow visual exploratory analysis of localized cyclic recurrences, would present then a research opportunity for the analysis of such spatio-temporal phenomena.

The analysis of cyclic behaviors is a subject of research in other scientific fields. Mathematical tools, such as harmonic analysis (Gasquet and Witomski, 2000; Bony, 2001; Katznelson, 2004), allow detecting cyclic recurrences in temporal data. We make the hypothesis that the combination of graphical representations, specially designed for visual analysis of cyclic recurrences, with such mathematical tools will improve the exploratory analysis of localized cyclic recurrences in spatio-temporal data.

We present a geovisualization approach, which combines visual and mathematical analysis to perform an identification of localized cyclic recurrences during an exploratory analysis of spatio-temporal data. Our approach is integrated into a geovisualization environment, GrAPHiST, designed for the analysis of spatio-temporal event data related to several topics. First, we present existing approaches regarding i) the visualization of the cyclic aspect of time in cartographic representations of spatio-temporal data; ii) the use of diagrams to identify cyclic recurrences in temporal data; iii) the possibilities offered by mathematical tools for the identification of cyclic behaviors and the combination of such mathematical tools with visual

35 representations. Then, we present our exploratory approach for the search of localized cyclic recurrences  
36 in spatio-temporal data, which combines specifically designed temporal diagrams and cartographic repre-  
37 sentations, with mathematical tools such as harmonic analysis and spatial clustering. Finally, through the  
38 application of our proposition to the analysis of height simulated datasets, we present that this proposition can  
39 be effective to identify localized cyclic recurrences within predominantly random datasets of spatio-temporal  
40 data.

## 41 2 Related works.

42 Several works propose a visualization of spatio-temporal data (Andrienko and Andrienko, 2006; Aigner et al.,  
43 2011; Kaddouri et al., 2014). The geovisualization environments providing a graphical representation of the  
44 temporal component of data are yet the best suited for an exploratory data analysis (Kaddouri et al., 2014).  
45 Amongst the graphical representations of time, some of them allow visual identification of cyclic recurrences  
46 in temporal data, and could be used for exploratory analysis of localized cyclic recurrences in geovisualization  
47 environments. Other techniques, using mathematical tools, may facilitate these visual analyses.

### 48 2.1 *The representation of the cyclic aspect of time in geovisual-* 49 *ization.*

50 Amongst the different existing works related to spatio-temporal data visualization, (Kaddouri et al., 2014)  
51 listed five main types of methods to visualize spatio-temporal data:

- 52 • the use of animation to represent an evolution of the spatial environment in real-time, or through  
53 chronological sequences;
- 54 • the use of *small multiples*, which consists in displaying, on several representations, the spatial environ-  
55 ment at several timesteps;
- 56 • the use of the *space-time cube*, which uses the third dimension to represent time, as it was explored by  
57 the *Time geography* (Hägerstrand, 1970);
- 58 • the use of semiologic rules (Cauvin et al., 2008; Kaddouri et al., 2014) to represent different temporalities  
59 (MacEachren, 1994) in cartographic representations;
- 60 • the use of multi-view interfaces, which show the three components of the spatio-temporal data (spatial,  
61 temporal, thematic), into three main synchronized windows.

62 According to (MacEachren, 1994) and (Davoine, 2014), multi-view interfaces are the best suited for  
63 the exploratory analysis of spatio-temporal data, allowing to identify patterns in the spatial and temporal

64 distribution of the data. The other methods listed by (Kaddouri et al., 2014) can be integrated into multi-  
65 views interfaces, to provide a visualization of relationships between the temporal and spatial components  
66 of the data, by allowing the user to establish visual links between the temporal and spatial windows of the  
67 interface. These methods are yet not all suited for exploratory analysis of spatio-temporal data through the  
68 cyclic aspect of time:

- 69 • the use of animation may impact the readability of the visualization (Kaddouri et al., 2014), and may  
70 not be adapted for exploratory analysis of the spatio-temporal distribution of data;
- 71 • the use of small multiple may either impact the readability of the visualization because of the huge  
72 number of representations (Kaddouri et al., 2014), or impact the resolution of the analysis because of  
73 the data aggregation needed to reduce the number of representations.
- 74 • the space-time cube, by representing the time on a linear axis, does not include a representation of the  
75 cyclic aspect of time.

76 The use of semiologic rules appears to be the best option to consider the cyclic aspect of time in geovi-  
77 sualizations of spatio-temporal data (Gautier, 2018). Combined with specific cartographic design, it allows  
78 us to visually establish relationships between spatial and temporal patterns. As an example, *Growth Ring*  
79 *Map* ((Bak et al., 2009; Andrienko et al., 2011; Aigner et al., 2011)) visualizes event data, each event being  
80 represented by a pixel wearing a color hue representing its season of appearance. Spatially close events are  
81 represented by aggregates of pixels, where pixels corresponding to the same season of appearance are reunited  
82 into concentric rings. This cartographic design allows us to identify, through the observation of aggregates of  
83 the same color hue, relationships between concentrations of events in specific spatial areas and concentrations  
84 of events during specific cyclic temporal intervals, forming patterns we call spatio-temporal clusters.

85 Some temporal diagrams may be used to carry out an exploratory analysis of cyclic recurrences. Inte-  
86 grating such diagrams in multi-view interfaces could allow extending the exploratory analysis to the search  
87 of localized cyclic recurrences.

## 88 ***2.2 Visualization of temporal recurrences.***

89 Some diagrams propose to combine the benefits of the timeline and the timewheel, by integrating the linear  
90 and cyclic aspects of time in a single representation (Edsall and Peuquet, 1997; Van Wijk and Van Selow,  
91 1999; Weber et al., 2001; Li, 2010). These diagrams, that we call *mixed diagrams* (Gautier, 2018), represent  
92 time in a linear way, through the succession of several instances of a considered temporal cyclic scale. As  
93 examples, we can cite:

- 94 • the *Spiral Graph* (Weber et al., 2001), based on a linear version of the timewheel, which takes the shape  
95 of a spiral, of which the rings represent successive instances of a temporal cyclic scale;

- 96 • the *tiles maps* (Van Wijk and Van Selow, 1999), which represent time through a linear and a cyclic  
97 scale, on two orthogonal axes according to two different temporal granularities. It creates a matrix of  
98 which each column represents an instance of the cyclic scale (“a day”), and each row represents the  
99 same relative temporal moment in these different instances (“4 p.m”);
- 100 • the *Time Wave* (Li, 2010), based on the combination of the structures of the timeline and the timewheel,  
101 and which are composed of a series of graphical patterns, each representing an instance of a temporal  
102 cyclic scale, aligned along an axis representing the linear dimension of time.

103 These diagrams allow visual identification of a cyclic recurrence in temporal data, through the obser-  
104 vation of alignments of similar graphic patterns along an axis, when the duration of the represented cyclic  
105 scale reaches the duration of the observed cycle’s period. A visual search for a cyclic recurrence can be  
106 performed through these diagrams, by following this process: the user must search which cyclic temporal  
107 scale corresponds to the observation of graphic alignments in these diagrams (Weber et al., 2001).

108 However, many visualization environments (Li, 2010; Swedberg and Peuquet, 2017; Menin et al., 2019),  
109 which integrate temporal diagrams, are designed for the visualization of spatio-temporal data through a cyclic  
110 representation of time, and not for the exploration of the possible cyclic behaviors in temporal data. Their  
111 goal is not to determine whether a phenomenon is cyclic or not, by allowing the identification of possible  
112 cyclic recurrences, but to provide a visual analysis of the temporal structure of phenomena, through one or  
113 several cyclic temporal scales. These cyclic scales can be used as temporal markers (Li, 2010), to analyze  
114 phenomena already considered as cyclic such as those related to the day-night cycle (Menin et al., 2019), or  
115 to analyze the temporal distribution of data according to usual cyclic representations of time such as the  
116 seasonal cycle (Swedberg and Peuquet, 2017). This objective limits the number of cyclic scales, which can  
117 be calibrated in these environments.

118 According to Hornsby and Egenhofer (Hornsby and Egenhofer, 2002), the cyclic scales used by the rep-  
119 resentations of time are, in most cases, based on the rhythms of nature or human activities, and correspond  
120 to usual and calendar periods such as days, months, hours, etc. The configurable scales in visualization  
121 environments are then often limited to these usual periods (Li, 2010; Swedberg and Peuquet, 2017). It limits  
122 the periods for which it is possible to identify a cyclic recurrence of events. Furthermore, the discontinuous  
123 nature of the series of configurable cyclic scales (the transition from a scale of one month, to a scale of one  
124 year, generally takes place without transition) prevents the observation of the formation of graphical align-  
125 ments, during a gradual modification of the cyclic scale. The observation of the formation of these alignments  
126 allows the user to know if he is approaching a cyclic temporal scale corresponding to a cyclic recurrence. To  
127 carry out a visual exploration of cyclic recurrences in temporal data through these mixed diagrams, it is,  
128 therefore, necessary to allow a dynamic and gradual modification of the duration of the represented cyclic  
129 scale (Weber et al., 2001).

130 The integration of such diagrams, in geovisualization environment, could then be a way to perform an

131 analysis of localized cyclic recurrences in spatio-temporal data. The major disadvantage of the provided  
132 visual analysis of cyclic recurrences, is to make the user explore amongst an undefined amount of possible  
133 durations for the represented cyclic scale. Suggesting exploration paths to the user could then be a way to  
134 improve such visual analysis.

### 135 ***2.3 Combining mathematical analysis of recurrences with graphic*** 136 ***representations.***

137 Identifying recurrences in data through mathematical analysis is a research topic in other scientific fields,  
138 such as DNA (Deoxyribose nucleic acid) analysis in biology (Ritz et al., 2011), in which many works have  
139 been done on the identification of sequences reappearances in character string data. Our goal is mainly to  
140 identify the cyclic behavior of the reappearances of similar patterns, rather than to identify the reappearances  
141 of similar patterns. However, many of these works propose to combine mathematical analysis of recurrences  
142 with graphical representations, specifically designed for the observation of patterns reappearances (Hamori  
143 and Ruskin, 1983; Jeffrey, 1990; Wu et al., 1993). These works have inspired other visualizations allowing a  
144 visual analysis, assisted by mathematical analysis, of patterns reappearances in textual data such as computer  
145 code (Church and Helfman, 1993) or musical score (Wattenberg, 2002). We can make the hypothesis, that  
146 integrating such mathematical analysis into a geovisualization environment, could be a way to support the  
147 user’s visual exploration to identify localized cyclic recurrences in spatio-temporal data.

148 Harmonic analysis is a branch of mathematics, which studies the representation of signals as combinations  
149 of elementary sinusoidal functions called “harmonics”, which can present different frequencies and amplitudes  
150 (Bony, 2001; Katznelson, 2004). With mathematical tools such as the Fourier transforms, these analyses make  
151 it possible to decompose a mathematical function into a sum of periodic functions of different frequencies  
152 (Gasquet and Witomski, 2000). The harmonic analysis of a signal, representing a physical phenomenon, allows  
153 obtaining the frequencies of possible cyclic recurrences in the phenomenon. Other mathematical methods  
154 propose more efficient ways to identify cyclic patterns in temporal data (Wang et al., 2018). However, the  
155 harmonic analysis by Fourier transform, easy to handle, may represent a good choice for a first integration  
156 of such a mathematical tool in a geovisualization environment.

## 157 **3 Combining visual and mathematical analysis for the** 158 **exploratory search of localized cyclic recurrences.**

159 We propose an exploratory approach for the identification of localized cyclic recurrences, based on a visual  
160 analysis using interactive graphic and cartographic representations, assisted by mathematical analysis tools.

161 Our visual analysis is based on the use of:

- 162 • interactive temporal diagrams, that can be used to perform an exploratory search of a cyclic recurrence  
163 in temporal data;
- 164 • a cartographic representation, that can be used to identify spatial cluster;
- 165 • specific semiologic rules and cartographic/graphic designs, allowing to identify spatio-temporal clusters;
- 166 • interaction functionalities, extending the search of cyclic recurrences performed in the temporal diagram,  
167 for the visual search of localized cyclic recurrences.

168 We propose to extend this visual analysis by combining it with mathematical tools performing back-  
169 ground analysis on the spatio-temporal data, to suggest to the user search paths for its exploratory analysis.  
170 According to the user actions, harmonic analysis by Fourier transform are performed on either the entire  
171 data, or on groups of data obtained by manual or automatic classification. Their results are suggested to the  
172 user as temporal scales that may correspond to a cyclic behavior in the spatio-temporal data.

173 Our approach is integrated into GrAPHiST (Gautier, 2018; Gautier et al., 2019), a multi-view geovisu-  
174 alization environment, dedicated to the exploratory analysis of punctual spatio-temporal event series, which  
175 may describe any type of spatio-temporal phenomena.

176 In this part, we present the general structure of GrAPHiST and the nature of the visualized data. We then  
177 present how the visual analysis supported by GrAPHiST allows the search of localized cyclic recurrences in  
178 spatio-temporal data. Then, we show how we improve the exploratory analysis of localized cyclic recurrences  
179 in spatio-temporal data, by combining this visual approach with mathematical analysis.

## 180 **3.1 *GrAPHiST***

### 181 *3.1.1 Represented data.*

182 GrAPHiST provides a "generic" exploratory of spatio-temporal phenomena, which can be related to dif-  
183 ferent topics, through visualization of event-based spatio-temporal data. Spatio-temporal phenomena, in  
184 GrAPHiST, are represented by event series related to the same topic (Gautier, 2018). Each event is consid-  
185 ered as an occurrent spatio-temporal entity, that can be described through the Pyramid Model of Mennis  
186 (Mennis et al., 2000): each event is composed of a temporal component (a moment of appearance), a spatial  
187 component (a location of appearance), and a thematic component (which type of event).

188 Events which form a phenomenon can be seen as close, mainly on a thematic criterion (the phenomenon  
189 "storm" is composed by every "storm" events), but also on a spatial or a temporal criterion (the phenomenon  
190 "storm" in the USA in 2008 is composed by every "storm" events occurred in 2008 in the USA). Defining  
191 which events are part of the same phenomenon is open to interpretation, and we let this choice to the user: a  
192 phenomenon can be seen as a selection, made by the user, of events he wants to analyze. This representation  
193 allows us to visualize data related to several topics with the same approach.

194 We focus our proposition on the visualization of spatio-temporal punctual events: each event corresponds  
195 to a punctual location in space and a punctual moment in time. These events can correspond to real  
196 punctual events observed in time and space, or at punctual moments when a variable represented by a time  
197 series related to a punctual location exceeds a threshold value.

198 A cyclic recurrence in spatio-temporal data will correspond, through this representation, to a regular  
199 reappearance of events, or a regular increase or decrease of the number of event appearances, which follow a  
200 certain period of reappearance. A localized cyclic recurrence will correspond to a cyclic recurrence contained  
201 in a specific spatial area, or a cyclic recurrence presenting different period of reappearance according to  
202 different spatial areas. For instance, a localized cyclic recurrence can correspond to the rise of the sea level  
203 above a threshold value every ten years at a location  $A$ , and every fifteen years at a location  $B$ .

### 204 *3.1.2 A multi-view structure.*

205 GrAPHiST follows a multi-view interface structure (Figure 1). Events related to the same phenomenon being  
206 considered as close on a thematic criterion, the visual analysis is focused on the spatio-temporal structure  
207 of the event series. The available graphic space of the interface is preserved for the representation of the  
208 spatial and temporal components of data. Therefore, GrAPHiST does not include a thematic window. Each  
209 window can be used to perform an analysis of spatial or temporal patterns in events distribution, such as  
210 the concentration of events appearance in a specific area (spatial cluster), or during a specific linear or cyclic  
211 temporal interval (temporal linear or cyclic cluster).

212 [Figure 2]

213 The spatial window integrates a map, which represents all events that occurred during the temporal  
214 interval represented in the temporal window (Figure 1.A). Events are represented by punctual entities. Spa-  
215 tially close events are aggregated and represented by graphical punctual entities of which size depends on the  
216 number of events.

217 The temporal window integrates a mixed diagram, representing events that occurred in the extent of  
218 the spatial window (Figure 1.B). Events are represented by punctual entities, temporally close events being  
219 aggregated and represented in the same manner as in the spatial window. The temporal window includes a  
220 timewheel-based diagram inspired by the *Rose Chart* (Nightingale, 1858) (Figure 1.C), using the same cyclic  
221 scale than in the mixed diagram. Each section of the diagram represents an equal temporal portion of the  
222 cyclic scale, and the number of events appearing during each portion is represented by the section's area.

## 223 *3.2 Visual analysis of localized cyclic recurrences.*

224 We present here our visual approach for the analysis of localized cyclic recurrences in spatio-temporal event  
225 data. We first present how our mixed temporal diagram allows performing a visual search of a cyclic recurrence

226 in temporal event data. We then present how specific semiologic rules and graphic/cartographic designs allow  
227 extending this approach to the visual analysis of localized cyclic recurrences in spatio-temporal data.

### 228 3.2.1 *Visual analysis of cyclic recurrences in temporal data.*

229 The visual identification of cyclic recurrences in temporal data is carried out through the use of an interactive  
230 mixed diagram. We propose a mixed diagram partly inspired by the tiles map (Van Wijk and Van Selow, 1999)  
231 and the Time Wave (Li, 2010), which takes the shape of a sawtooth periodic function. Time is represented on  
232 two axes according to the same temporal granularity. The abscissa axis represents time according to a linear  
233 scale, and the ordinate axis represents time according to a cyclic scale. An instance of the corresponding  
234 cyclic scale is represented by an oblique linear curve. The representation of several instances of the cyclic  
235 scale takes the shape of a series of broken lines. The graphical entities are placed along the curve of the  
236 diagram according to the moment of appearance of the represented event, or according to the “barycenter”  
237 of the moments of appearance of the aggregated events.

238 The duration  $T$  of the represented cyclic scale can be dynamically and gradually modified by the user  
239 (Figure 2). When  $T$  decreases, the number of broken lines in the diagram increases, and the lines appear more  
240 closely spaced and more vertical. When  $T$  increases, the number of broken lines in the diagram decreases,  
241 and the lines appear more spaced and more horizontal.

242 The visual search for cyclic recurrences is carried out through a gradual modification of  $T$ , using a cursor in  
243 a control interface. During this modification, the user has to observe the formation of alignments of graphical  
244 entities on the diagram. The formation of such alignments is observable when the value of  $T$  approaches the  
245 duration of the period  $P$  of a cyclic recurrence. The alignments of graphical entities take first the shape of  
246 one or more oblique lines. When entities, corresponding to cyclic events, are forming such alignments for a  
247 scale of duration  $T_1$ , the orientation of the corresponding lines indicates whether the period  $P$  is less than or  
248 greater than  $T_1$ :

- 249 • if  $P < T_1$ , the line(s) formed by the alignment of graphic entities will be descending.
- 250 • if  $P > T_1$ , the line(s) formed by the alignment of graphic entities will be ascending.

251 As the value of  $T$  approaches that of  $P$ , the orientation of the graphical alignment approaches the orientation  
252 of the abscissa axis. When  $T = P$  (Figure 2.H), the corresponding entities form one alignment parallel to  
253 the abscissa axis.

254 [Figure 3]

255 The timewheel-based diagram included in the temporal window is an additional tool for the visual analysis  
256 of cyclic recurrence. According to the cyclic scale corresponding to their period of reappearance, cyclic events  
257 appear together in the same cyclic temporal interval. Their existence causes, if the proportion of cyclic events  
258 is not too weak, a concentration of events in this cyclic temporal interval, forming a cyclic temporal cluster.

259 This pattern can be observed in the timewheel-based diagram, when few sections present a higher area  
260 than the others. The observation of the formation of a graphical alignment, in the mixed diagram, can be  
261 supported by the observation of sections presenting a higher radius in the timewheel-based diagram (Figure  
262 2.E-H). These sections have their highest area when  $T = P$  (Figure 2.H). The user can increase the number  
263 of angular sections of the timewheel diagram. A bigger number of sections, representing smaller intervals of  
264 time, facilitates the estimation of the temporal extent of the observed cluster.

### 265 3.2.2 *Visual analysis of localized cyclic recurrences in spatio-temporal data.*

266 **Semiologic rules and graphic/cartographic designs.** The visual identification of localized cyclic re-  
267 currences is carried out through the use of specific semiologic rules and graphic/cartographic designs, that  
268 allow establishing relationships between temporal patterns (cyclic recurrences and temporal clusters) and a  
269 spatial cluster.

270 We use events classifications and semiologic rules, which take three different aspects according to the  
271 paradigm chosen by the user, that we call spatial entry and cyclic temporal entry:

- 272 • From a spatial entry: events are sorted and represented, using color hue, according to their location of  
273 appearance. The relationship between GrAPHiST's windows is oriented from the map to the temporal  
274 diagrams (Figure 3.A).
- 275 • From a cyclic temporal entry: events are sorted and represented, using color hue and a chromatic  
276 circle, according to their moment of appearance related to a cyclic scale. The relationship between  
277 GrAPHiST's windows is oriented from the circular diagram to the sawtooth diagram and the map  
278 (Figure 3.B).

279 [Figure 4]

280 In each case, proposed classification and semiologic rules follow the same principles:

- 281 • events are divided into several classes:
  - 282 – for a spatial entry, geographical space is divided into several areas, and each class represents events  
283 appearing in the same area.
  - 284 – for a cyclic temporal entry, the represented temporal cyclic scale is divided into several regular  
285 temporal intervals, and each class represents events appearing during the same temporal interval.  
286 For this specific case, the temporal intervals used to classify the events correspond to those used  
287 in the timewheel-based diagram, each class corresponding to an angular section of the diagram.
- 288 • an instance of the corresponding visual variable is affected to each class (Figure 4):
  - 289 – for a spatial entry, a color hue is assigned to each spatial area;

– for a cyclic temporal entry, the different cyclic temporal intervals are projected on a chromatic circle, and the corresponding color hue is assigned to each temporal interval.

We then use specific graphic/cartographic designs to represent, in each aggregate of events, the proportion of the different event classes existing in the aggregate (Figure 4):

- In the circular diagram, as in the Rose Chart, the proportion of each event class in a cyclic temporal interval symbolized by an angular section of the diagram, is represented by the area of different axial subsections.
- In the map and the mixed diagram, aggregates of events are represented by pie charts, of which the size represents the number of aggregated events, and the different sections represent the proportion of the different events classes amongst the aggregated events.

These representations, that may show a concentration of events related to the same spatial area in an aggregate of temporally close events, or a concentration of events related to the same temporal interval in an aggregate of spatially close events, allow visual identification of spatio-temporal clusters.

[Figure 5]

**Extending the search of cyclic recurrences with semiologic rules.** A representation of events through a spatial entry (Figure 5.A.1), separating events in several spatial groups and giving the same color to events related to the same area in the temporal diagram, allows performing the visual analysis presented in section 3.2.1 on each group of events. The user can, during a gradual modification of the represented cyclic scale, perform a visual search of cyclic recurrences in a group of spatially close events, by observing the formation of alignments of graphical entities presenting the corresponding color (Figure 5.A.2).

The timewheel-based diagram represents still an additional tool for the visual analysis of a cyclic recurrence in a group of spatially close events. The existence of a cyclic recurrence in a located area causes the existence, in this area, of a spatio-temporal cluster. Its identification can be carried out, in the timewheel-based diagram, through the observation of close diagrams sections presenting a higher proportion of the corresponding color.

[Figure 6]

The identification of localized cyclic recurrences using a cyclic temporal entry is done in two steps. The first and main step consists of performing the exploratory search of the cycle's duration directly on the map. The existence of a localized cyclic recurrence causes the existence of a cyclic spatio-temporal cluster related to a scale of which duration is equal to the cycle's period. The search for the cycle's duration can then be done by searching the cyclic temporal scale which corresponds to the observation of a spatio-temporal cluster on the map. To achieve this, the user can gradually modify the duration of the represented cyclic scale. The color of graphical events in the map being determined by their cyclic temporal distribution, changing

322 the value of the temporal scale changes their color in the map. The user can then identify spatio-temporal  
323 clusters on the map, by observing the formation of pie charts presenting both a notable size and a high  
324 proportion of the same color.

325 The second step of the analysis consists in checking, in the mixed diagram, if the observed spatio-temporal  
326 cluster corresponds to the existence of a cyclic recurrence. When a cluster is observed on the map, selection  
327 and filtering functions allow the user to only display the events of the corresponding area in the temporal  
328 diagrams. If graphical alignments are formed by the corresponding events on the mixed diagram, the user  
329 can validate the existence of a localized cyclic recurrence. The user can then modify the duration of the  
330 represented cyclic scale to observe the formation of one alignment parallel to the horizontal axis, presenting  
331 at least one graphical entity on each broken line. Observing alignment, without at least one entity on each  
332 broken line, means that the duration of the cyclic scale corresponds to a harmonic of the cycle's period  
333 (Figure 5.B.2).

### 334 ***3.3 Using background mathematical analysis to improve the ex-*** 335 ***ploratory search of localized cyclic recurrences.***

336 To improve the exploratory search of localized cyclic recurrences, we propose to combine our visual approach  
337 with mathematical analysis, executed in background, able to suggest exploratory paths to the user. In this  
338 part, we show how we combine our mixed temporal diagram with a harmonic analysis by discrete Fourier  
339 transform. Then, we show how this harmonic analysis can be integrated into an exploratory search of  
340 localized cyclic recurrences, and how this analysis is executed according to the user's interaction to suggest  
341 him different research paths.

#### 342 *3.3.1 Mixed diagrams and harmonic analysis.*

343 We propose to combine our mixed temporal diagram with a harmonic analysis performed on the studied  
344 data, in the background of the graphical representation. When data are displayed on the temporal diagram,  
345 the following actions are done on the temporal data.

- 346 • A temporal signal is created by sampling the event series we are studying (the sampling interval can  
347 be calibrated by the user). The graphical representation of the obtained signal takes the shape of a bar  
348 chart (Figure 6.A).
- 349 • A harmonic analysis is applied to the obtained sampled signal. We use a discrete Fourier transform,  
350 which allows performing a harmonic analysis on a discrete series of values. The frequencies correspond-  
351 ing to the most significant peaks of the obtained spectrum are selected (Figure 6.B).
- 352 • The duration of the periods corresponding to the selected frequencies is graphically represented, by

353 being projected on the cursor used to modify the duration of the cyclic scale in the control interface  
354 (Figure 6.C). Each dot on the cursor represents one of the periods obtained from the harmonic analysis.

355 The obtained periods constitute a list of suggestions of “remarkable” cyclic temporal scales that the user  
356 can “inspect”. The user can change the duration of the cyclic scale to these values, to check whether the  
357 formation of graphic alignments is observable on the mixed diagram (Figure 6.D). Figures 2 and 6 present  
358 the same simulated data. In Figure 6, the background mathematical analysis suggests a cyclic scale close to  
359 the cycle’s period found in Figure 2.

360 [Figure 7]

### 361 *3.3.2 Harmonic analysis on spatially gathered events, for the search of localized cyclic re-* 362 *currences.*

363 The harmonic analysis previously presented provides a way to support the exploratory analysis of cyclic  
364 recurrences through the temporal diagram. This analysis is carried out on the whole population of events. To  
365 support the exploratory analysis of localized cyclic recurrences in spatio-temporal data, we propose to extend  
366 the combination of our visual approach with mathematical analysis executed in background, by considering  
367 the spatial distribution of events in those analyses. To achieve this, we propose to execute a series of different  
368 harmonic analysis on several groups of events, gathered according to their spatial location. These groups are  
369 defined according to the actions of the user regarding the chosen paradigm for the exploratory analysis.

370 When any semiologic rules are used to represent events in the different windows of GrAPHiST, a harmonic  
371 analysis is carried out on the entire population of events. The analysis results are proposed to the user as  
372 cyclic scales suggestions, in the shape of dots of the same color in the control interface (Figure 6). This  
373 approach gives exploration paths for the search of cyclic recurrences in the entire studied spatial extent.

374 [Figure 8]

375 When the user chooses to perform an analysis through a spatial entry, the events are sorted according to  
376 a specific division of space imposed by the user (Figure 7.A.1). A specific harmonic analysis is carried out  
377 on each group of events obtained from this spatial classification (Figure 7.B). The results of each analysis  
378 are proposed to the user as cyclic scales suggestions in the shape of dots of different colors in the control  
379 interface, corresponding to the colors representing each area (Figure 7.C). This approach gives exploration  
380 paths for the search of localized cyclic recurrences through a specific division of space calibrated by the user.

381 When the user chooses to perform an analysis through a cyclic temporal entry, the user does not suspect  
382 a specific spatio-temporal distribution of events. To provide exploration paths for the analysis of cyclic  
383 recurrences in located areas, several harmonic analyses are done in groups of spatially close events, obtained  
384 with a spatial clustering function. In the context of the implementation of GrAPHiST, we use for this task the  
385 clustering function of the Openlayers3 Javascript library. In the background of the graphic representation,

386 events are gathered according to their spatial proximity, using a maximum distance parameter, under which  
387 two events are gathered. This maximum distance is calibrated by the user. After this clustering, a color is  
388 randomly affected to each group, and their convex hulls are displayed on the map, to highlight the location  
389 of the different corresponding areas (Figure 7.A.2). A specific harmonic analysis is carried out, still in  
390 background, on each group. The results of each analysis are proposed to the user as cyclic scales suggestions  
391 in the shape of dots of different colors in the control interface, corresponding to the colors randomly selected  
392 for each area. This approach gives exploration paths for the search of localized cyclic recurrences through a  
393 division of space procedurally created with clustering functions.

## 394 4 Case study.

395 To validate our approach, we applied the exploratory analysis provided by GrAPHiST on a series of eight  
396 procedurally created datasets. For each dataset, the analysis has to provide the visual identification of a  
397 localized cyclic recurrence amongst the spatio-temporal data, and an estimation of the corresponding period  
398 of reappearance.

### 399 4.1 *Construction of simulated event data.*

400 The objective of this case study was to validate the possibility to use our approach to find localized cyclic  
401 recurrences in event data, and to evaluate the precision of the analysis results.

402 To achieve this experiment, we had to use event series presenting such spatio-temporal structures. Some  
403 phenomena are known to present cyclic behaviors, as it is the case for meteorological or sea-level evolution  
404 phenomena (Gautier, 2018). Analyzing the corresponding datasets could be a way to validate the possibility  
405 to identify localized cyclic recurrences in spatio-temporal data. However, knowing the existence of these  
406 cycles, and their corresponding period of reappearance, would influence the analysis of such event series. To  
407 validate the possibility of identifying cycles presenting an unknown period, we had to use datasets preventing  
408 us from being influenced by an a priori knowledge or suspicion about the cycles we had to search for. We  
409 had to use datasets with cyclic behaviors, but of which the period of reappearance was unknown. Such an  
410 experiment appeared then to be impossible to conduct with data related to a real phenomenon.

411 Above all, this experiment implied the use of datasets presenting localized cyclic events with a greater or  
412 lesser spatial and temporal dispersion, and a more or less significant proportion of random events. We used  
413 datasets formed by procedurally created events. Our hypothesis was that if our approach could effectively  
414 provide a visual analysis, able to identify localized cyclic recurrences in these simulated event data, the  
415 discovery of unsuspected localized cyclic recurrences in real data would also be possible.

416 Each dataset was composed of a series of events forming a localized cyclic recurrence, and a series of  
417 randomly created events, of which place and time of appearance were randomly generated. The creation

418 parameters of the cyclic component of each dataset were randomly chosen, then stored in a log file, in order  
 419 to be accessible afterward but unknown during the experiment. The objectives were to identify the localized  
 420 cyclic recurrences of each dataset and to estimate its parameters. The estimated results were then compared  
 421 with the stored parameters. More precisely, the task consisted in identifying each localized cyclic recurrence,  
 422 and estimating, for each identified localized cyclic recurrence:

- 423 • the geographical coordinates of the center  $C$  of the spatial area where the cyclic events appear;
- 424 • the spatial dispersion  $disp_c$ , defining the size of the spatial area where the cyclic events appear;  $disp_c$   
 425 is measured in degrees: the borders of the area are the meridians and parallels corresponding to  
 426  $long = long_C + -disp_c$  and  $lat = lat_C + -disp_c$ ;
- 427 • the duration  $P$  of the cyclic recurrence’s period, which can be estimated when a graphical alignment,  
 428 parallel to the abscissa axis of the diagram, can be observed;
- 429 • the linear temporal extent  $E$  covered by the cyclic recurrence, delimited by the temporal moments  $T_0$   
 430 and  $T_N$ , estimated by observing the extent of the corresponding alignment, along the abscissa axis;
- 431 • the temporal dispersion  $disp_t$  of the cyclic recurrence.  $disp_t$  is a parameter randomly chosen, used to  
 432 calculate the duration of the temporal interval when events appear for each instance of the cycle, and  
 433 which is equal to  $2 * \Delta_t$ : “events appear every  $P$  days, more or less  $\Delta_t$  days”, where  $\Delta_t = P * disp_t$ .  
 434  $disp_t$  is estimated by observing the extent of the corresponding alignment, along the ordinate axis.

435 The experiment was done on height datasets, divided into “A” and “B” datasets, presenting respectively  
 436 a proportion of 80% and 90% of randomly created events. For each “A” and “B” datasets, the parameters  
 437  $disp_c$  and  $disp_t$  are randomly chosen in different values intervals:  $[1.5,2.5]$  (datasets  $A_1, A_3, B_5, B_7$ ) and  
 438  $[1.5,2.5]$  (datasets  $A_2, A_4, B_6, B_8$ ) for  $disp_t$ ;  $[0.08,0.25]$  (datasets  $A_1, A_2, B_5, B_6$ ) and  $[0.25,0.5]$  (datasets  
 439  $A_3, A_4, B_7, B_8$ ) for  $disp_c$ . For each dataset, the moment of the first occurrence of the cyclic component,  
 440 and the number of its instances, were randomly defined. For each instance,  $X$  events were created,  $X$  being  
 441 randomly chosen between one and ten for each instance.

## 442 **4.2 Experiments and results.**

443 For each dataset, we carried out an exploratory analysis through a cyclic temporal entry (Figure 8). Each  
 444 analysis is done through a visual and interactive exploration executed by the user, with the following steps:

- 445 1. Semiologic rules are applied to the event series: events are represented according to their cyclic moment  
 446 of reappearance, with a color scale formed by a discrete rainbow chromatic circle created from 6 basis  
 447 colors. In the background, events are gathered according to their spatial proximity, and a harmonic  
 448 analysis by discrete Fourier transform is executed on each group of events.

- 449 2. The duration of the cyclic temporal scale is modified to reach the different durations suggested from  
450 the harmonic analysis results, until a spatio-temporal cluster is identified on the map, through the  
451 observation of a pie chart presenting a higher proportion of one color.
- 452 3. The events located near the spatio-temporal cluster are selected, and the unselected events are hidden.
- 453 4. If one or several graphical alignments are observed on the mixed diagram, the spatio-temporal cluster  
454 corresponds to a localized cyclic recurrence. If not, the events are deselected, and the user continues  
455 its exploration for the other suggested cyclic scales.
- 456 5. The user adjusts the duration of the cyclic scale, in order to obtain one alignment parallel to the  
457 horizontal axis of the mixed diagram.  $P$  and  $E$  are estimated at this step with it (Figure 8).
- 458 6. The number of angular sections is modified in the circular diagram, in order to identify the extent of  
459 the temporal cluster.  $disp_t$  is estimated at this step with the circular diagram (Figure 8).
- 460 7. The colors of the chromatic circle are modified, in order to give one color (blue) to the events of the  
461 temporal cluster, and another color (red) to the rest of the events.
- 462 8. The events are deselected and all events are displayed on the map. The estimation of the cyclic  
463 recurrence area is refined by observing the pie charts bearing the corresponding color.  $C$  and  $disp_c$  are  
464 estimated at this step, by measuring the latitude and longitude of the observed area's borders.

465 [Figure 10]

466 For each dataset, the exploratory analysis allowed the identification of the global area of appearance of  
467 the cyclic recurrence. The estimation of the area's boundaries was yet imprecise. Table 1 presents the results  
468 of the analysis performed on the eight datasets. The carried out exploratory analysis allowed us to precisely  
469 estimate the period of the cycle for each dataset (less than 2% margin of error; 3rd column of Table 1), except  
470 for  $A_2$  dataset, where the estimated period corresponded to a harmonic of the cycle. On the other hand, the  
471 estimation of the temporal extent and cyclic dispersion of each cycle were imprecise (respectively up to 26%  
472 and 15% of margin of error; 4th and 5th columns of Table 1).

473 [Table 2]

474 Despite the lack of precision for the estimation of the spatial and temporal extent of the localized cyclic  
475 recurrences, these results validate the possibility to find those patterns with our approach. For each dataset,  
476 it allowed revealing the existence of localized cyclic recurrences within series of predominantly random spatio-  
477 temporal events, to identify their global location, and to accurately estimate their period of recurrence.

## 5 Discussion.

The proposed approach shows a lack of precision in the identification of the spatial and temporal extent of the observed localized cyclic recurrences. The borders of these extents were visually estimated by the user, using the computer’s cursor and tools giving the latitude and longitude, or temporal moment, corresponding to the cursor graphic position on the screen. This estimation could be improved by integrating better tools to estimate the borders of these extents, such as the attraction of the cursor when it passes over a graphical entity. Other interaction modalities, such as the possibility to create and represent the temporal or spatial convex hull of selected events, could also improve the precision of the obtained results.

However, the main goal of our approach is reached, in the sense that the visualization methods supported by GrAPHiST provide an identification of localized cyclic recurrences, its global location, and a good estimation of its period of reappearance. The search for localized cyclic recurrences follows the principles of exploratory data analysis: it is the visual identification of graphic patterns by the user, during the modification of the cyclic scale, which allows detecting the presence of spatio-temporal clusters and localized cyclic recurrences in the data. This visual approach is part of a more global approach, supported by GrAPHiST, for the exploratory analysis of spatio-temporal dynamics in spatio-temporal data. Such analysis bears intrinsically a part of subjectivity, and the results will depend on many factors regarding the user, such as its expertise. However, this approach presents the advantage of not be bound to the hypothetico-deductive principles followed in the majority of statistical and GIS analyses (Andrienko and Andrienko, 2006). These analyses may not be well adapted when the user does not know what he has to look for, which may be the case with spatio-temporal data describing new kinds of phenomena. By providing a free exploration of data, the exploratory analysis allows the discovery of unsuspected structures and generating new hypotheses about the data (Tukey, 1977; Andrienko and Andrienko, 2006).

Identification of localized cyclic recurrences, through a spatial entry, implies to use the adequate spatial division of space to regroup in the same class the events presenting a cyclic behavior. This analysis needs a first hypothesis from the user on the spatio-temporal structure of the analyzed event series, which may not always be the case during an exploratory analysis. When the user does not have suspicions about the spatio-temporal distribution of events, a temporal entry suits better for the analysis of unsuspected spatio-temporal patterns. An analysis through a spatial entry has to be reserved for analysis through specific divisions of space, such as water-basin or administrative districts. It can notably be used to validate a hypothesis about the spatial distribution of localized recurrences, established after a first analysis made through a cyclic temporal entry.

We use a harmonic analysis by discrete Fourier transform as background-executed to suggest research paths to the user in its exploratory analysis of cyclic behaviors. Other mathematical tools exist, and propose a better analysis of recurrence patterns in temporal data (Wang et al., 2018), notably in those presenting

512 an imperfect cyclic behavior, where the strict reappearance of the same pattern is not always observed.  
513 However, to propose our approach, we wanted to use a more simple mathematical tool, easier to implement  
514 in a geovisualization environment. If the reusability of such an approach in other scientific domains is  
515 validated, further developments could then integrate more efficient mathematical analysis.

516 Our approach presents an interest in the analysis of spatio-temporal phenomena such as flooding or sea-  
517 level rising. However, this approach is not suited for the identification of cyclic recurrences, of which the period  
518 of reappearance evolves, appearing more or less frequently over time. The current graphic representations  
519 are designed to identify such evolution of cyclic behaviors' period. To solve this problem, other graphic  
520 representations have to be elaborated.

521 Finally, our case study proves that our approach does work to find localized cyclic recurrences in spatio-  
522 temporal data. Yet, the usability of our approach, and its efficiency compared to strictly mathematical  
523 approaches, used for instance to find cyclic recurrence in tide gauge data for the analysis of sea-level rise, are  
524 to be confirmed. User tests have then to be done, to conclude about the reusability of our approach in other  
525 scientific domains. However, our approach is supported by an operational geovisualization environment. It  
526 can already be presented to different scientific communities to open the discussion about its reusability.

## 527 **6 Conclusion.**

528 We proposed an approach for the exploratory analysis of localized cyclic recurrences in spatio-temporal event  
529 data, combining visual analysis through specifically designed and interactive graphical representations, and  
530 background-executed mathematical analysis that assists the user in its exploratory analysis. Through an  
531 application of our approach to the analysis of height simulated datasets, we proved that this approach allows  
532 the identification of localized cyclic recurrences amongst widely randomly appearing spatio-temporal events.

533 The observation of cyclic behaviors isolated in space, or the observation of the different periodicities of  
534 a phenomenon in space, can be helpful for the understanding, or even the forecast of spatio-temporal phe-  
535 nomena. Different applications can be imagined, such as the analysis of tide gauge, seismic or meteorological  
536 data, but also the analysis of social data. Our approach is integrated into an operational geovisualization  
537 environment, GrAPHiST, able to handle spatio-temporal data related to different thematics.

538 Our approach presents some limits, which can be pushed by the elaboration of new visualization methods.  
539 Our approach being already implemented in an operational geovisualization environment<sup>1</sup>, this environment  
540 can already be used as a base for the design of these new visualization methods. This prototype can also be  
541 a concrete object of discussion, concerning the reusability of the proposed exploratory analysis approach in  
542 different scientific domains.

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<sup>1</sup>[http://steamer.imag.fr/?page\\_id=735](http://steamer.imag.fr/?page_id=735)

## 7 Acknowledgments.

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## 8 Tables.

Table 1: Experiment results

Dataset	Random events prop.	$P$ imprecision rate	$E$ imprecision rate	$disp_t$ imprecision rate
$A_1$	80 %	1.9%	0.2%	0.5%
$A_2$	80 %	X	11.7%	15.0%
$A_3$	80 %	0.1%	0.1%	1.2%
$A_4$	80 %	0.6%	6.8%	3.0%
$B_5$	90 %	0.2%	14.3%	6.0%
$B_6$	90 %	0.4%	26.0%	12.0%
$B_7$	90 %	0 %	4.9%	3.0%
$B_8$	90 %	1.6%	13.8%	3.0%

## 9 Figure captions.

546  
547 Figure 1: General structure of GrAPHiST. Visualization of storm events in the USA between 2004 and  
548 2018. Color value represents the linear moment of appearance of events. A: Spatial view. B: Sawtooth mixed  
549 temporal diagram. C: Timewheel-based temporal diagram. The base map image comes from OpenStreetMap  
550 (2020). The represented data come from the Open Access Storm Events Database of the US National Oceanic  
551 and Atmospheric Administration (2020).

552 Figure 2: Visual search of cyclic recurrences by modifying the represented cyclic scale in GrAPHiST (simu-  
553 lated data).

554 Figure 3: Using semiologic rules to establish links between spatial and temporal views into GrAPHiST  
555 (simulated data). The base map image comes from OpenStreetMap (2020).

556 Figure 4: Application of semiologic rules in GrAPHiST. The base map image comes from OpenStreetMap  
557 (2020).

558 Figure 5: Search for a localized cyclic recurrence in GrAPHiST (simulated data). The base map image comes  
559 from OpenStreetMap (2020). A: Through a spatial entry. B: Through a cyclic temporal entry.

560 Figure 6: Use of harmonic analysis in *GrAPHiST* to assist the search for cyclic recurrences (simulated data).

561 Figure 7: Use of harmonic analysis on spatially grouped events in GrAPHiST. The base map image comes  
562 from OpenStreetMap (2020). A.1: Homicides events in Chicago are grouped by the user using the spatial  
563 extent of Chicago's main neighborhoods (spatial entry). A.2: Homicides events in Chicago are automatically  
564 clustered according to their spatial proximity (cyclic temporal entry). B: Spectrum obtained from simulated  
565 data after a manual spatial classification (spatial entry). C: Representation of the suggested periods obtained  
566 from the harmonic analysis. These data come from the Crime Database of the Open Access Chicago Data  
567 Portal, property of the City of Chicago (2020). We only use crime data here to illustrate the different  
568 events spatial classifications used for background harmonic analysis. We do not consider the search of cyclic  
569 recurrences in crime data as necessarily relevant.

570 Figure 8: Identification of cyclic events in GrAPHiST (*B5* dataset, simulated data). The base map image  
571 comes from OpenStreetMap (2020).

572 10 Figures.

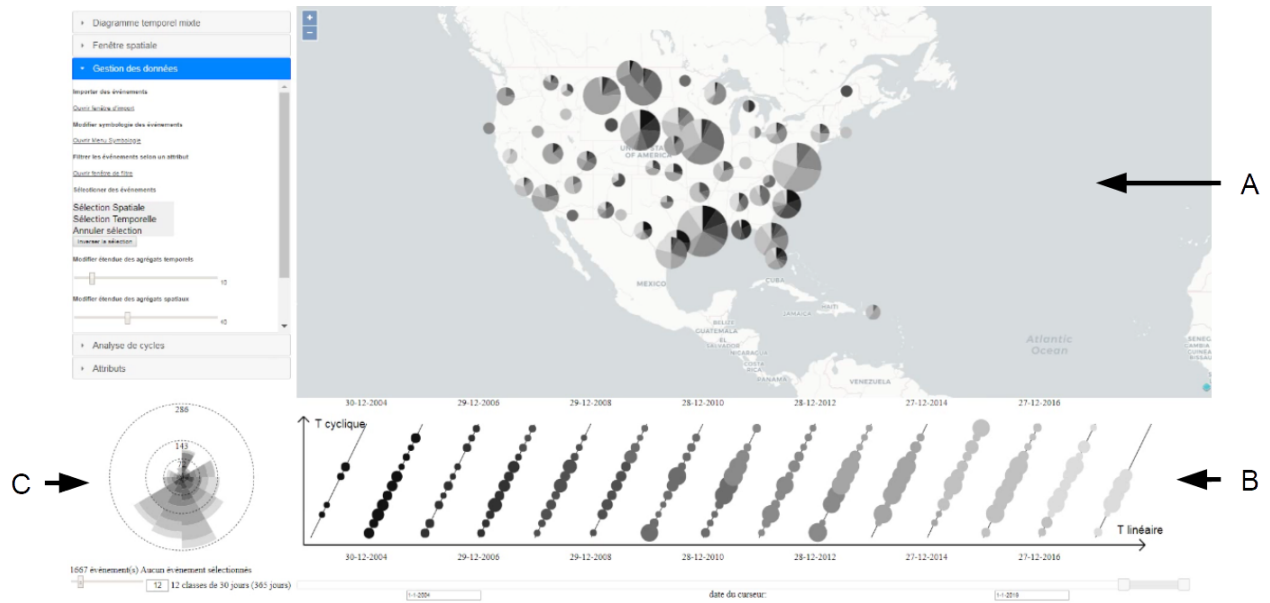


Figure 1: General structure of *GrAPHiST*. Visualization of storm events in the USA between 2004 and 2018. Color value represents the linear moment of appearance of events. A: Spatial view. B: Sawtooth mixed temporal diagram. C: Timewheel-based temporal diagram. The base map image comes from OpenStreetMap (2020). The represented data come from the Open Access Storm Events Database of the US National Oceanic and Atmospheric Administration (2020).

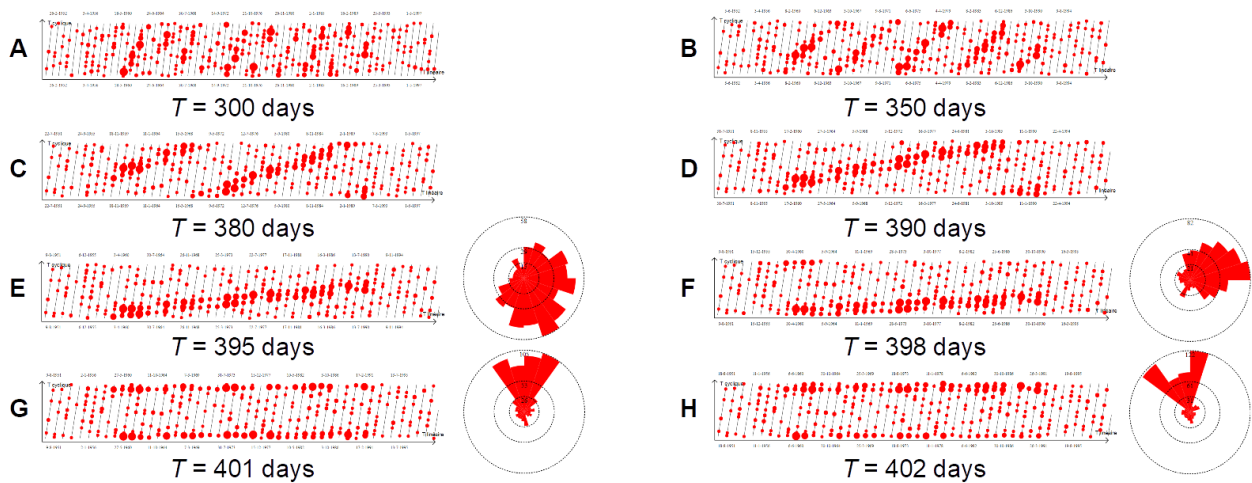
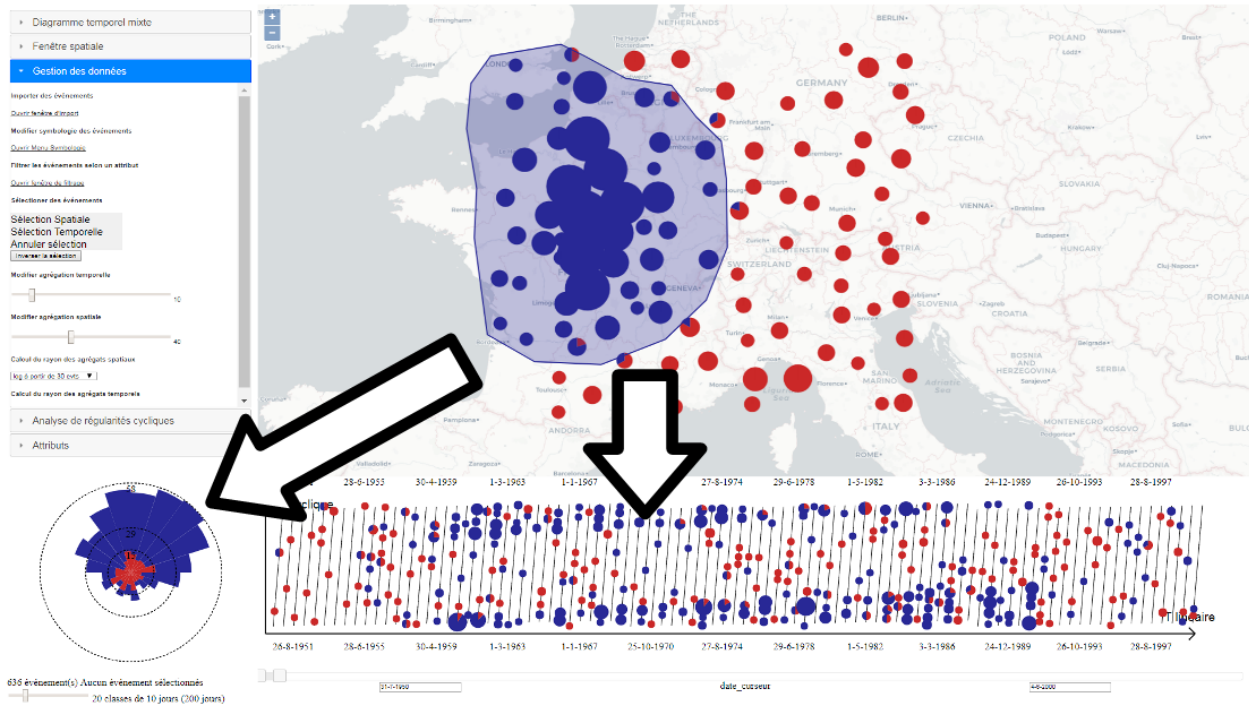
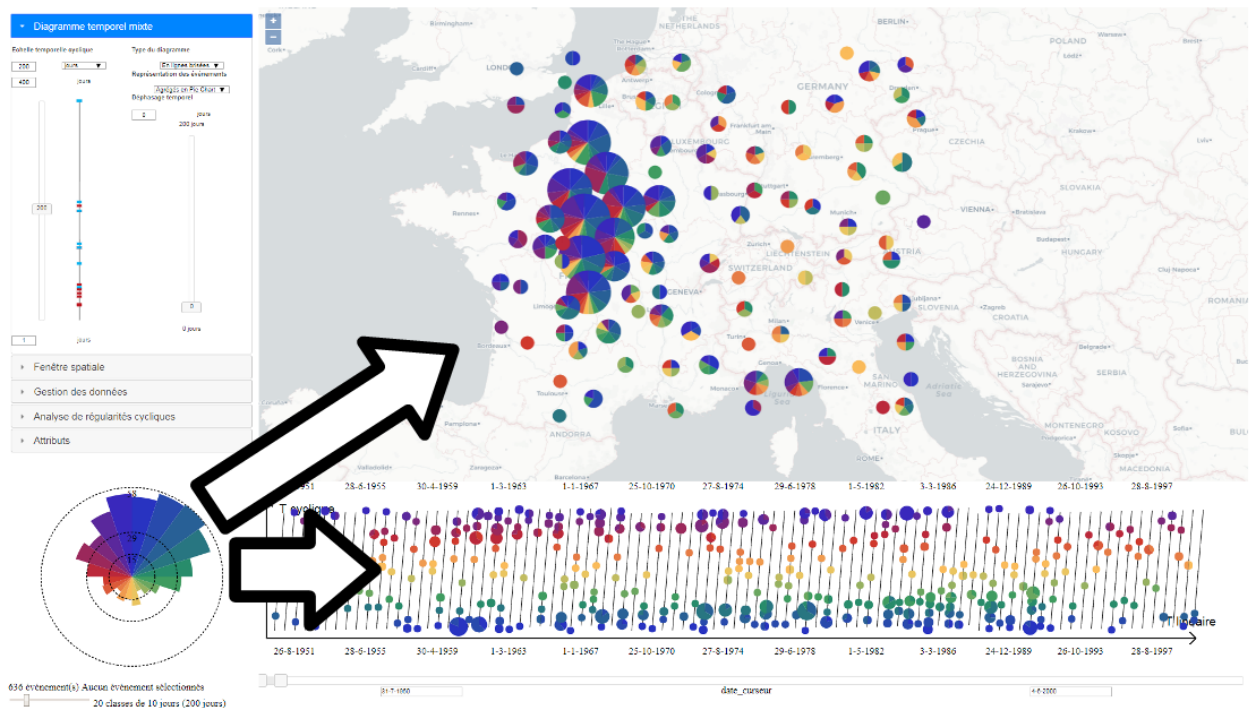


Figure 2: Visual search of cyclic recurrences by modifying the represented cyclic scale in *GrAPHiST* (simulated data).



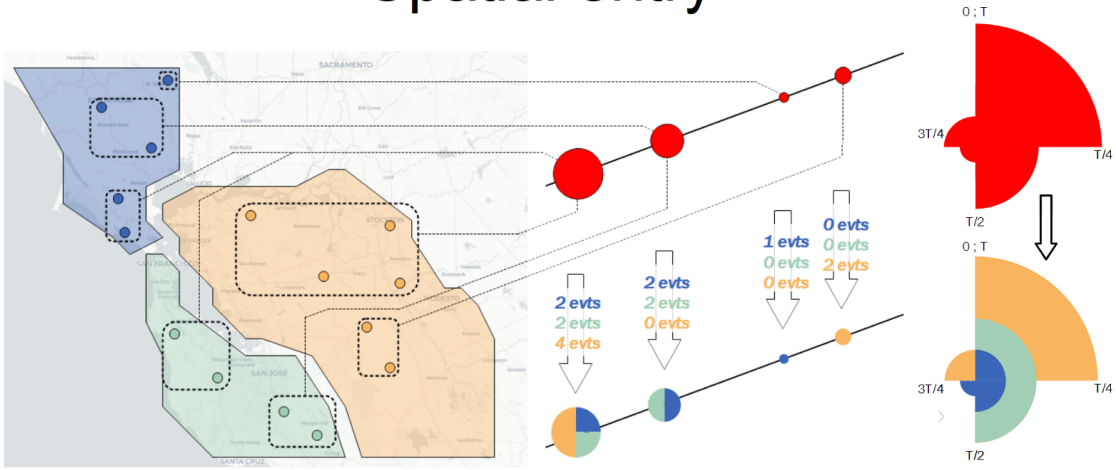
**A: Spatial entry**



**B: Cyclic temporal entry**

Figure 3: Using semiologic rules to establish links between spatial and temporal views into *GrAPHiST* (simulated data). The base map image comes from OpenStreetMap (2020).

# Spatial entry



# Cyclic temporal entry

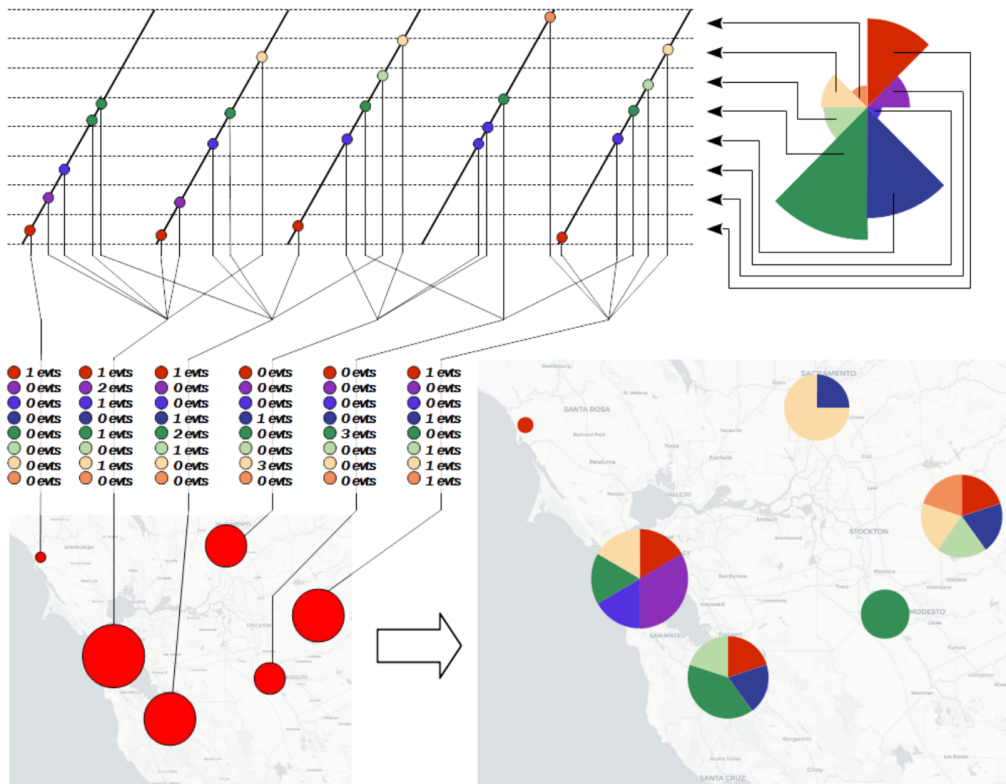
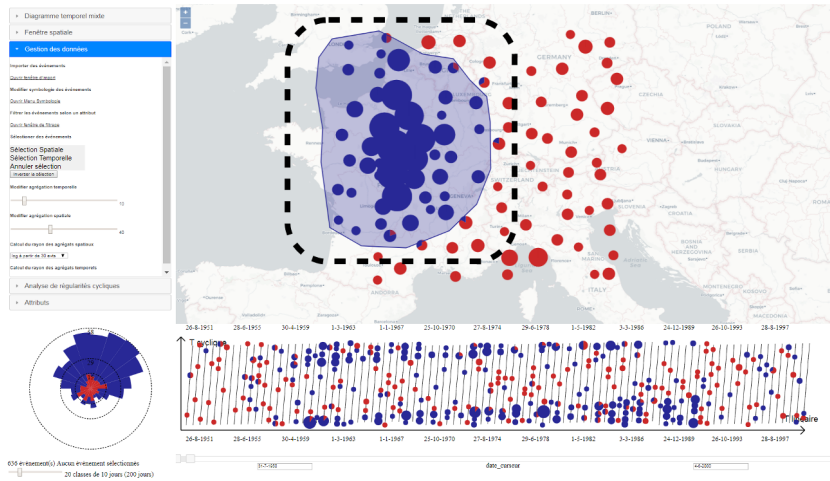


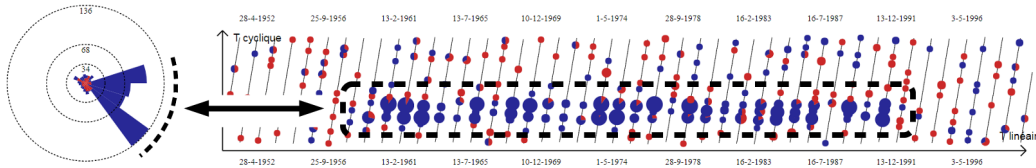
Figure 4: Application of semiotic rules in *GrAPHiST*. The base map image comes from OpenStreetMap (2020).

# A : Spatial Entry

A.1



A.2



# B : Cyclic Temporal Entry

B.1



B.2

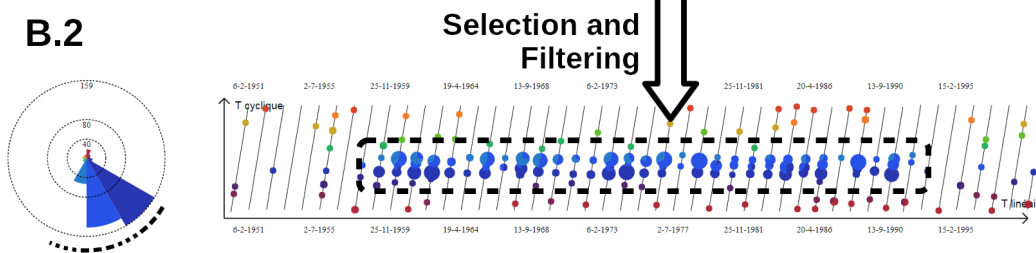
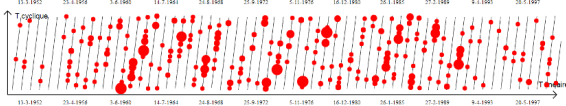
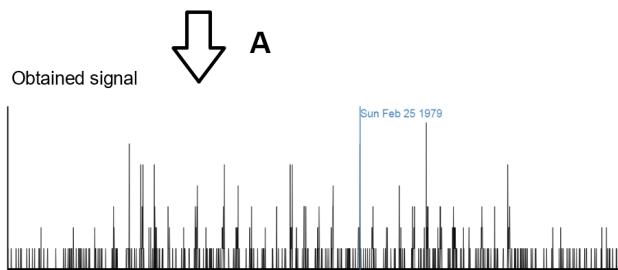
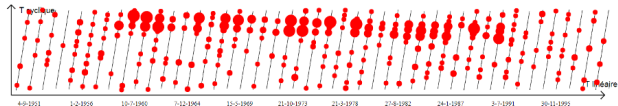


Figure 5: Search for a localized cyclic recurrence in *GrAPHiST* (simulated data). The base map image comes from OpenStreetMap (2020). A: Through a spatial entry. B: Through a cyclic temporal entry.

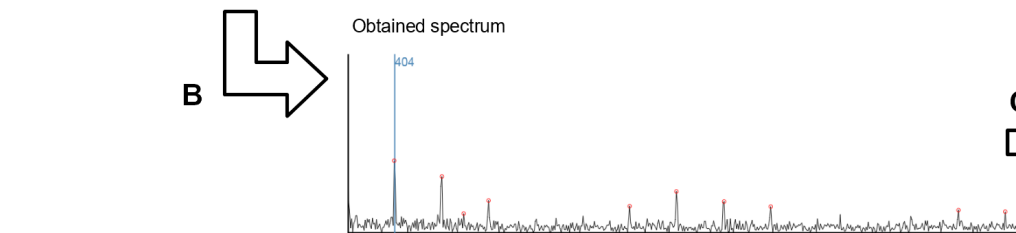
T = 200 days



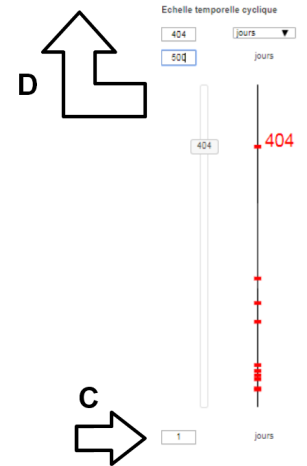
T = 404 days



A



B



D

C

Figure 6: Use of harmonic analysis in *GrAPHiST* to assist the search for cyclic recurrences (simulated data).

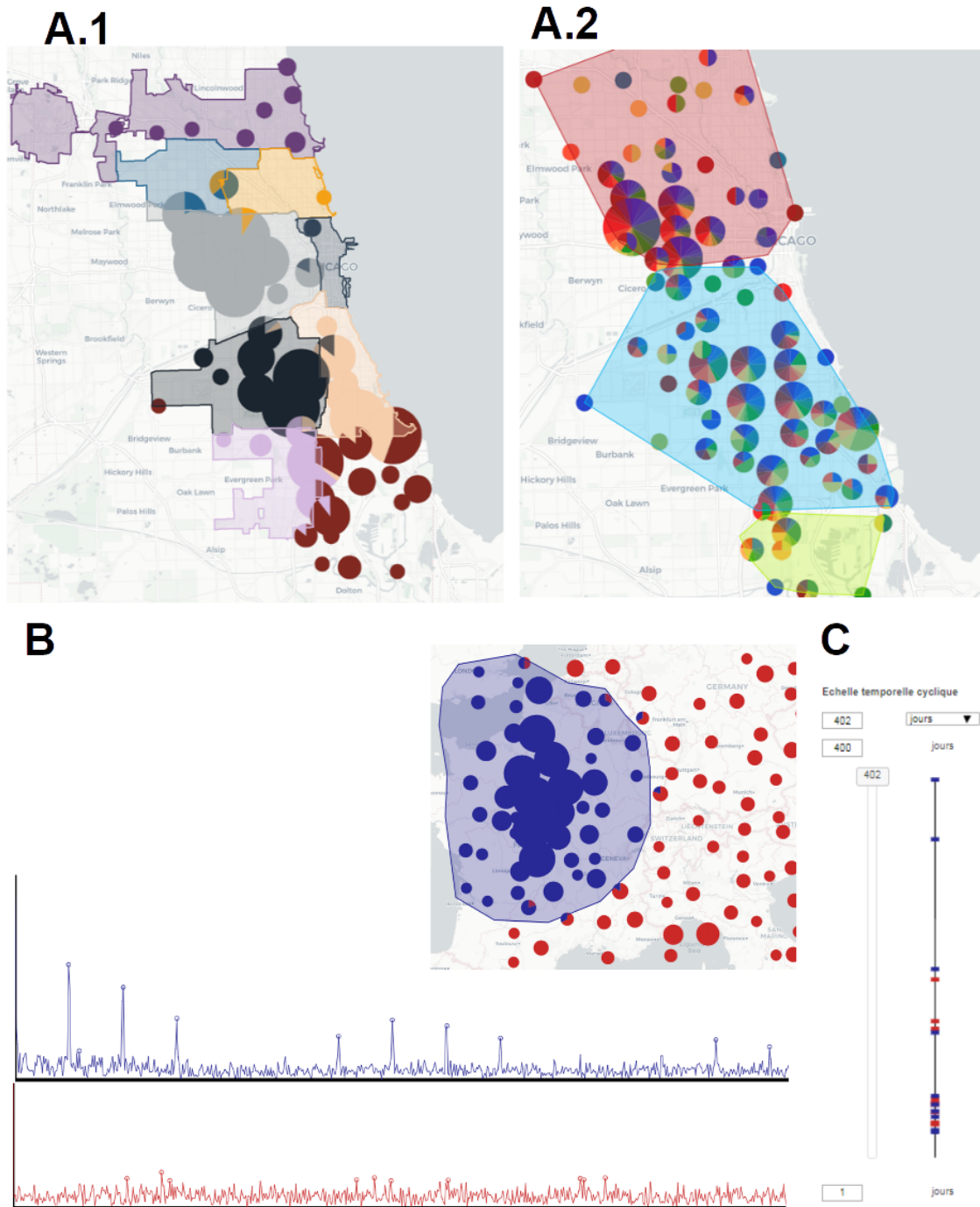


Figure 7: Use of harmonic analysis on spatially grouped events in *GrAPHiST*. The base map image comes from OpenStreetMap (2020). A.1: Homicides events in Chicago are grouped by the user using the spatial extent of Chicago’s main neighborhoods (spatial entry). A.2: Homicides events in Chicago are automatically clustered according to their spatial proximity (cyclic temporal entry). B: Spectrum obtained from simulated data after a manual spatial classification (spatial entry). C: Representation of the suggested periods obtained from the harmonic analysis. These data come from the Crime Database of the Open Access Chicago Data Portal, property of the City of Chicago (2020). We only use crime data here to illustrate the different events spatial classifications used for background harmonic analysis. We do not consider the search of cyclic recurrences in crime data as necessarily relevant.

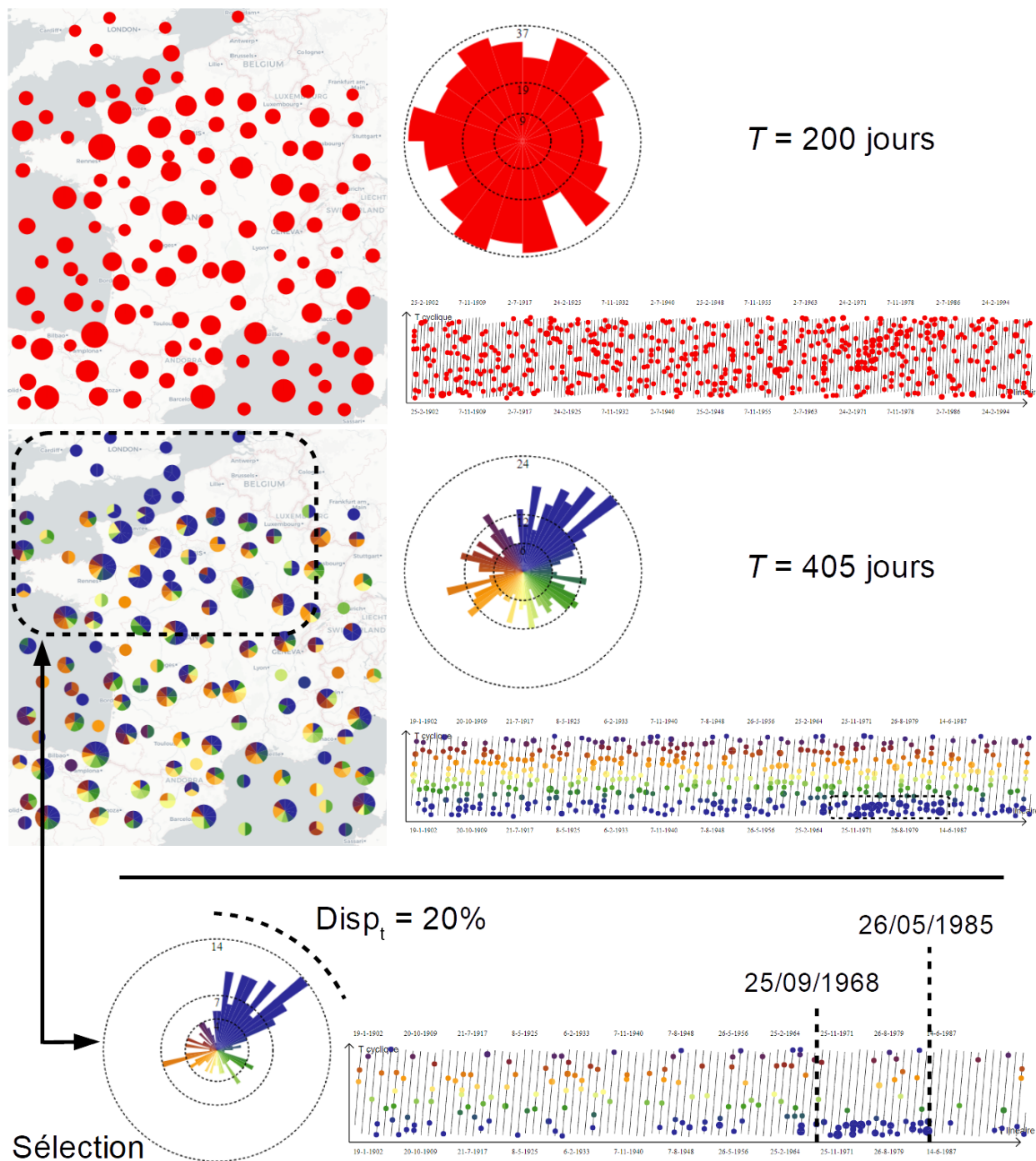


Figure 8: Identification of cyclic events in *GrAPHiST* (*B5* dataset, simulated data). The base map image comes from OpenStreetMap (2020).