Highly sessional aggressive behaviors link to temporal dynamics shared across space

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ABSTRACT
Aggressive behaviors are violent actions or disputes that one individual effectuates over another in which physical harm might happen and occurs in a social environment. These criminal events have negative consequences for public health and citizen’s security, especially in Latin American cities. Predictive crime aims to use analytical techniques on crime databases to identify potential criminal activity. Most research focuses on other types of crime, such as homicide and crime against property. However, there is little research to describe predictive patterns for aggressive behavior at the city scale. This paper studies possible sessional patterns of aggressive behavior crime and its relationship with temporal dynamics shared across different city areas in Bogotá (Colombia), a Latin American city severely affected by this phenomenon. For this, we propose a Spatio-temporal analysis strategy based on predictability, a grounded information theory measure of sessionality, and independent component analysis. Using this approach, we studied more than three million registers reported to the city emergency line from 2014 to 2018 related to aggressive behaviors. Our results show that many city areas exhibit high sessionality values and share multiple temporal dynamics in 8 of 19 regions (localities). Notably, most of these areas present both patterns in 7 of 19 regions. Remarkably, these patterns emerged in regions that account for the 71% of aggressive behavior reports. These results agree with modern crime theories that consider Spatio-temporal dynamics, such as routine activity theory, suggesting that the citizen’s routines may generate particular social dynamics which significantly influence aggressive behavior.

INDEX TERMS aggressive behavior, predictive security, routine activity theory of crime, sessionality, predictability, independent component analysis (ICA).

I. INTRODUCTION
Identifying and characterizing aggressive behavior patterns is a fundamental task in designing objective and cost/effective citizens’ security policies for intelligent cities [1]. Aggressive behaviors correspond to violent actions or disputes that one individual effectuates over another in which physical harm might happen and occurs in a social environment [2], [3]. Understanding this kind of criminal behavior is paramount for citizen security and public health planning [4]. These actions are considered one of the most important triggers of severe personal injuries and homicides. For instance, in large Latin American cities such as Bogotá (Colombia), aggressive behavior represents one of the leading causes of more severe crimes such as homicides [5]. Several studies link these kinds of crime to particular environmental conditions, for instance, to unfavorable socio-economic situations, including low income, unemployment, illiteracy, or the concentration of vulnerable population [5], [6], the presence of street gangs [7], the alcohol consumption [8], or the occurrence of particular social events [7], among others. Unfortunately,
identifying these exogenous variables and their relationships with aggressive behaviors remains an open problem due to the complexity underlying this social phenomenon [8]. Alternatively, the availability of large volumes of crime-related data registered by the official security information systems opens an opportunity to enhance the understanding of aggressive behavior patterns [9], [10].

Most quantitative characterizations using only crime data are performed independently for space and time dimensions. The spatial analyses include, for instance, grid counting, covering ellipses, kernel density, and heuristics [9], among others. This analysis focuses on describing local crime incidence across different geographical scales [11], aiming to identify areas with high crime rates (hotspots) by assuming that crime would likely occur where crime already occurred. This assumption partially satisfied in aggressive behaviors, which also link to the occurrence of particular events in time, for instance, nighttime entertainment [12], [13]. Other analyses, such as self-exciting processes [14], [15] and ProMap [16], rely on the near-repeated crime theory [17], which states that future crimes will occur near current crimes in time and place. Therefore, areas showing recent high crime incidence will also see higher crime nearby in the immediate future, assuming that crime is contagious and spread through local environments. This assumption is supported by evidence on other types of crime like residential burglary [18], but for which there is no supporting data on the case of aggressive behaviors [9]. From a temporal perspective, and based on the assumption that cyclical patterns, such as the day of the week and even the season, may influence crime, sessional characterization of time series has also been studied [9]. These sessional descriptions emerged on different crimes, such as petty crimes and burglary, but there is no evidence of these patterns for aggressive behaviors at the city scale [9].

Recent work related to the Spatio-temporal analysis of crime focuses mainly on improving the spatial definition of risk levels using the temporal variable and, in some cases, covariates [19]. For example, the use of heat maps that characterize risk variations on different time scales (hours, days, weeks, or months) can show an increase or decrease in crime patterns. To reveal the Spatio-temporal patterns of crime, different approaches have been proposed, based on: a) Spatio-temporal probability density [19], [20], b) regression models with covariates [5], [19], [21], [22], c) graph representations [23], [24], some with analysis of crime displacement or crime co-occurrence [25]–[28], and d) machine learning techniques [24], [29]. Although the characterization of seasonality and increase-decrease features may be relevant for the characterization of aggressive behaviors phenomena [13], to our knowledge, aggressive behavior crime lacks these quantitative temporal descriptions at the city scale.

The main objective of this work was to study the existence of sessional patterns of aggressive behavior crime and its relationship with temporal dynamics shared across different city areas. The proposed approach has three main contributions compared to previous work. First, from the methodological perspective, we proposed a method to characterize for the first time the temporal dynamics of crime with sessional patterns shared across different city areas at a daily scale. Secondly, we identified a consistent number of components across years that robustly explain the observed dynamics. Finally, we showed that the high number of incidents in the city areas linked to these sessional and shared patterns. This approach can be used to explore Spatio-temporal phenomena likely characterized by spatial patterns sharing sessional temporal dynamics. The proposed method is related to the routine activity theory [15], [30]. This theory suggests that sessional variations observed in crime link people’s everyday activities, resulting in the convergence in time and space of motivated offenders, suitable targets, and the absence of capable guardians. In accordance, a latent variable analysis method extracts the underlying temporal patterns shared for different spatial locations, rooted in the observation that people’s routine activities may coincide in time for various city areas [31]. For instance, nighttime entertainment or dynamics of people transportation may overlap in time for different city areas [32]. A set of predictability indices describe possible cyclic patterns underlying temporal patterns of crime occurrence in each city area, providing a quantitative description of aggressive behaviors’ sessionality [33]. Finally, city areas with similar temporal dynamics and the corresponding sessionality indices constituted the spatio-temporal feature proposed to describe aggressive behavior. Historical data of more than three million aggressive behavior incidents reported by citizens to the emergency line of Bogotá allowed studying the proposed approach. To our knowledge, this analysis represents the first large-scale quantitative exploration of the occurrence of these particular aggressive behavior dynamics at the city scale.

II. MATERIALS AND METHODS

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II. MATERIALS AND METHODS

Fig. 1 shows the methodology proposed to identify the degree to which aggressive behavior occurrence exhibits temporal and spatial patterns. Four primary blocks process temporal and spatial patterns: data acquisition, preprocessing, temporal patterns analysis, and spatial patterns analysis. Data acquisition and preprocessing blocks provide the inputs for temporal and spatial pattern analyses.

A. DATA ACQUISITION AND PREPROCESSING

Aggressive behavior incidents reported to the emergency line of the city of Bogotá were used to explore possible temporal and spatial patterns related to this kind of criminal event. The emergency line information system (Número Único de Seguridad y Emergencias - NUSE) collects data about citizen’s incident reports, including its spatio-temporal information. A total of 3,024,784 registers related to aggressive behaviors between January 1 of 2014 and December 31 of 2018 were
Aggressive behaviors can be predicted over time, considering the context, predictability allows quantifying how much aggressive behavior levels over time (constancy) and the dependence between time and levels of aggressive behaviors (contingency). Therefore, contingency measure is crucial since it allows us to identify the degree to which the phenomenon exhibits periodic periodicity patterns due to cyclical factors (e.g., routine activities).

To compute the predictability analysis of aggressive behaviors the model first constructs a time series $S_{d,l}$ by adding daily events $(d)$ by locality $(l)$ from the incidents $I_{d,l}$ at time $(t)$ and locality $(l)$. Then, incidents outside the 99th percentile of $S_{d,l}$ were replaced with the mean value of this time series. Next, the total number of crimes per day was computed. This number of crimes was quantized in three crime levels representing different aggressive behavior states: low, medium, and high. Quantization levels were determined using a uniform quantization, i.e., quantization levels were uniformly spaced in three levels with the range as the difference between the maximum and the minimum number of crimes reported by day in a locality [35]. Following this, a frequency matrix $N$ was constructed with the time series quantized by date. This frequency matrix summarized the relationship between the aggressive behavior occurrences and time. Rows in $N$ correspond to the phenomenon states (i.e., low, medium, and high) and columns to the days of the week (i.e., Monday to Sunday). Each element of the matrix $N_{ij}$ corresponded to the number of times the phenomenon was in state $i$ at time $j$ over the analysis period. From $N$, three quantities describing periodicity were constructed, namely, constancy $(C)$, contingency $(M)$, and predictability $(P)$, as described in detail in the predictabilityIndex procedure in the Algorithm 1.

Algorithm 1. Method for calculating Spatio-temporal pat-
terns of incidents of aggressive behaviors \( I_{t,l} \) in the time \( t \) and locality \( l \). The initial procedure uses the `predictabilityIndex` algorithm to compute the predictability index \( P \) for each locality \( l \). The `states` is the number of crime levels to quantify the number of crimes on a daily scale. Next, the procedure `spatialComponents` computes \( c \) shared spatial components using the incidents \( I_{t,l} \) and “fastICA” numerical algorithm. The \( c \) components were obtained by factoring a matrix \( A \) with the incidents in different localities \( l \) and days of the year \( d \).

```
procedure SpatioTemporalPatterns(I_{t,l})
predictabilityIndex(I_{t,l}, states)
spatialComponents(I_{t,l})
end procedure
```

```
procedure predictabilityIndex(I_{t,l}, states)
S_d ← groupDays(I_{t,l})
S_d ← removeOutliers(S_d)
N_{i,j} ← quantizeMatrix(S_d, states, weekdays)
X_i ← \sum_j N_{i,j}
Y_j ← \sum_i N_{i,j}
H_X ← − \sum_l (X_i/Z) \cdot \log(X_i/Z)
H_Y ← − \sum_l (Y_j/Z) \cdot \log(Y_j/Z)
H_{XY} ← − \sum_l \sum_j (N_{ij}/Z) \cdot \log(N_{ij}/Z)
C ← 1 − H_Y/\log(states)
M ← (H_X + H_Y − H_{XY})/\log(states)
P ← 1 − (H_{XY} − H_X)/\log(states)
end procedure
```

```
procedure spatialComponents(I_{t,l})
A^{l\times d} ← \text{incidentsMatrix}(I_{t,l}, \text{localities, dayOfYear})
S^{d\times T}, T^{c\times d} ← \text{fastICA}(A^{l\times d})
end procedure
```

C. SPATIAL PATTERN ANALYSIS: INDEPENDENT COMPONENT ANALYSIS

After the temporal pattern analysis, a spatial Independent Component Analysis (ICA) method separated the multivariate signal of crime occurrences (i.e., daily aggressive behavior reported for different localities) into additive sub-components [36]. These subcomponents corresponded to groups of localities with a shared time dynamic of aggressive behaviors. ICA aims to identify the groups of localities that are statistically independent by optimizing higher-order statistics, such as kurtosis [35]. ICA technique can also be considered a blind source separation technique, in which the observed signal (i.e., the observed number of crimes per locality) may result from a linear combination of different independent sources [37]. Therefore, the central assumption underlying this spatial analysis is that the observed number of crimes in a locality resulted from the linear combination of independent sources of temporal dynamics of crime shared across localities.

1) Independent component consistency

The spatial characterization of aggressive behavior occurrences was performed using ICA. For this, a matrix \( A^{l\times d} \) representing the level of occurrence of this kind of crime incident in Bogotá was constructed. In this matrix, \( l \) is the number of spatial units (number of localities), and \( d \) is the number of temporal units (number of days in the year), leading to an \( A^{19\times 365} \) matrix (Sumapaz locality was omitted due to its low level of occurrence of crime compared to its
area). In spatial ICA, the $A^{l \times d}$ matrix is factorized into two matrices $S^{l \times c}$ and $T^{c \times d}$ that contain information about the $c$ sources of shared activity (see Fig. 3). These sources can be interpreted as clusters of spatial units with statistically independent temporal behaviors across each year. The spatial components procedure defined in the Algorithm 1 describes the matrix factorization procedure used to obtain the sources. FastICA [36] was used for the numerical estimation of this ICA procedure.

To determine the best number of independent components (ICs), the number of ICs that provided the highest similarity level across years (2014 to 2018) was computed. Four different numbers of independent components were evaluated $\#IC = [3, 4, 5, 7]$. Similarity level was estimated based on Person correlation among vectorized representation of each IC. This approach is based on the goodness-of-fit (GoF) among IC from brain signals [38]. This matching or pairing process between ICs is commonly performed to two related ICA decompositions because this matrix factorization method lacks order on the resulted components [37]. In particular, given two time periods ($X$ and $Y$ years), each IC from $X$ was related to the more similar IC component of $Y$ (maximal Person correlation value). Then, the average similarity value was computed to represent the similarity between the two periods. Finally, each approach was repeated for each couple of periods, and the mean value of similarity among IC was computed. It is important to note that the number of components in this analysis is related to the assumption of the number of latent factors or clusters expected of aggressive behavior in Bogotá.

2) ICA across years

Based on the previous analysis results, a group of aggregated ICA was computed to identify the common behavior at the group level during the whole temporal variable. In particular, the matrix $A$, described in the previous section, was concatenated over the temporal scale for each year. Thus, a new $B^{l \times m}$ variable is introduced here, where $t$ is the temporal variable resulting from the temporal concatenation for each year. Finally, this $B$ grouped variable was used as an input in a new ICA.

III. RESULTS

This work studies possible sessional patterns of aggressive behavior crime and its relationship with temporal dynamics shared across different localities. First, we report evidence supporting these sessional patterns, and then we show how this sessionality relates to shared temporal dynamics. Following, we report additional features of these patterns in both time and space.

A. HIGHLY SESSIONAL AGGRESSIVE BEHAVIORS RELATES TO SHARED TEMPORAL DYNAMICS

Fig. 4 shows the spatial pattern obtained for the aggressive behavior reports aggregated in the temporal scale of days, together with the proposed sessionality description for each locality. This figure shows five ICs (groups of localities) resulting from the spatial group ICA analysis. Each IC is represented by a city map highlighting in blue the set of localities sharing a particular temporal dynamic in aggressive behavior occurrences. Gauges in each locality report its predictability or sessionality value.

As observed in Panel A in Fig. 4 (and Fig. 5), different localities exhibit different levels of sessionality in the crime occurrences. In particular, there is a set of localities with high levels of sessionality on aggressive behaviors, including localities Ciudad Bolivar (19) (predictability = 0.9), Bosa (07) (0.88), and Usme (05) (0.85), among others. In contrast, other localities showed low predictability levels, such as localities Teusaquillo (13) (0.06) and Los Martires (14) (0.15).

As observed in Fig. 4, most localities with high levels of predictability (top seven, predictability $\geq 0.73$) arise on the same IC (see Panel A at Fig. 4). This result extends to the other four ICs (see panels B, C, D, and E), containing localities with high predictability levels. It is worth recalling that temporal dynamics differ among ICs. Therefore, this result indicates that aggressive behavior in highly sessional localities relates to one or more shared and particular temporal dynamics. In contrast, localities at yellow are not present in any IC and show low levels of sessionality. For instance, the localities with the highest levels of predictability Ciudad Bolivar (19) and Bosa (07) arise on three of five ICs, indicating that these localities share at least three different kinds of dynamics. The localities with the lowest predictability Los Martires (14) and Barrios Unidos (12), respectively, did not emerge in any IC. This relationship between high sessionality and the number of dynamics varies depending on the locality. For instance, localities San Cristobal (04) and Usme (05) relate only to one type of temporal dynamic (see Panel A in Fig. 4). In contrast, locality Kennedy (08) links to the five ICs studied.
FIGURE 4. Group ICA estimating the spatial patterns of occurrence of aggressive behaviors in the city of Bogotá. Five ICs were explored in this analysis. A, B, C, D, E show each IC found for years 2014 to 2018 using localities as the spatial scale. The gauges in plot A report the predictability index associated with each locality. The bottom left table reports detailed numerical values of predictability.

B. LOCALITIES EXHIBIT DIFFERENT SESSIONALITY LEVELS ON AGGRESSIVE BEHAVIOUR

Fig. 4 shows the sessionality resulting from the analysis of localities. This figure reports predictability measures computed considering three quantization levels over the number of aggressive behavior incidents reported for each locality in time windows of seven days. In particular, it shows the predictability value by locality and the complementary predictability measures: constancy and contingency. The bar size indicates the predictability value. The blue region corresponds to the constancy and the orange region to the contingency. To aid the interpretation of these indices, the figure included the two time series (three months of aggressive behavior occurrences on daily aggregations) of aggressive behavior for the localities with the highest and lowest predictability.

As previously discussed, Fig. 5 shows that localities have high and low predictability values. However, this figure also indicates that sessionality indices greatly vary across localities. The top plot on the right side corresponds to the Ciudad Bolívar (19) time series, the locality with the highest predictability value. As observed, this time series describes a cyclical behavior with a consistent increase in incidents every seven days, during the weekends. The bottom plot corresponds to the Teusaquillo (13) time series, the locality with the lowest predictability value. This locality exhibits a more complicated behavior hardly characterized as a periodic pattern. However, the total number of incident values for the Teusaquillo (13) is lower than the Ciudad Bolivar (19) values, as observed in Fig. 2.

The bar diagram on the left of Fig. 5 shows the predictability index split into constancy and contingency. Regarding localities with high predictability, such as Suba (11), Kennedy (08), and Engativa (10), the predictability index mainly
In contrast, constancy and contingency measures contribute in similar proportion to the predictability index of Ciudad Bolivar (19), Bosa (07), Usme (05), and San Cristobal (04) localities.

In addition to predictability analysis over the 2014-2018 period, we analyzed the predictability index individually for each year under study and its annual stability. Once again, a seven days time window and three quantization levels were considered for this analysis. Table 1 shows the square difference between the average predictability value per locality (between 2014 and 2018) and the predictability value for each year. This variability measure quantifies the predictability stability at the locality level on the five years under study, taking as reference the total predictability for the whole studied period.

In general, low variations in predictability were observed along the different years, i.e., most localities were highly stable in predictability. However, high differences between the predictability average value and predictability index were observed for Antonio Nariño (15), Barrios Unidos (12), Chapinero (02), and Los Martires (14) localities in 2014. A high difference in predictability index is obtained for Santa Fe (03) locality in 2015 and Antonio Nariño (15) in 2018. These localities also exhibited a lower predictability index for the global predictability analysis over the 2014-2018 period (see Fig. 5). Finally, localities such as Bosa (07), Engativa (10), Fontibon (09), Tunjuelito (06), and Usme (05) seem to exhibit a relatively lower difference among average predictability values and the predictability index estimated each year over 2014-2018, indicating high stability in pre-

| Year | Antonio Nariño | Santa Fe | Los Martires | Barrios Unidos | Chapinero | Usme | Candelaria | Teusaquillo | Ciudad Bolivar | Engativa | Suba | Bosa | Fontibon | Puente Aranda | Rafael Uribe Uribe |
|------|----------------|---------|--------------|----------------|-----------|------|-----------|-------------|----------------|----------|------|------|---------|-------------|-------------------|
| 2014 | 0.14           | 0.01    | 0.18         | 0.08           | 0.09      | 0.01 | 0.13      | 0.15         | 0.01           | 0.04     | 0.02 | 0.02 | 0.02    | 0.05         | 0.06              |
| 2015 | 0.03           | 0.23    | 0.01         | 0.01           | 0.03      | 0.05 | 0.05      | 0.04         | 0.01           | 0.01     | 0.04 | 0.04 | 0.01    | 0.05         | 0.04              |
| 2016 | 0.02           | 0.01    | 0.01         | 0.03           | 0.01      | 0.02 | 0.01      | 0.02         | 0.01           | 0.01     | 0.04 | 0.04 | 0.03    | 0.05         | 0.06              |
| 2017 | 0.02           | 0.01    | 0.01         | 0.03           | 0.01      | 0.02 | 0.02      | 0.02         | 0.01           | 0.01     | 0.04 | 0.04 | 0.03    | 0.05         | 0.06              |
| 2018 | 0.14           | 0.03    | 0.02         | 0.02           | 0.02      | 0.02 | 0.02      | 0.02         | 0.01           | 0.01     | 0.01 | 0.01 | 0.03    | 0.05         | 0.06              |
dictability.

C. LOCALITIES SHARE COMMON TEMPORAL PATTERNS IN AGGRESSIVE BEHAVIOR

Similarity matrices at the bottom-right in Fig. 6 show a concordance measure among ICs computed on different years when a different number of components were used (3, 4, 5, and 7). Absolute Pearson correlation was computed for every possible couple of ICs and couple of years, and, the maximal value for each ICs. Let $j$ and $q$ a couple of year to compute the similarity across their ICs, then, $c_{i,j}$ represent the $i-th$ independent component for the $j-th$ year, and $c_{p,q}$ represents the $p-th$ independent component for the $q-th$ year. Every possible value for $p$ (every ICs for the $q-th$ year) were compared against the $i-th$ IC for the $j-th$ year. Thus, $p-th$ IC that maximize the similarly with the $i-th$ IC represent the most similar IC from $q-th$ year compared than $c_{i,j}$. This step was repeated for each possible value of $i$ and the mean value provided the similarity measure in this case. As observed, ICA with five components provided the highest similarity levels for the studied years, with an average of the absolute Pearson correlation coefficient of 0.92. Therefore, group ICA analysis was applied with this number of components.

Fig. 6 also shows the five components resulting from using ICA for each year. As observed, most ICs coincide spatially across years, indicating that localities in each IC share common dynamics. For instance, the components labeled in column A seem to emerge with minor differences (see, for example, locality Suba (11) in 2018 or locality Fontibon (09) in 2016) during all years.

IV. DISCUSSION

A. SUMMARY OF FINDINGS

This paper studies sessional patterns of aggressive behavior, temporal dynamics underlying these crimes shared across space, and their relationship. A dataset consisting of more than three million registers related to these incidents in Bogotá, a large city affected by this problem, was analyzed using a Spatio-temporal approach to describe sessionality and shared temporal dynamics across space. In contrast to previous predictive crime approaches, which mainly focused on other crimes, this study describes for the first time predictive patterns of interpersonal acts of aggression, a growing social phenomenon with negative public health consequences, high economic costs, and multiple implications for the criminal justice system.

Spatio-temporal pattern analysis based on information theory and blind source separation showed that, as predicted by modern crime theories such as routine activity [30], aggressive behavior incidents are not randomly distributed over space or time. In particular, the temporal pattern analysis to characterize sessional patterns (Fig. 4) showed that residential localities have high predictability indices. At the same time, aggressive behavior incidents in eastern and central business district areas were less predictable, a behavior explained by more random time series. In addition, spatial analysis using group ICA (see Fig. 6) unveiled that groups of localities share similar temporal dynamics of aggressive behaviors. Notably, both patterns, spatial and temporal, were highly robust along time. Moreover, the Spatio-temporal analysis suggests that localities exhibiting highly sessional aggressive behaviors link to particular shared temporal dynamics.

Most recent works in Spatio-temporal analysis (see Table 2) focus on improving performance in the capacity of prediction. However, the confidence in the prediction in a specific region is not analyzed. Therefore, there is no confidence measure associated with the prediction of events for this region. Additionally, very few studies (see Table 2) are concerned with grouping spatial regions about the periodicity of occurrence of aggressive behaviors. Finding common patterns grouped by possible independent causes provides insight into the dynamics of aggressive behaviors in the city. This analysis may be relevant to take substantive actions to mitigate the occurrence of incidents.

B. SESSIONAL VARIATIONS ON AGGRESSIVE BEHAVIORS

Sessionality constitutes one of the most relevant temporal predictive features identified in the literature for different types of crime, including homicides, crimes against property, assaults, and thefts, among others [44–49]. However, to our knowledge, there is little evidence supporting the existence of this temporal pattern in the case of aggressive behaviors. Previous results described sessional occurrences of everyday crime. Showing, for example, increases on weekends and holidays as herein described (see Fig. 5), but for other types of crimes. Changes in the space of sessionality were also described but not for aggressive behavior [49]. Felson [13] showed that subjects with an active nightlife, which represents a routine and therefore sessional activity, are more likely to participate or witness violent encounters. However, this report was performed on a small population. In contrast, the evidence herein reported is constructed on millions of aggressive behavior reports, considering additional events to the ones related to nightlife.

Other works have characterized similar sessional patterns on interpersonal violence, but for narrow domains, for instance, sport [50], aggression in cyberspace [51], or violence or particular working places [52], and for different levels of temporal aggregation. It is also worthy to note that despite the high impact this type of violence has in Latin America [53], most studies on sessionality of crime describe patterns occurring in cities located in Europe or North America and for other types of crime [53], [54]. There are few studies reporting sessionality on crime for Latin America, and most of them focus on different types of crime [45], [55]. This
work provides the first large-scale evidence (more than three million records registered during five years) of this sessional pattern on daily aggregations of aggressive behaviors at a Latin American city.

This work defines sessionality through the grounded notion of predictability. Predictability is a well-rooted information theory-based measure to describe the degree of periodicity in a time series \[33\]. This measure results from adding constancy and contingency. In the sessional description of aggressive behaviors, constancy measures if the number of crime events is the same (constant), and contingency estimates the degree to which the daily patterns of crime repeat, for instance, across weeks. Thus, maximum predictability can be attained by complete constancy, complete contingency ( repeatability), or a combination of both. When the number of aggressions in a locality is the same for all days, the constancy is the highest. For a maximum contingency, the number of crimes would be different each day, but these values are the same for the same day in all weeks. Our results

TABLE 2. Comparative table of state-of-the-art methods in Spatio-temporal crime analysis (ST). The table highlights three components of the approaches: (a) Analysis or characterization of common patterns, (b) Analysis of periodicity, (c) Analysis of predictability in the reported results

| Category                        | References | Commons analysis | Periodicity analysis | Predictability analysis |
|---------------------------------|------------|------------------|----------------------|-------------------------|
| ST crime mapping                | [19]       | yes              | not                  | not                     |
| ST crime mapping                | [19]       | not              | not                  | not                     |
| ST crime patterns               | [21]       | yes              | not                  | not                     |
| ST crime patterns               | [19]       | yes              | not                  | not                     |
| ST crime patterns               | [21]       | yes              | not                  | not                     |
| ST crime patterns               | [20]       | yes              | not                  | not                     |
| ST crime patterns               | [5], [40]  | yes              | not                  | not                     |
| ST crime patterns               | [41]       | not              | not                  | not                     |
| ST crime patterns               | [21], [22], [26] – [29], [42], [43] | not | not | not |
| ST crime hotspot discovery      | [19], [24] | not              | not                  | not                     |
| ST crime co-occurrence pattern  | [25]       | yes              | not                  | not                     |
| ST crime co-occurrence pattern  | [23]       | not              | not                  | not                     |
| Proposed approach               |            | yes              | yes                  | yes                     |

FIGURE 6. Similarity level across spatial pattern of ICs versus number of ICs. The maps show the five independent components obtained across years and matrices show the pair to pair similarity level among them. Five IC produced maximal similarity level among years (0.92 similarity level). In contrast, three independent components resulted in the lower similarity level value among years (0.25 similarity level).

This work defines sessionality through the grounded notion of predictability. Predictability is a well-rooted information theory-based measure to describe the degree of periodicity in a time series [33]. This measure results from adding constancy and contingency. In the sessional description of
suggest localities with high predictability have a similar contribution of contingency (see orange bars in top localities at Fig. 5) and constancy (see orange blue in top localities at Fig. 5). Therefore, weekly sessional changes are present in aggressive behavior time series, with a certain level of constancy along time, for these localities.

In localities with the highest predictability, aggressive behavior incidents showed marked peaks on weekend days (Saturday and Sunday), as illustrate Fig. 5. These results are consistent with de Melo et al. [56] about the temporal dynamics of homicides in Brazil using the days of the week as a temporal scale, and also may relate to the routine activity theory because activities performed regularly are different on weekends and weekdays. In particular, in these localities, in contrast to weekdays, weekend activities associate with entertainment and leisure activities. [57]–[59]; thus, these activities might produce conditions that may trigger aggressive behaviors, such as an increase of social interactions, alcohol consumption, and family conflicts among others. Thus, providing a possible explanation for the observed high sessionality.

The stability measure for predictability computed per year over 2014–2018 (see Fig. 5), showed that Bosa (07), Engativa (10), Fontibon (09), Tunjuelito (06), and Usme (05) exhibit a low variation on predictability on these years. In particular, Bosa (07), Engativa (10), and Usme (05) resulted in high predictability indices and constancy values. This result suggests that aggressive behavior dynamics in these localities relates to recurrent cyclical factors or routine activities that stay stable over the last five years.

C. SHARED TEMPORAL PATTERNS ACROSS SPACE
Crime patterns commonly show changes through city spatial units. Homicides, crimes against property, robbery, rape, among different crimes, seem to exhibit these changes in space. Nevertheless, there is little evidence describing how aggressive crime behaviors may change across different city areas. Most evidence in this type of crime focuses on factors increasing the risk of presenting aggressive behaviors at the personal level, for instance, childhood violence or alcohol consumption, among others. The spatial pattern analysis (see Fig. 6) aimed to understand how the spatial pattern of aggressive behavior crime emerges across several localities in Bogotá. The group ICA result summarizes crime pattern similarities in the different city areas (localities) for the five years under study. The number of factors considered for this decomposition (five) provided a robust representation of crime occurrence across each year, see Fig. 6. Therefore, the same number of components was used for the group-level analysis.

Each component in ICA comprises two elements: 1) a set of localities sharing a temporal dynamic (see blue regions on Fig. 4), and 2) the temporal dynamic itself. Analysis of the components show that a large set of localities (8/19) share a temporal dynamic (see Panel A at Fig. 4). Nevertheless, these eight localities also share other temporal dynamics (see Panels B to E at Fig. 4), indicating that localities may share more than one temporal dynamic; for instance, Kennedy (08) locality share the five temporal dynamics. To our knowledge, this is the first evidence pointing to shared patterns of aggressive behavior shared across city areas for this type of crime. A similar crime occurrence-based decomposition approach that highlighted similar shared patterns was recently described for constructing hotspots of crime [65]. However, this approach was explored for other types of crime.

This work describes crime patterns using only incident reports without considering underlying socio-economical or environmental local variables or particular person characteristics, similar to related recent approaches [41], [49], [65]. Consequently, the relationship between factor temporal dynamics in terms of underlying latent variables is hard to establish. Nevertheless, it is worth observing that localities sharing temporal patterns on the factors herein described have similarities in socio-economics and cultural aspects. For instance, localities such as Bosa (07), Kennedy (08), and Ciudad Bolivar (19), which emerge in three components (see Panels B, D, and E at Fig. 4), ranks among the localities with the highest poverty indices in Bogotá according to the unmet basic needs percentage [70]. In addition, other possible correlates on the emerging groups of localities may also be considered. For instance, components A, B, E include the localities Engativa (10), Suba (11), and Kennedy (08), which have the highest population density indices [71], stating a possible role of local underlying socio-economical and environmental factors in the aggressive behaviors herein described.

To interpret these results, we hypothesized that, as the routine activity theory suggest, beyond these spatial correlates, the temporal dynamics observed in the components might reflect particular social interactions or rhythms in social interactions (for instance, nightlife, leisure, and transport activities, among others) [72]–[74], for which offenders, victims, and absence of capable guardians likely converge [30]. Remarkably, our analysis showed that, as expected in large cities, these dynamics are shared for different city areas [74]. Importantly, these dynamics may be conditioned by underlying social, economic, and environmental factors [72]–[74]. Nevertheless, the characterization of possible latent factors underlying these shared dynamics and the interactions that result in observed temporal patterns should be further studied.
D. HIGH SESSIONALITY RELATED TO SHARED SPATIAL PATTERNS

Our results show that aggressive behavior is not random in time and space in the case of Bogotá. Therefore, following recent literature describing links between these two dimensions [49], [75]–[78], we studied a possible relationship between time and space. Specifically, we investigated the level of predictability on aggressive behavior exhibited by localities emerging at the same component, as illustrated in Fig. 4. This analysis showed that localities with high levels of sessionality (as characterized by predictability) also share multiple temporal dynamics (as described by ICA). Notably, 7 of 8 localities emerging at component A ranked with the highest predictability, i.e., these localities have both high predictability and a shared temporal pattern. Moreover, not only one but multiple temporal dynamics were shared by localities with high predictability (see Section III-A). Therefore, multiple shared temporal dynamics link to the observed high sessionality of aggressive behavior.

Most of the research on crime patterns focuses on descriptions of time and space independently [75]. However, current data make such Spatio-temporal disaggregation achievable, as exemplified in recent literature [49], [75]–[78]. These works have shown, for instance, that vehicle theft in downtown parks and recreational park areas increases on Saturdays [79], suggesting that hotspots shift quickly in response to the structure of daily life [75]. These works point to novel crime occurrence mechanisms, such as daily shifts in populations, particular space-time settings, and spatial-temporal landscapes related to crime, as well as intra-week patterns in time and space of particular crimes [75]. Unfortunately, these patterns for aggressive behaviors are poorly understood. The work herein presented contributes by providing the evidence pointing to a related role on space and time for aggressive behavior, particularly linking periodicity and shared dynamics on particular city areas.

The pattern that related sessionality and shared components in different localities also seem to be supported on modern theories of crime, such as routine activity and crime pattern theories [30], [80]. These theories state that activities can only occur at a finite number of locations and times and that offenders’ and victims’ movement is structured and regulated by the daily routines of them, as well as the social and physical environments within which they interact [75]. An assertion that may explain both: 1) the observed shared temporal dynamics, because they may result from routine activities naturally shared by different locations, especially for the ones with similar socio-economic and environmental conditions, and 2) the high values of periodicity herein reported, which may also emerge as a consequence of the periodic nature of these routines.

Finally, it is worth noting that our results also show that there are localities in Bogotá for which aggressive behavior cannot be explained by the patterns herein described (see localities in yellow in Panel A). However, as observed in Fig. 2 these localities also account for a high number of incidents related to aggressive behaviors (29%, see Fig. 2). Remarkably, under the model of conformation of Latin America cities proposed by [81], these localities contain central business districts, commercial spines, elite residential sectors, and industrial parks, for which particular routine activities would be different. In contrast, the other localities, which account for the 71% (see Fig. 2) of crime reports, are mainly residential and probably share typical routines. This geographical perspective has also been explored to improve crime understanding and may further complement the analysis herein proposed for aggressive behaviour [82].

V. CONCLUSIONS

We studied the sessional patterns of aggressive behavior crime occurrences, and their relationship with temporal dynamics shared across different city areas. For this, we proposed a novel Spatio-temporal analysis method based on the citizen’s reports of aggressive behavior occurrences. The analysis aimed to characterize possible sessions on the aggressive crime occurrences and groups of localities with similar temporal dynamics. Our results show that some city areas, mainly the residential ones, may exhibit high sessional patterns of aggressive behavior for the first time. This behavior emerges from the linear combination of multiple shared temporal dynamics. Nevertheless, further work should be performed to improve understanding of these dynamics, mainly for other city areas that seem to lack this sessionality.

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REFERENCES

[1] C. Buraniuk, “Police plan to use AI to predict crime,” New Scientist, vol. 240, no. 3206, pp. 6–7, 2018.
[2] S. A. Warrick-Swansen, “Risk factors of comorbidity between aggressive behaviors and depressive disorders in school-aged children,” 1998.
[3] J. Liu, G. Lewis, and L. Evans, “Understanding aggressive behaviour across the lifespan,” Journal of psychiatric and mental health nursing, vol. 20, no. 2, pp. 156–168, 2013.
[4] H. Straithreim, “The rise and spread of behavioral public policy: An opportunity for critical research and self-reflection,” International Review of Public Policy, vol. 2, no. 2: 1, 2020.
[5] M. Quick, J. Law, and G. Li, “Time-varying relationships between land use and crime: A spatio-temporal analysis of small-area seasonal property crime trends,” Environment and Planning B: Urban Analytics and City Science, vol. 46, no. 6, pp. 1018–1035, 2019.
[6] L. E. Cohen, J. R. Kluegel, and K. C. Land, “Social inequality and predatory criminal victimization: An exposition and test of a formal theory,” American sociological review, pp. 505–524, 1981.
[7] E. A. Vasquez, B. Likkel, and K. Hennigan, “Gangs, displaced, and group-based aggression,” Aggression and Violent Behavior, vol. 15, no. 2, pp. 130–140, 2010.
[8] L. Kraus, N.-N. Setz, K. D. Shield, G. Gmel, and J. Rehm, “Quantifying harms to others due to alcohol consumption in germany: a register-based study,” BMC medicine, vol. 17, no. 1, pp. 1–9, 2019.

[9] W. L. Perry, “The role of crime forecasting in law enforcement operations,” Rand Corporation, 2013.

[10] B. Ariel, “Technology in policing,” Police innovation: Contrasting perspectives, p. 485, 2019.

[11] Cornish, Derek B and Clarke, Ronald V, “The rational choice perspective,” Environmental criminology and crime analysis, vol. 21, pp. 21–47, 2008.

[12] R. Clarke, P. Eckblom, M. Hough, and P. Mayhew, “Elderly victims of crime and expectations risks,” The Howard Journal of Criminal Justice, vol. 24, no. 1, pp. 1–9, 1985.

[13] R. B. Felson, “Routine activities and involvement in violence as actor, witness, or target,” in Crime Opportunity Theories, pp. 113–125, Routledge, 2017.

[14] G. O. Mohler, M. B. Short, P. J. Brantingham, P. J. Brantingham, F. P. Schoenberg, and G. E. Tita, “Self-exiting point process modeling of crime,” Journal of the American Statistical Association, vol. 106, no. 493, pp. 100–108, 2011.

[15] A. Reinhart et al., “A review of self-exciting spatio-temporal point processes and their applications,” Statistical Science, vol. 33, no. 3, pp. 299–318, 2018.

[16] S. D. Johnson, K. J. Bowers, D. J. Birks, and K. Pease, “Predictive mapping of crime by promap: accuracy, units of analysis, and the environmental backcloth,” in Putting crime in its place, pp. 171–198, Springer, 2009.

[17] K. J. Bowers and S. D. Johnson, “Who commits near repeats? a test of the boost explanation.,” Western Criminology Review, vol. 5, no. 3, 2004.

[18] M. Townsley, R. Homel, and J. Chaseling, “Repeat burglary victimisation: Spatial and temporal patterns,” Australian & New Zealand journal of criminology, vol. 33, no. 1, pp. 37–63, 2000.

[19] Y. Hu, F. Wang, C. Guin, and H. Zhu, “A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation,” Applied geographic research, 2016.

[20] C. Jiang, L. Liu, X. Qin, S. Zhou, and K. Liu, “Discovering spatial-temporal indication of crime association (stica),” ISPRS International Journal of Geo-Information, vol. 10, no. 2, p. 67, 2021.

[21] C.-H. Yu, W. Ding, M. Morabito, and P. Chen, “Hierarchical spatio-temporal pattern discovery and predictive modeling,” IEEE Transactions on Knowledge and Data Engineering, vol. 28, no. 4, pp. 979–993, 2015.

[22] J. Carter, E. R. Louderback, D. Vildosola, and S. S. Roy, “Crime in an affluent city: Spatial patterns of property crime in coral gables, florida,” European Journal on Criminal Policy and Research, vol. 26, no. 4, pp. 547–570, 2020.

[23] Z. Wang and H. Zhang, “Construction, detection, and interpretation of crime patterns over space and time,” ISPRS International Journal of Geoinformation, vol. 9, no. 6, p. 339, 2020.

[24] Y. Zhang and T. Cheng, “Graph deep learning model for network-based predictive hotspot mapping of spatio-temporal events,” Computers, Environment and Urban Systems, vol. 79, p. 101403, 2020.

[25] M. Celik, “Partial spatio-temporal co-occurrence pattern mining,” Knowledge and Information Systems, vol. 44, no. 1, pp. 27–49, 2015.

[26] M. Kalantari, B. Yaghmaei, and S. Ghezelbash, “Spatio-temporal analysis of urban crime leveraging multisource crowdsensed data,” Personal and Ubiquitous Computing, pp. 1–14, 2021.

[27] J. L. Ripp, P. J. Cuvelier, K. A. Bollen, and D. J. Bauer, “Crimes of opportunity or crimes of emotion? testing two explanations of seasonal change in crime,” Social Forces, vol. 82, no. 4, pp. 1333–1372, 2004.

[28] V. Cecatto, “Homicide in sao paulo, brazil: Assessing spatial-temporal and weather variations,” Journal of Environmental Psychology, vol. 25, no. 3, pp. 307–321, 2005.

[29] M. A. Andresen and N. Malleson, “Crime seasonality and its variations across space,” Applied Geography, vol. 43, pp. 25–35, 2013.

[30] L. A. J. Quetelet, A. tropical criminology and the development of his faculties. Cambridge University Press, 2013.

[31] S. J. Linning, M. A. Andresen, and P. J. Brantingham, “Crime seasonality: Examining the temporal fluctuations of property crime in cities with varying climates,” International journal of offender theory and comparative criminology, vol. 61, no. 16, pp. 1866–1891, 2017.

[32] M. Oliveira, E. Ribeiro, C. Bastos-Filho, and R. Menezes, “Spatio-temporal variations of crime in urban areas: The travelling waves of crime,” EPJ Data Science, vol. 7, no. 1, p. 29, 2018.

[33] C. Craig, R. W. Overbeeck, M. V. Condon, and S. B. Rinaldo, “A relationship between temperature and aggression in nfl football penalties,” Journal of Environmental Psychology, vol. 5, no. 2, pp. 205–210, 2016.

[34] E. R. Leukfeldt and M. Yar, “Applying routine activity theory to cybercrime: A theoretical and empirical analysis,” Deviant Behavior, vol. 37, no. 3, pp. 263–280, 2016.

[35] L. van Reemst, “A theoretical framework to study variations in workplace violence experienced by emergency responders,” Erasmus L. Rev., vol. 9, p. 135, 2016.

[36] L. Jaitman, “Frontiers in the economics of crime: lessons for latin america and the caribbean,” Latin American Economic Review, vol. 28, no. 1, pp. 1–36, 2019.

[37] P. Sanguineti, D. Ortega, L. Berniell, F. Álvez, D. Mejía, J. C. Castillo, and P. Brassiolo, “Towards a safer latin america. a new perspective to prevent and control crime,” 2015.

[38] B. P. Manso, “The structure of crime in sào paulo,” Homicide in Sao Paulo, pp. 107–111, 2016.

[39] S. N. de Melo, D. V. S. Pereira, M. A. Andresen, and L. F. Matias, “Spatio-temporal pattern discovery and predictive modeling,” IEEE Transactions on Knowledge and Data Engineering, vol. 44, no. 1, pp. 27–49, 2015.

[40] B. P. Manso, “The structure of crime in sào paulo,” Homicide in Sao Paulo, 2015.

[41] O. Hyvärinen and E. Oja, “Independent component analysis: algorithms and applications,” Neural Networks, vol. 13, no. 4-5, pp. 411–430, 2000.

[42] J. V. Stone, Independent Component Analysis: A Tutorial Introduction. A. P. Press, 2004.

[43] M. A. Andresen and N. Malleson, “Crime seasonality and its variations across space,” Applied Geography, vol. 43, pp. 25–35, 2013.
[58] M. Zhong, J. D. Hunt, and X. Lu, “Studying differences of household weekday and weekend activities,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2054, no. 1, pp. 28–36, 2008.

[59] J. Studer, S. Baggio, M. Mohler-Kuo, P. Dermota, J.-B. Daeppen, and G. Gmel, “Differential association of drinking motives with alcohol use on weekdays and weekends,” Psychol. Addict. Behav., vol. 28, pp. 651–658, Sept. 2014.

[60] J. Liu, “Concept analysis: aggression,” Issues in mental health nursing, vol. 25, no. 7, pp. 693–714, 2004.

[61] M. McMurrin, H. Hoyte, and M. Jinks, “Triggers for alcohol-related violence in young male offenders,” Legal and Criminological Psychology, vol. 17, no. 2, pp. 307–321, 2012.

[62] U. Haggård-Grann, J. Hallqvist, N. Långström, and J. Möller, “The role of alcohol and drugs in triggering criminal violence: a case-crossover study?,” Addiction, vol. 101, pp. 100–108, Jan. 2006.

[63] A. H.-A. Beck, “Alcohol-Related Aggression—Social and neurobiological factors,” Deutsches Ärzteblatt International, vol. 110, p. 711, Oct. 2013.

[64] B. N. Horwitz, J. M. Ganiban, E. L. Spotts, P. Lichtenstein, D. Reiss, and J. M. Neiderhiser, “The role of aggressive personality and family relationships in explaining family conflict,” J. Fam. Psychol., vol. 25, pp. 174–183, Apr. 2011.

[65] G. G. Zanabria, J. A. Silveira, J. Poco, A. Paiva, M. B. Nery, C. T. Silva, S. F. A. de Abreu, and L. G. Nonato, “CrimAnalyzer: Understanding crime patterns in são paulo,” IEEE Transactions on Visualization and Computer Graphics, pp. 1–1, 2020.

[66] J. M. Caplan and L. W. Kennedy, Risk Terrain Modeling Manual: Theoretical Framework and Technical Steps of Spatial Risk Assessment for Crime Analysis. Createspace Independent Pub, 2010.

[67] A. Gomez-Lievano, H. Youn, and L. M. A. Bettencourt, “The statistics of urban scaling and their connection to zipt’s law,” PLoS One, vol. 7, p. e40393, July 2012.

[68] L. Mezquita, G. Ortet, and M. I. Ibáñez, “Personality traits and alcohol use and misuse,” The Palgrave Handbook of Psychological Perspectives on Alcohol Consumption, p. 105, 2021.

[69] R. Gómez-Leal, A. Megías-Robles, M. J. Gutiérrez-Cobo, R. Cabello, and P. Fernandez-Berrocal, “Personal risk and protective factors involved in aggressive behavior,” Journal of interpersonal violence, p. 0886260520926322, 2020.

[70] J. Shiels, “A tutorial on independent component analysis,” 2014.

[71] L. A. Guzman and J. P. Bocarejo, “Urban form and spatial urban equity in bogota, colombia,” Transportation research procedia, vol. 25, pp. 4491–4506, 2017.

[72] X.-Y. Yan, C. Zhao, Y. Fan, Z. Di, and W.-X. Wang, “Universal predictability of mobility patterns in cities,” Journal of The Royal Society Interface, vol. 11, no. 100, p. 20140834, 2014.

[73] D. Santani, J.-I. Biel, F. Labhart, J. Truong, S. Landolt, E. Kuntsche, and D. Gatica-Perez, “The night is young: urban crowdsourcing of nightlife patterns,” in Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 427–438, 2016.

[74] Y. Liu, Y. Zhang, S. T. Jin, and Y. Liu, “Spatial pattern of leisure activities among residents in beijing, china: Exploring the impacts of urban environment,” Sustainable cities and society, vol. 52, p. 101806, 2020.

[75] A. Newton and M. Felson, “Editorial: crime patterns in time and space: the dynamics of crime opportunities in urban areas,” Crime science, vol. 4, no. 1, p. 1, 2015.

[76] C. R. Herrmann, “The dynamics of robbery and violence hot spots,” Crime Science, vol. 4, no. 1, pp. 1–14, 2015.

[77] M. Felson and R. Boivin, “Daily crime flows within a city,” Crime Science, vol. 4, no. 1, pp. 1–10, 2015.

[78] L. A. Tompson and K. J. Bowers, “Testing time-sensitive influences of weather on street robbery,” Crime science, vol. 4, no. 1, pp. 1–11, 2015.

[79] W. Adams, C. R. Herrmann, and M. Felson, “Crime, transportation and malignant mixes,” in Safety and Security in Transit Environments, pp. 181–195, Springer, 2015.

[80] C. R. Herrmann, “The dynamics of robbery and violence hot spots,” Crime Science, vol. 4, no. 1, pp. 1–14, 2015.
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