International Journal of Conflict and Violence

DOI: 10.4119/UNIBI/ijcv.637
IJCV: Vol. 12/2018

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Vol. 12/2018

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Suggested Citation: **APA:** Barabash, N., Zhukov, D. (2018). Terrorism as a Self-Organised Criticality Phenomenon, 2018. *International Journal of Conflict and Violence*, *12, 1-13.* doi: 10.4119/UNIBI/ijcv.637
Harvard: Barabash, Natalia, Zhukov, Dimitry. 2018. Terrorism as a Self-Organised Criticality Phenomenon, 2018. *International Journal of Conflict and Violence 12: 1-13.* doi: 10.4119/UNIBI/ijcv.637

ISSN: 1864-1385

Terrorism as a Self-Organised Criticality Phenomenon

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An examination of the heuristic capabilities of the self-organized criticality (SOC) theory for studying social processes, reviewing key ideas of the theory and the methods of identifying pink noise as an SOC attribute. The authors analyze terrorism in twenty countries in the period from 1970s to 2014. The source of the background data is the Global Terrorism Database, maintained by the START Consortium. SOC approaches and methodology were used to identify and explain such non-linear effects as spontaneous outbreaks of terrorism. It is found that numerical series that reflect changes in the terrorism volume are essentially pink noise. This allowed the universal explanatory schemes of SOC theory to be applied to interpret such systems features and dynamics and demonstrate that in many countries, terrorism is a self-organized criticality phenomenon. Systems in the state of SOC are capable of abrupt growth in activity without any apparent reason. One of the parameters of the numerical series studied – power-law exponent –can serve as an indicator of the internal state of the societies prone to terror threats.

Keywords: self-organised criticality, pink noise, terrorism

Acknowledgements:

This article was based on research work carried out by the SRI FRCEC within its official tasks in the sphere of scientific activity (task No. 074-00497-18-00 of the Russian Ministry of Education and Science, project No. 2.12622.2018/12.1).

This study was conducted with financial support from the Russian Foundation for Basic Research (project No. 17-06-00082a, "Application of self-organised criticality theory in the study and simulation of social systems and historical processes"). The authors are grateful to two anonymous reviewers, whose remarks and advice pointed the way to new meanings in this research. The authors would also like to thank START (National Consortium for the Study of Terrorism and Responses to Terrorism), who provided us with terrorism activity data.

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This article aims to identify pink noise in terrorism activities in several countries over the past few decades. Since pink noise is an attribute of self-organised criticality (SOC), it makes SOC-based hypotheses and interpretation possible. The study examines numerical series describing the number of terrorism events by month in different countries. Our aim is to demonstrate that SOC theory can be applied to social studies.

1. Approaches

Bak and collegues (Bak, Tang, and Wiesenfeld 1988; Bak 1996) introduced the term "self-organised criticality" to describe specific patterns in different systems. When a system is displaying SOC, then any impulse (even a short, weak and local one) will not damp out; instead, it provokes cause-and-effect chains that span the entire system. The system is overrun with numerous reactions and counter-reactions. Thus, a local disturbance can have global implications. Thus, a local disturbance can have global implications. The cause and effect ratio is no longer commensurate.

Criticality can appear in systems having specific properties: complexity, numerous feedback loops and sensitivity to weak perturbation. Bak et al. demonstrated that such systems are prone to cause avalanches: abrupt disequilibration and breakdown of key system parameters without apparent cause. SOC theory discovers and explains how macroscopic system dynamics are connected with numerous microscopic events. It is the self-organisation of microscopic processes that causes the avalanches (the abrupt transformations) that appear to be spontaneous.

Any system produces numerous signals and noises. A signal can be a record of its parameter dynamics in time, or an event line it generates. Inside a system displaying SOC, a complex of micro- and macroscopic events and their implications cause different scale perturbations. This is pink noise (1/f-noise), which is an attribute of SOC (Figure 1B).

SOC theory is a sibling of fractal geometry (Mandelbrot 1982; Frame and Mandelbrot 2002), and in a way, pink noise is a fractal process – a wave making ripples of different size.

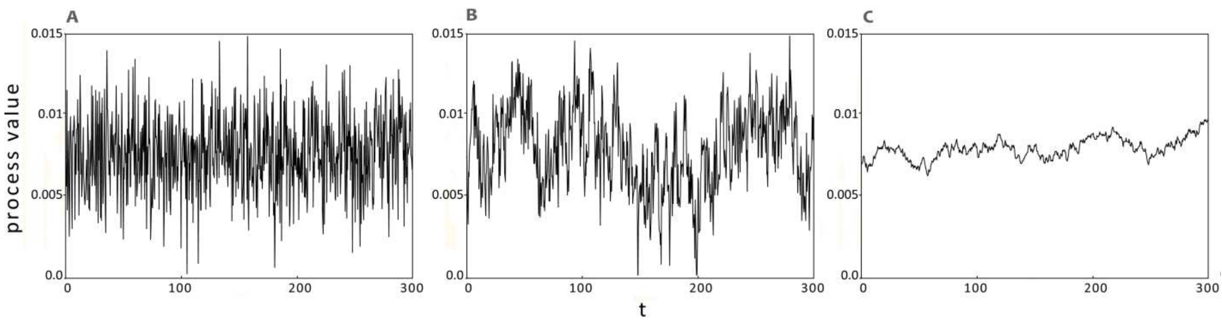
In nature, many systems have been discovered to emit pink noise. Pink noise is like the voice of the universe (from fluctuating star luminosity to the electric activity in the human brain).

The application of SOC theory to social processes is also interesting because it describes non-linear effects: spontaneous system activity and disaster mechanisms. Small and large fluctuations in the system are not necessarily provoked by powerful external perturbation. They can be caused by macroscopic manifestation of microscopic properties of the system.

Typologically, pink noise approaches white and red (Brownian) noises (Figure 1).

White noise is a chaotic process. Red noise is a conservative process with a strong, though short-term, memory. In this case, each following value will depend on the preceding one. Pink noise is something in between white and red noises. It is associated with long-term trends, coexisting with accidental events.

Figure 1: Examples of white (A), pink (B) and red (C) noises



Bak defined pink noise in nature as "punctuated equilibria" (1996, 29–31, 143):

> Large intermittent bursts have no place in equilibrium systems, but are ubiquitous in history, biology, and economics... The complex status is on the border between predictable periodic behavior and unpredictable chaos... Systems with punctuated equilibria combine features of frozen, ordered systems with those of chaotic, disordered systems. Systems can remember the past because of the long periods of stasis allowing them to preserve what they have experienced through history, mimicking the behaviour of frozen systems. Meanwhile, they can evolve because of intermittent bursts of activity.

The identification of a process as pink noise warrants a researcher to refer to SOC theory in order to describe the essence and dynamics of the system that generated this process.

2. Literature

Initially, SOC was introduced to explain how nature works (Bak, Tang, and Wiesenfeld 1988; Bak 1996; Sneppen et al. 1995). But even classical works have admitted the possibility of applying this theory to social phenomena.

Initiatives for adaptation of SOC ideas and methodology by cross-disciplinary researchers were brought forward by Turcotte (1999; Turcotte and Rundle 2002), Buchanan (2000), Brunk (2001, 2002a, 2002b), Borodkin (2005), Kron and Grund (2009) and Malinetskii (2013).

The first studies identify SOC in social processes were dedicated to the history of wars (Roberts and Turcotte 1998; Cederman 2003), and strikes and class conflicts (Biggs 2005). The authors of these papers were able to identify evidence of SOC (such as power-series distribution) and showed how social processes could be interpreted through the universal explanations of SOC theory.

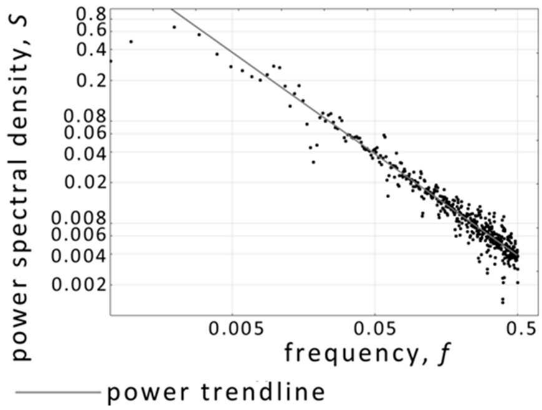
A more recent work examines social and political conflicts in Iraq, Afghanistan and Northern Ireland (Picoli et al. 2014). Zhukov and his colleagues attempted to study the effects of SOC in social processes (2016). Historical data supplied evidence for the hypothesis that changing noise colour is a good indicator of the strength, direction and time of transformations in the social system in question. Shimada and Koyama (2015) also made a valuable contribution with their observations. They showed that SOC effects may indicate a system's potential and readiness for social changes. Thietart found SOC effects in a large corporation (2016). Tadić et al. (2017) show the SOC mechanism in online social dynamics.

Thus, the possibility and heuristic efficiency of applying SOC to the analysis of social phenomena has been described in literature. However, despite its major success in the natural sciences, SOC theory is still used very little within social studies (with the exception of economics).

3. Methodology

Pink noise can be identified though spectral analysis. Using fast Fourier transform, the complex signal is broken down into an array of simple harmonics. Each harmonic is reflected by a point on a spectrogram (Figure 2); its coordinates represent the harmonic frequency and power.

Figure 2: An example of a pink noise spectrogram



Note: Spectrograms are normally portrayed in logarithmic space, so the hyperbola looks like a straight line.

Sometimes (such as in Figure 2), the allocation of points/harmonics can clearly reflect a trend – a statistical pattern. The distribution of signal power by frequency can in some cases be described with a power function:

$$S = v\frac{1}{f^{\alpha}}\ , \tag{1}$$

where S is power; f is frequency; v is ratio coefficient; α is power-law exponent. α is important for the identification of noise type. With α≈2 the noise is considered to be red. If α≈0, then there are reasons to believe that it is white noise, although other techniques are required in order to precisely identify white noise. In pink noise, normally α≈1. If the signal in question follows power law (1), then α can be calculated from the results of spectrum analysis.

Bak pointed out that in case of pink noise, α can be in the range of 0 to 2 (2013, 69). Evidently, when approaching the limits of this range, pink noise gradually transforms into white or red.

For the purposes of this study, we used "Spectral (Fourier) analysis" in Statistica with the following settings: pad length to power 2: yes; subtract-mean: yes; detrend: yes; data smoothing: no. A standard R^2 tool was used to verify the trend and, thereby, the value of α. The closer R^2 is to 1, the more solidly the trend line approximates the points on the spectrogram.

In our research, R^2 declined significantly when α approached 0. The determination of α does not allow for a positive identification of white noise. However, when both α and R^2 are rather low, it is then very likely that the process in question is more chaotic than pink or red noise. Also it needs to be mentioned that because of the nature of statistical patterns, a moderate deviation of R^2 from 1 does not mean that the trend line lacks representativeness.

The methodology is explained in more detail in a paper by Zhukov et al. (2016).

4. Source Data and Chronological Framework

Monthly data on terrorism events was sourced from the Global Terrorism Database (GTD) (National Consortium 2016). This very insightful and reliable database contains information about more than 150,000 terror attacks all over the world since 1970 to date. The database is maintained by the START research centre (The National Consortium for the Study of Terrorism and Responses to Terrorism).

For the purposes of the study, we selected the countries and time periods where terror attacks had occurred over at least six months during the year (Table 1). For instance, following this criterion, terrorism was not common in Germany in 2000–2010.

For cross-temporal comparison of α values, the available numerical series were split periods.

For most countries, the period before the early 1990s (I) should be studied separately from the period from the beginning of the 1990s to date (II). As a rule, sources of terrorism activity in the first period were different in the second period. Namely, since the 1990s Islamic fundamentalism has become a powerful driver of terror, whereas in the previous decades terrorism was predominantly a tool used by ethnic/nationalist separatists and left-wing radical organisations and movements. The data for 1993 was partially lost in the GTD, so we can take 1992 as the late limit of period (I), and 1994 as the early limit of period (II).

Where possible, we devoted special attention to the period between 2008 and 2014 (III) in all countries. Unfortunately, we could not study the year 2016 (or 2017) separately, because it is too difficult to interpret the α value in this case.

Table 1: Size and chronological framework of GTD source data

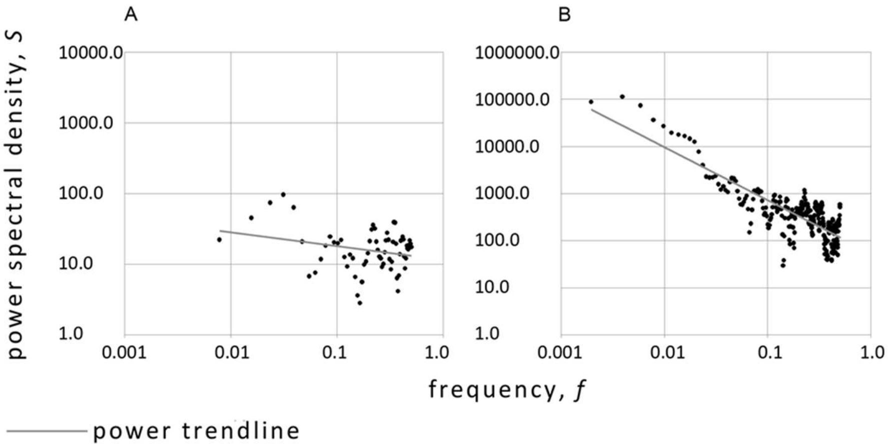
Country	Period	Number of terror attacks
Algeria	1991–2014	2,721
Afghanistan	2002–2014	7,613
United Kingdom	1971–2014	4,919
Israel	1979–2014	1,988
India	1983–2014	9,048
Indonesia	1995–2014	653
Iraq	2003–2014	15,845
Spain	1971–2010	3,243
Colombia	1975–2014	7,954
Lebanon	1979–2014	2,348
Nigeria	2006–2014	2,128
Pakistan	1986–2014	11,490
Russia	1994–2014	2,060
United States	1970–2014	2,683
Turkey	1987–2014	2,548
Philippines	1978–2014	4,830
France	1973–2014	2,578
Germany	1970–1997	1,090
Sri Lanka	1984–2009	2,924
South Africa	1979–1996	1,850

Time limits of periods (I), (II) and (III) were adjusted for some countries (moved within a corresponding time frame) based on the specific country and data availability.

5. Results

Figure 3 shows examples of spectrograms of pink noise (A) and signal with near-zero α (B). Both types were identified in the terror attack intensity fluctuations in different countries.

Figure 3: Terror attack intensity spectrograms



A – UK, 2008 – 2014, α=0.19, R^2=0.071
B – Pakistan, 1986 – 2014, α=1.12, R^2=0.679

In Pakistan, R^2 is technically far from 1. However, the trend is evident on spectrogram B from Figure 3. It is especially conclusive in comparison to a rather chaotic configuration of points on spectrogram A. This typical example brings hope that even mediocre values of R^2 will not always render it impossible to interpret α. Table 2 shows α values for terrorism intensity fluctuations in twenty countries over periods (I), (II) and (III).

The significant changes in α that coincided with major transformations inside some countries speak in favour of the methodology applied. For instance, we found that α decreased in Spain from 0.64 (period I) to 0.17 (period II); and in the United Kingdom from 0.7 (period II) to 0.19 (period III). In Spain, by the end of the 1990s, the Basque separatists had gradually changed from terror to legal actions. Similar processes occurred in Northern Irish separatism in the United Kingdom. Previous terrorism actors became weak, while the new (Islamism-based) ones obviously proved not to be very strong. By contrast, in Columbia, α rose from 0.35 (period I) to 0.87 (period II) with a declining tendency in period (III). Although the standoff between the government and left radicals had started in Colombia back in the 1970s, it was in the 1990s (early period II) when FARC was in its prime. Furthermore, these were also the years when the country faced organised far-right terrorism.

To identify the types of terror activity and group the countries by such types, a cluster analysis of α values for 2008–2014 was conducted (Table 2, penultimate column).

Results of cluster analysis are provided on a tree diagram on Figure 4. It was created using the cluster analysis module in Statistica with the following settings: clustering method: joining (tree clustering); linkage rule: weighted pair-group average; distance measure: Euclidean distances. At each step, the algorithm moves two clusters together with minimal variability. The linkage distance grows with every step (Figure 5). As a rule, this process goes from slow to abrupt. The cut-point between slow and rapid growth (M on Figures 4 and 5) is normally interpreted as the borderline between natural and purely artificial clusters.

Table 2: Power-law exponents in spectrograms

Country	Period I			Period II			Period III		
	years	α	R^2	years	α	R^2	years	α	R^2
Algeria	–	–	–	1994-2014	0.77	0.527	2008-2014	0.73	0.485
Afghanistan	–	–	–	2002-2014	1.17	0.628	2008-2014	1.17	0.656
United Kingdom	1971-1992	0.67	0.476	1994-2014	0.7	0.480	2008-2014	0.19	0.071
Israel	1979-1992	0.68	0.491	1994-2014	0.6	0.524	2008-2014	0.63	0.547
India	1983-1992	0.66	0.636	1994-2014	0.52	0.361	2008-2014	0.41	0.227
Indonesia	–	–	–	1995-2014	0.25	0.121	2008-2014	0.25	0.142
Iraq	–	–	–	2003-2014	0.98	0.641	2008-2014	1.23	0.693
Spain	1971-1992	0.64	0.419	1994-2010	0.17	0.033	–		–
Colombia	1975-1992	0.35	0.123	1994-2014	0.87	0.582	2008-2014	0.73	0.505
Lebanon	1979-1992	0.77	0.480	1994-2014	0.89	0.519	2008-2014	0.89	0.493
Nigeria	–	–	–	–	–	–	2008-2014	0.78	0.421
Pakistan	1986-1992	0.47	0.143	1994-2014	1.08	0.700	2008-2014	0.79	0.554
Russia	–	–	–	1994-2014	0.56	0.480	2008-2014	0.78	0.554
United States	1970-1992	0.99	0.580	1994-2014	0.17	0.061	2008-2014	-0.115	0.041
Turkey	–	–	–	1994-2014	0.63	0.415	2008-2014	0.82	0.427
Philippines	1978-1992	0.56	0.423	1994-2014	0.91	0.665	2008-2014	0.77	0.732
France	1973-1992	0.41	0.408	1994-2014	0.5	0.262	2008-2014	0.09	0.006
Germany	1970-1997	0.36	0.159	–	–	–	–	–	–
Sri Lanka	1984-1992	1.11	0.593	1994-2009	0.85	0.641	–	–	–
South Africa	1979-1996	0.95	0.642	–	–	–	–	–	–

Source data: monthly volume of terrorism events according to GTD.

At clustering distance M, the system identifies four clusters, four of which can be considered as adequate. In India, a low α value obviously reflects interference of signals from different terrorism sources. The United States is an exceptional and single cluster.

The analytical tools applied are indifferent to factors such as a country's location on the map or income level. However, as a result of the analysis we have the United States, France and the United Kingdom on one end (Figure 4), and Afghanistan and Iraq on the other. This may indicate the ability of these procedures to discover some hidden information potential in the source numerical series.

Figure 6 demonstrates country migration between clusters (except India), that formed in periods I and III (see Table 2). Western countries migrated to clusters with smaller α or dropped out due to a lack of statistical data. In period III, one can observe the formation of a vast cluster "Lebanon – ...– Israel" in the zone close to pink noise.

Figure 4: Tree diagram with the results of clustering sixteen countries by α value in 2008–2014

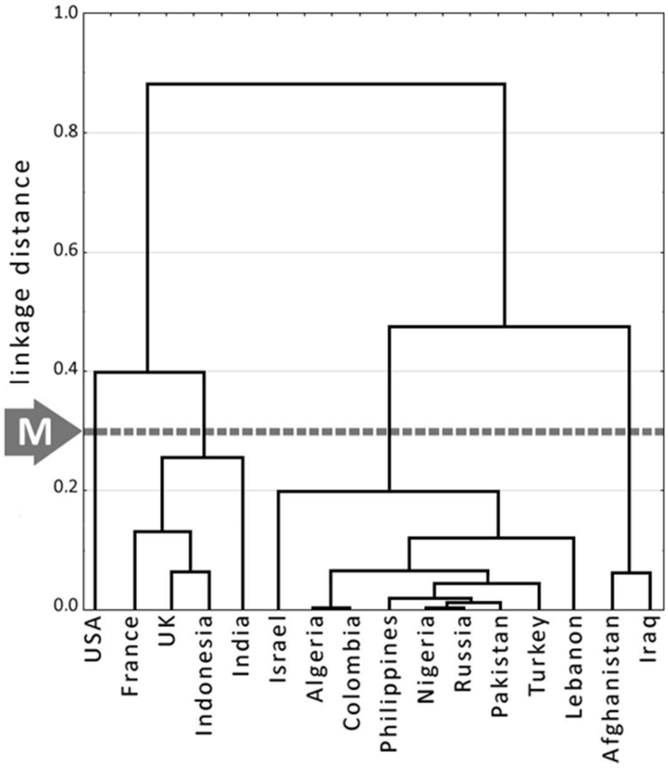


Figure 5: Linkage distance/step number correlation

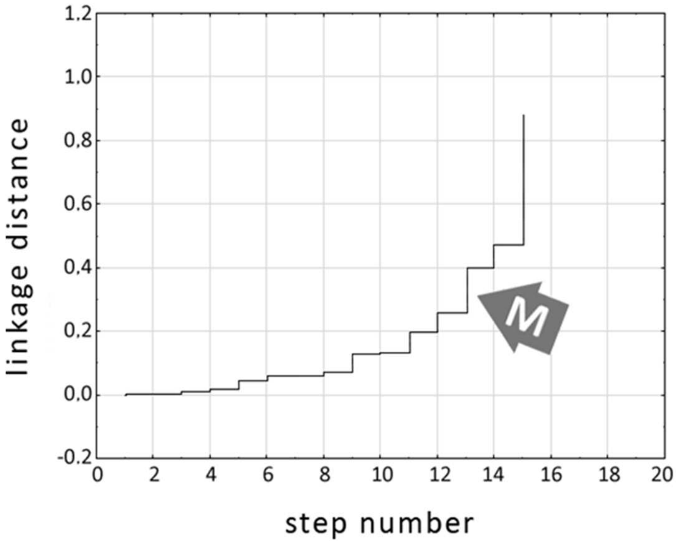
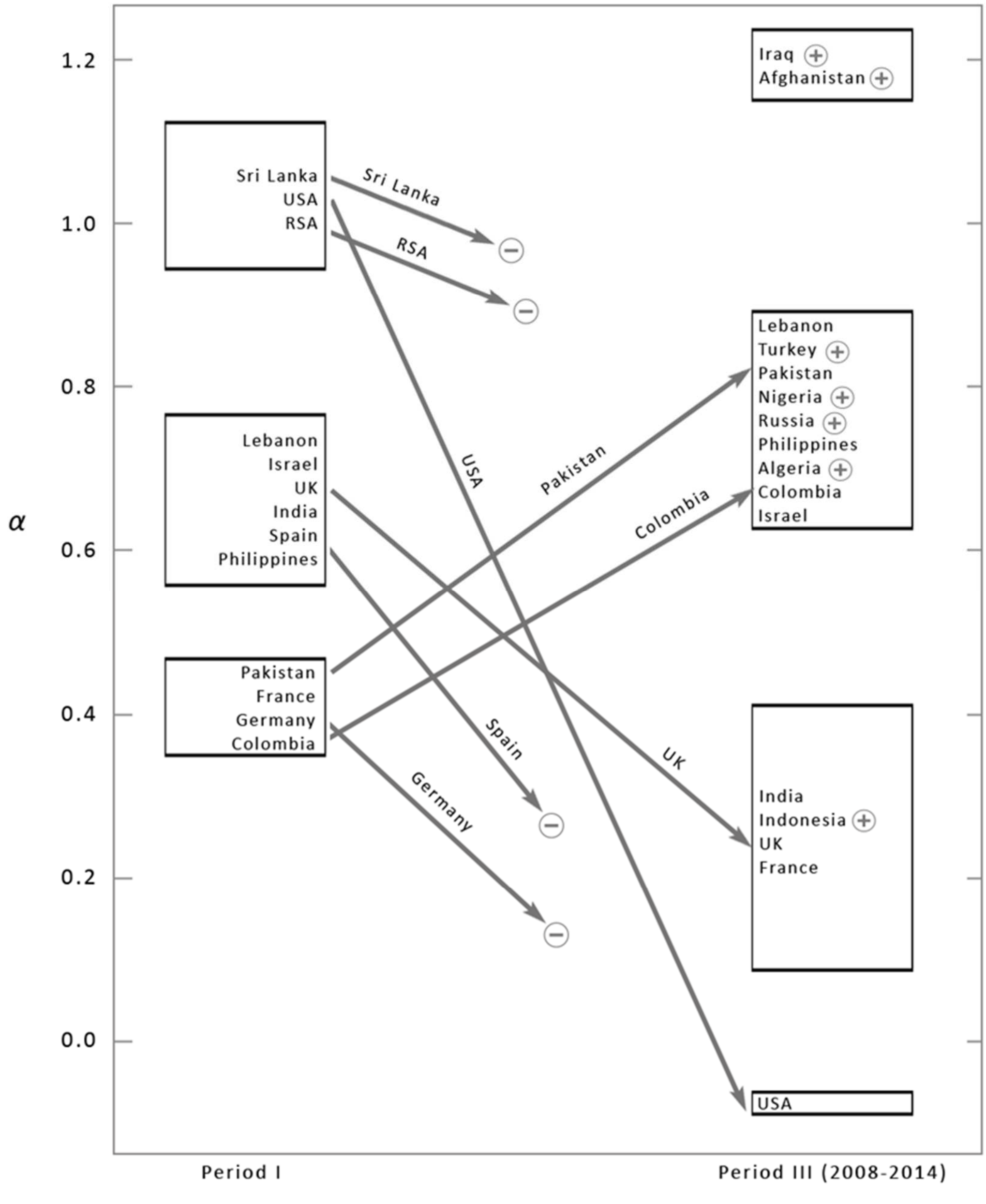


Figure 6: α-based clusters in 1970s–1990s (period I) and 2008–2014 (period III)



Note: some countries were added (+) or removed (-) following the rise/disappearance of terrorism as system-wide phenomenon and/or changes in statistics.

6. Interpretation and Hypotheses

Depending on the colour of the noise in the numerical series and based on the explanatory logic of SOC theory, we have shown three types of terrorism activity. This typology is not based on the level/intensity of terrorism activity. The specific reasons and factors producing a rise or decline in terrorism may have different implications in different types of social systems. Therefore, it is important to understand the specific profile of the society and terrorism actors – what they are capable or incapable of.

Low α values are common in the societies where terrorism does not have a systemic internal source. In this scenario, terror outbreaks, even major events, may be caused by short-term and locally-limited extraordinary factors and a random combination of conditions. Also, the transition from high activity to low may be abrupt and chaotic. This reflects such societies' openness to external sources of terrorism. The "white" type countries obviously do not have systemic readiness and need for grand-scale perturbations. Such "societies" may be targets of threats, but long-term terrorism activity is not generated from within.

Furthermore, we can assume that underground terrorist groups in such countries are, most likely, an atomised array of non- or little-connected actors.

Red noise is common in the societies going through a terrorist war in a hot or latent phase. As in all other types, the intensity of activity in this scenario can be both high and low. But the transition from high to low, if any, goes very slowly under the influence of some evident and rather strong objective factors. It means that the system is affected by some determining factors, which consistently reproduce the same level of terror activities. Such factors can be both generators and depressors of activity. In the "red" type countries, processes are very firmly controlled by the main actors. In this case, underground terrorist groups must be tight-knit, well-disciplined and solid.

The actor generating terrorist activity in pink noise is probably a partially controlled system. It has long-term memory and is probably capable of strategic planning, but it does not have full control over its activity. Pink noise is produced in a system where the elements are connected, at least on the information level.

"Pink" societies have inherent system potential for a significant rise in the number of terrorism events. Pink noise is an indicator of criticality. In this case, random events are accompanied by long-term trends and an accumulation of experience in the system. Events of any scale can occur in such societies. Strong perturbations are caused by ordinary fixed factors inherent to the system. It is possible that such factors are not even strong or prominent to an observer.

Such a situation is extremely dangerous for system stability because of a high probability of avalanches – major outbreaks of terrorism without a long visible preparation period and a likely cause. Any reduction in law enforcement may lead to a rapid upsurge in terrorism. Moreover, as long as such potential inherent to the system exists, no counter-terrorism measures can completely end the avalanche effects. Even a long-lasting reduction in terrorism activity does not eliminate systemic microscopic processes that enable macroscopic avalanches.

We believe that the change in colour is an indicator of transformation in the internal properties of a system that generates the process in question. Namely, the transition from a low α value to the pink noise is a sign of self-organisation, the system being bombarded by all sorts of external impulses and the emergence of stable feedback loops.

The following conclusions can be drawn from Figure 4, which shows clusters/types of terrorism activities. In recent years, the majority of the studied countries can be classified as the "pink" type, with the exception of Western countries such as the United States, France, Spain, the United Kingdom and Germany, which are "white" type.

The "Israel…Pakistan" cluster is described by pink noise with a significant share of erratic behaviour. The latter factor, obviously, does not save the system from large-scale avalanches, but to a certain extent can offset the trends that render such avalanches inevitable.

The "Turkey…RSA" cluster is dominated by pink noise, which makes large-scale outbursts of terrorism in these countries very likely. In these cases, terrorism appears to be a self-sustaining systemic phenomenon. However, we cannot assert the same about RSA and Sri Lanka, because the data used in the analysis referred to the previous period.

The “Afghanistan...Iraq” cluster is also “pink”, but tending strongly towards “red”. In these countries, terrorism has essentially become a tool of civil war.

7. Counter Examples

Could the effects of SOC in terrorism be a projection of self-organised criticality, which is possibly intrinsic to criminal activities in general? To answer this question, let us compare power-law exponents of terrorist events with other types of crime.

Annual homicide dynamic was obtained from two sources: a study by Fink-Jensen (2015) for 1940-1999, and the statistics of the United Nations Office On Drugs and Crime (UNODC) for 2000–2015. UNODC data is available to the public (https://data.unodc.org/). But extensive-period data is available just for a few countries.

Table 3 displays α and R^2 values for the periods 1940–2015 and 1955–2015. The first period includes the Second World War and postwar years, and the second one excludes those years. But the aggregate statistics on both periods can form a picture on the dynamic of homicides.

Pink noise can be identified in many series. On the microscopic level, societies have inner potential to generate this type of criminal activity. However, a group of countries is clearly prone to red noise. That includes Italy, France, the United Kingdom, Belgium, Spain, Germany, Hungary, Canada, Japan, the United States. For these countries, α is within the range from 1.41 to 2.23. In the “red” group, homicide dynamic is marginal.

Table 3: Power-law exponents in spectrograms

Country	1940-2015		1955-2015	
	α	R^2	α	R^2
Iceland	-0.13	0.04	0.12	0.02
Ireland	0.31	0.18	0.36	0.38
Norway	0.43	0.26	0.34	0.22
Mauritius	0.62	0.53	0.42	0.46
Sri Lanka	0.64	0.34	0.62	0.46
Luxembourg	0.69	0.53	0.70	0.59
New Zealand	0.69	0.48	0.79	0.71
Denmark	0.74	0.48	0.77	0.62
Switzerland	0.85	0.54	0.88	0.63
Italy	0.97	0.56	1.90	0.92
Sweden	1.00	0.55	1.02	0.56
Austria	1.02	0.65	1.00	0.74
Australia	1.04	0.64	1.24	0.68
Portugal	1.04	0.78	0.92	0.76
Netherlands	1.05	0.75	1.24	0.84
France	1.13	0.56	1.50	0.71
United Kingdom	1.23	0.77	1.44	0.81
Turkey	1.29	0.75	0.88	0.82
Finland	1.31	0.75	0.95	0.68
Chile	1.32	0.74	0.46	0.38
Belgium	1.41	0.77	1.17	0.67
Spain	1.56	0.84	1.45	0.90
Germany	1.57	0.81	1.69	0.90
Hungary	1.58	0.72	1.46	0.65
Canada	1.59	0.76	1.69	0.82
Japan	1.83	0.79	1.19	0.81
United States	2.23	0.91	2.21	0.91

Source data: annual homicide statistics, rate per 100,000 population.

This indicates that there are strong factors depressing criminal activities. Possibly, the civil society or the police state in these countries may have control mechanisms strong enough to suppress the criminal potential and neutralize sharp surges.

Table 4 shows that "red" group countries have smaller α values for terrorism compared with homicides. The patterns inherent to homicides are different to those of terrorism. This is especially true for the United States, where α is very low for terrorism, compared with an extremely high value for homicides.

For detailed comparison of α values in different types of criminal activities, we would need monthly data, which is not available to us, with the exception of Russia. The reports of Russian Ministry of Internal Affairs are available to the public (https://mvd.ru/folder/101762). Based on these reports, we produced numerical series reflecting the dynamic of acts of terror, total crime, extremist crimes, homicides, and theft (http://ineternum.ru/bd_extr/). We also analysed the series reflecting monthly victims (deaths and casualties) of terrorism in Russia (death and casualties). These numbers were sourced from the Global Terrorism Database (National Consortium 2016) and RAND Database of Worldwide Terrorism Incidents (RAND 2018).

Table 4: Comparison of α values for homicides and terrorism in the red group countries

Country	Terrorism							Homicides			
	Period I			1994-2014		2008-2014		1940-2015		1955-2015	
	years	*α*	*R²*	*α*	*R²*	*α*	*R²*	*α*	*R²*	*α*	*R²*
France	1973-1992	0.41	0.408	0.5	0.262	0.09	0.006	1.13	0.56	1.50	0.71
Germany	1970-1997	0.36	0.159	–	–	–	–	1.57	0.81	1.69	0.90
Spain	1971-1992	0.64	0.419	0.17	0.033	–	–	1.56	0.84	1.45	0.90
UK	1971-1992	0.67	0.476	0.70	0.480	0.19	0.071	1.23	0.77	1.44	0.81
USA	1970-1992	0.99	0.580	0.17	0.061	-0.115	0.041	2.23	0.91	2.21	0.91

Table 5: Power-law exponents in spectrograms

Data source / data type	period	*α*	*R²*
MIA RF / terrorism crimes	2006-2015	0.64	0.527
MIA RF / extremist crimes	2006-2015	0.41	0.224
MIA RF / homicides and attempted homicides	2006-2015	1.04	0.552
MIA RF / theft	2006-2015	1.23	0.45
MIA RF / all crimes	2006-2015	1.14	0.518
GTD / terror attacks	1994-2014	0.56	0.48
GTD / victims of terror attacks	1994-2014	0.07	0.015
RAND / terrorism incidents	1998-2008	0.72	0.441
RAND / victims of terrorism	1998-2008	0.00	0.000

Source data: monthly numeric series of terrorism, extremist and other crime in Russia.

Note: MIA RF: Crime in the Russian Federation (Ministry of Internal Affairs of Russia); GTD: Global Terrorism Database; RAND: RAND Database of Worldwide Terrorism Incidents.

The criminal underworld in Russia shows the signs of pink noise (see Table 5). However, when it comes to extremist crime, the dynamic is significantly more chaotic. In Russia, extremist crimes are those similar to acts of terror in their motives, but having less grave repercussions (such as, hooliganism motivated by ethnic hostility). As expected, α values show that such crimes are mainly spontaneous.

α approaches 0 in the series, reflecting the dynamic in victims of terrorism (Table 3). This outcome could be expected as well, since in such crimes, the number of casualties often depends on many random factors and can vary greatly.

We believe that pink noise in criminal activities is generated by intrinsic social parameters, and needs a separate analysis. Obviously, terrorism must be connected to the general state of the society and, consequently, general state of respective criminal underworld. However, the data at hand does not indicate that SOC effects in the numeric series of terrorism are a direct and simple reflection, i.e. a particular case, of SOC effects, discovered in criminal activities.

8. Conclusion

We conducted a spectrum analysis of signals reflecting changes in terrorism activity in twenty countries over the last few decades. A significant share of such signals represents pink noise. This allows us to refer to the universal explanatory schemes of the SOC theory to interpret the inherent features and dynamics of the systems that generate such signals.

In many countries terrorism is found to be self-organised phenomenon, which allows us to formulate certain hypotheses about non-linear effects, which manifest themselves in the intensity of terrorism activity.

In terms of SOC theory and several cognate concepts, microscopic regularities and trivial daily micro-events generate complex macroscopic behaviour, which is described as intermittent stability. Abrupt transformations (crisis, revolutions, outbreaks of activity) are not necessarily provoked by some strong and extraordinary determining factor. Macroscopic perturbations may be caused by ordinary, trivial properties of the system and a weak external disturbance. Complexity and numerous loop relations make the system display criticality and prevent it from putting down initial impulses. Criticality is a state of superimposition of a great multitude of changes of a wide array of components.

Changes in the nature of signals may point at quality changes of the corresponding systems. A formal parameter - power-law exponent - may serve as a criterion for classifying terrorism activity in different countries.

Such findings give hope that the ideas and methodology of SOC theory can be heuristically efficient in social studies.

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