Modeling Social and Geopolitical Disasters as Extreme Events: A Case Study Considering the Complex Dynamics of International Armed Conflicts

Reinaldo Roberto Rosa, Joshi Neelakshi, Gabriel Augusto L. L. Pinheiro, Paulo Henrique Barchi, and Elcio Hideiti Shiguemori

1 Introduction

In this chapter we address one of the great causes of a man-made disaster that can reach planetary proportions. These are the *armed conflicts*, which throughout the history of humanity have been the main cause of the great wars. A great war in general involves a great destruction of social, cultural, and artistic heritages and, in addition, a huge number of victims (e.g., the 2nd World War resulted in over 60 million deaths) [36]. In this way, great wars are *extreme events* because they induce all those disasters that are inherent to armed conflicts which can reach geopolitical proportions [3, 24] (See Appendix 1).

In a more general context than the one identified above, careful study involving causes and effects of extreme events that result in disasters (natural or man-made) is of paramount importance not only for society in general, but specifically for many areas of science and technology. This is due to the fact that it is mainly through science and technology that humanity will 1 day be able to predict, mitigate, and even control or avoid the causes and effects of major disasters. Therefore, a pragmatic study of armed conflicts, considering the great wars, must necessarily involve a multidisciplinary approach with emphasis on at least the following fundamental sciences: geopolitics, sociology, psychology, semiotics, mathematics,

R. R. Rosa (✉)
Lab for Computing and Applied Mathematics-INPE, São José dos Campos, SP, Brazil
e-mail: reinaldo.rosa@inpe.br

J. Neelakshi · G. A. L. L. Pinheiro · P. H. Barchi
CAP-INPE, São José dos Campos, SP, Brazil
e-mail: gabriel.pinheiro@inpe.br; paulo.barchi@inpe.br

E. H. Shiguemori
Geo-intelligence Division, Institute of Advanced Studies (IEAV), Rov. Tamoios,
São José dos Campos, SP, Brazil

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physics, and chemistry. However, for the modeling of extreme events, especially within the context of social sciences, it is necessary to bring to the detailed study of the phenomenon the modern approaches of computational mathematics, statistical physics, and complex systems theory [27].

The concept of a complex system has evolved significantly over the past two decades. There are many approaches in physics, biology, engineering, mathematics, computer science, and in some interdisciplinary areas that mention, consider, and define a *complex system* [9, 38], however without rigorously presenting an approach that explicitly includes *extreme events* as a property of *complexity* [61, 64], and, even more, addressing its causes in terms of endogenous, exogenous, or hybrid nature [55]. That is, a concept that allows, at least partially, to identify and even measure the degree of complexity based on processes that manifest crises, extreme events (as shocks and disasters), and systemic phase transitions [65].

As will be seen throughout this chapter, complex systems far from the thermodynamic equilibrium [46, 60] can be studied effectively through the non-homogeneous energy transfer cascade model which is the main process describing turbulent-like behavior [33, 47]. Its adequacy to the problem of armed conflicts in a complex network allows to characterize and measure complexity in the so-called *sociosphere* [40], a systemic concept already addressed by the *general theory of systems* (GTS) [14, 60]. From the GTS the concept of sociosphere (a modern concept of biosphere) is presented from the complex interaction that occurs between the human being and the planet, giving rise to a region where conditions are such that our planet is theoretically capable of sustaining life.

The Earth ecosphere, where the interaction between the living and nonliving components takes place, is shaped and transformed by human activity. Thus, the human being merges nature into society. More precisely, the sociosphere can be considered as an inter-subjective ecosphere around our planet, defining the society-nature system [22]. The term comprises the way of social mediation among *agents* (human or social groups) takes place as economical and geopolitical processes.

The fact that such agents determine interactions that may be cooperative or conflicting, balanced or out of equilibrium, permanent, or fleeting in relation to the environment are some of the aspects that make the sociosphere a complex system with the following properties: expressive number and diversity of agents, direct and indirect connections, linear and nonlinear interactions, structurality, hierarchy, and collective phenomena that can strengthen or weaken the permanence of the system as a whole. In this scope a widely used concept for complex systems is as follows: complex systems are those consisting of many different agents interacting nonlinearly and it cannot be split into simpler subsystems without neglecting its collective properties [9, 38]. Although complex systems as a whole are difficult to model, the characterization of spatiotemporal complexity by scaling laws is highly attractive and has many applications in the study of complex dynamics from many systemic interacting elements [35, 61, 64].

In the next section we will describe spatiotemporal complexity based on the concept of scaling laws when associated with a complex dynamics that can be characterized by a multiplicative energy transfer cascade. In the rest of the text we will use this description as a basis for modeling the dynamics of endogenous and exogenous armed conflicts.

2 Modeling Social Spatiotemporal Complexity

Formal complex systems are entities composed of well-defined components. The integrability of the components acts together as to form a functioning whole with spatiotemporal collective dynamics and responses to the environment. Some properties that distinct complex systems have in common are the following: (i) *high density*, (ii) *diversity*, (iii) *nonlinear connectivity*, (iv) *collective behavior*, (v) *structurality*, (vi) *thermodynamic permanence*, (vii) *far from equilibrium states*, and (viii) *scaling hierarchy* [53, 60]. As a practical example of complex systems exhibiting such properties, in the spatiotemporal domain, are: (a) the bird flocks [15], (b) the fish schools phenomena [50], and (c) the social crowds [23, 42]. In these high density complex systems, even when the diversity is low (but never null), their nonlinear interconnected nature leads to emergent behavior. From the property of **collective behavior** emerges **structurality** whose **permanence** is susceptible both to endogenous and exogenous stimuli. The structure is then dissipative and its stability can be characterized from the variation of its thermodynamic characteristics. This means that complex systems can trip across thresholds into sudden transitions and they can react disproportionately to seemingly small triggers, or transform as a result of influences from within the **scaling hierarchy** structure itself (e.g. hysteresis and self-organization).

In general, the complex exchange of non-homogeneous information across group agents may result in a spectrum of spatiotemporal patterns characterizing collective behaviors. While complex collective patterns in animal groups are readily identifiable by trained visual inspection, a mathematical method from raw stochastic data is not yet well established. However, considering the previous definition of complex systems, the possibility of measurement stochastic data brings information on the scaling hierarchy and its autocorrelation function. This reduction of the effective dimensionality of a complex system makes it possible to establish a mathematical approach known as Kramers–Moyal (KM) treatment [10, 23].

The KM approach is based on the hypothesis that there are several large Markov–Einstein time scales, which can be traced back to hydrodynamic-like memory effects. Above this time scale spectra the process can be mapped to an Ornstein–Uhlenbeck process [21] via the application of the developed extended structure function method [23]. This is in agreement with the classical theory of overdamped $1/f^{\beta}$ noise which characterizes, for example, Brownian motion, reaction–diffusion pattern formation, and turbulence, from its power spectrum density (PSD). In this context, complex dynamics such as non-homogeneous turbulence can be described from multifractal singularity spectra [12, 33, 43, 63].

Between the two example of systems, uniform [15, 50] and highly non-uniform [42], we identify the systems of social conflict that can be approximated by elements containing only two distinct types: agents and reagents that, in practice, exchange their roles collectively. This allows us to initiate a first modeling that can be effective in the study of armed conflicts. Therefore, understanding the transfer energy cascade following a scaling hierarchy from an agent–reagent system and the correspondent non-homogeneous turbulent-like behavior becomes also essential for many social complex systems [6, 7, 28, 42].

2.1 Multiplicative Cascade for Extreme Conflicts Events

When an effective observable, expressing the energy of the system, exceeds a certain critical value, a sort of viscous character originating from agent–reagent sociological frictions may appear. Moreover in such a scaling hierarchy the exchange of information is limited only within a local region so that the transfer of the energy in a group may become incoherent. Therefore, in a systemic approach, the complex regimes of a social dynamical system may be similar to the turbulent motion of a complex viscous fluid. Along this line it is possible to propose an analytic method to characterize complexity from a systemic stochastic fluctuation which should be sensitive, in the time domain, to the occurrence of extreme events. A such time series can then be analyzed from their respective power spectrum density (PSD) [10, 21, 33] (see Appendix 2).

To simplify the notation, the elements of our agent–reagent multiplicative cascade are called simply *agents*. The diversity of agents is binomial. We use the colors black and white. When the colors are opposite the agents are in conflict (see Fig. 1a). We start the cascade from a non-homogeneous criterion containing a conflicting pair ($A_1 \times A_2$). The energy (or information) that characterizes the conflict is distributed between the agents and is interpreted as a function of a wave number $K = 1/scale$. In the cascade, as wave number falls over time, the amount of agents increases in a binary proportion. Agents of lower levels are called $pro - agents$ (PA) (they allies when they have the same color). The energy of the conflict will dissipate until a *disaster state* in which the maximum energy dissipation will occur. This scenario is compatible with a non-homogeneous cascade type model (see Fig. 1b). Hence, our approach is based on the so-called *p-model* mechanism [37, 56] that allows us to create a non-homogeneous cascade in a way which is entirely compatible with the fluctuations observed in stochastic time series.

2.2 P-Model for Social Conflicts

The P-model approach for non-homogenous turbulent-like cascade was proposed by Meneveau and Sreenivasan [37]. It gives a new insight into the kinetic energy dissipation in cascading process of eddies in the inertial range of a fully developed turbulence, and it is based on the special case of weighted transfer.

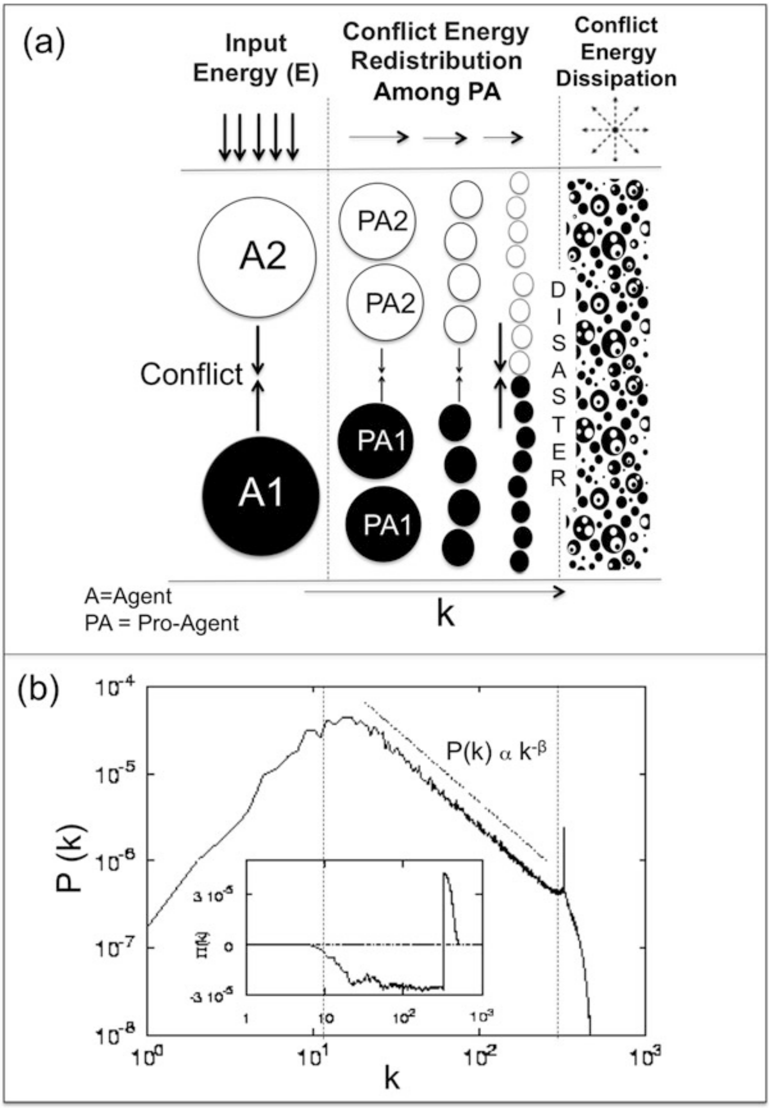


Fig. 1 The multiplicative cascade for non-homogeneous binomial turbulent-like process. (**a**) The scaling hierarchy for social conflicts; (**b**) the respective expected power spectrum density pattern showing the transition from the inertial range to the extreme event which is the response to the high dissipative regime. The embedded picture shows the enstrophy as a function of the wave number

From a theoretical point of view, P-model is a generalized form of two-scale cantor set with balanced distribution of length which shows multifractal properties of one-dimensional sections of the dissipation field. The generalized form starts from the classical view of eddy cascade before the inertial range of fully developed turbulence, where flux of energy (E_K) actually dissipates at Kolmogorov length scale β from eddies of size L_K. Then, each eddy of size L_K is divided into two equal parts, $L_K/2$ expressed as L_{K_1} and L_{K_1} each; however, in each cascade step, the flux of energy is distributed, as a probability, unequally in fraction of p_1 and $p_2 = 1 - p_1$ where $p_1 + p_2 = 1$. This process is iterated over fixed p_1 until eddy reaches to Kolmogorov scale β [5, 31, 41].

The *p-model* multiplicative cascade is given by

$$\alpha = \frac{log_2\, p_1 \;+\; (\omega - 1)\, log_2\, p_2}{log_2\, l_1 \;+\; (\omega - 1)\, log_2\, l_2} \tag{1}$$

and

$$f(\alpha) = \frac{(\omega - 1)\, log_2\, (\omega - 1) \;-\; \omega\, log_2\, \omega}{log_2\, l_1 \;+\; (\omega - 1)\, log_2\, l_2} \tag{2}$$

Starting with a non-homogeneous energy distribution, one transfers a fraction $f(\alpha)$ of the *multifractal mass* from one half to the other in a randomly chosen direction [58]. This is equivalent to multiplying the originally uniform density field on either side by factors. The same procedure is repeated M times, recursively at ever smaller scales using fractions varying α on segments of length $L/2^n$, where the multiplicative weight ω is parameterized as $1 - (1 - 2p)$, resulting the discrete array $C(m)$ where m counts as time steps. This p-model algorithm procedure given by Venema [1, 16] can produce time series where the variance is finite if you would extrapolate its power spectrum to infinite large scales [49].

Time series, $C(m = t)$, with $M = 2^{11}$, representing non-homogeneous turbulent conflict is generated using the Venema algorithm [1], where the inputs are: the size of the time series in number of points (M), the PSD power spectrum (β_{PSD}), and the value of p, which is the fractional distribution of energy in non-homogeneous turbulent-like cascade [4, 18, 20, 26, 34]. The homogeneous dissipative process near the thermodynamic equilibrium is recovered when $(\beta_{PSD}, p) = (-5/3, 0.5)$.

Deviations from the homogeneous cascade are compounded by abrupt changes in the frequency and magnitude of social conflict. Such changes are called *eXtreme Events* (XE) and their cause may be due to factors more internal than external. When the level of conflict increases significantly due to internal interactions, the extreme event is called endogenous (XE_{endo}). When the external energy transfer or abrupt dissipation is the main cause of XE, then it is called an extreme exogenous event (XE_{exo}). In the power law domain, events of the type XE_{endo} and XE_{exo} belong to different classes of universality. In order to generate time series XE_{endo} and XE_{exo} we will adopt the SDGA formalism [55] (see Appendix 2). Typical endogenous and exogenous processes, combining p-model and SDGA, are obtained for ($\beta_{PSD} \approx -0.4, p = 0.25$) and ($\beta_{PSD} \approx -0.7, p = 0.25$), respectively. Figure 2 shows XE time series for different combinations of p and β_{PSD}.

The cumulative energy of the process in the time domain is defined as normalized average $< C(\tau) >$ where τ is a chosen window time interval along the signal. The

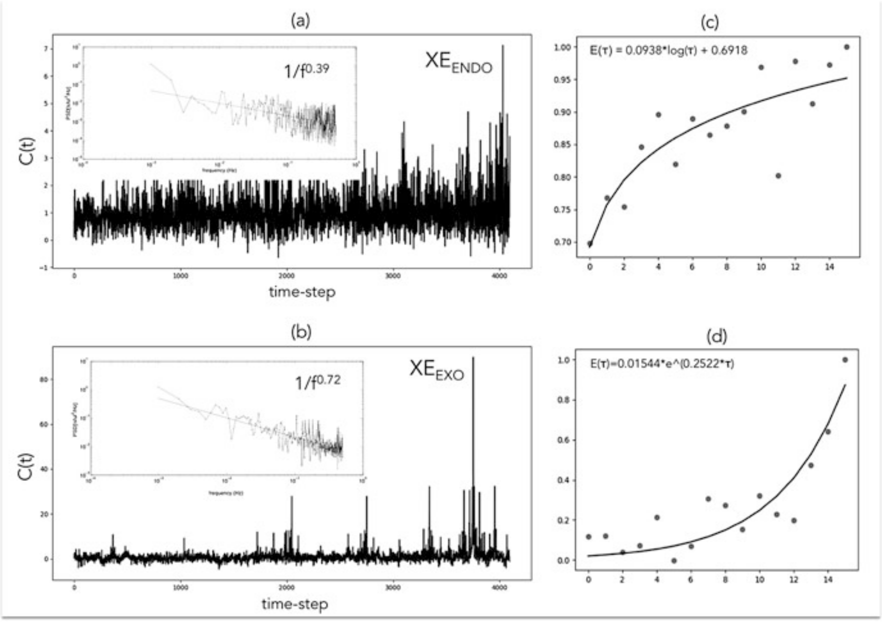


Fig. 2 Two typical time series simulated from p-model fixing $p = 0.25$ and varying the value of β. (**a**) A XE_{endo} pattern from $\beta = -0.39$. (**b**) A XE_{exo} pattern from $\beta = -0.72$. The respective PSDs are shown using embedded smaller pictures. Figure (**c**) and (**d**) shows the respective cumulative energy expressing the typical functional patterns for endogeny (log) and exogeny (exponential)

trend of the cumulative energy over each $\tau = 250$ time steps is shown in Fig. 5c and d. It is noteworthy that the typical trends are nonlinear being logarithmic for XE_{endo} and exponential for XE_{exo}.

3 Modeling Geopolitical Conflicts

Armed conflicts are, at some scale, associated with geopolitical factors (in their broadest meaning, which involves aspects of rights and security directly related to citizenship, culture, economics, and politics). In this way, as shown in Appendix 1, armed conflicts are those involving threats, defenses, and attacks with the active or passive use of weapons in a geopolitical domain.

In the geopolitical domain, the terrorist attacks are today one of the central problems in our social environment [62]. It is notable in this context that the rate per decade of international armed conflicts has increased more than 85% since the severe event on September 11, 2011 [24, 36]. Since then terrorist attacks have also been associated with other types of armed conflict involving geopolitical and economic interests where small and large nations stand out as strategic parts of the complex and global armed sociological conflict (for simplicity, only international armed conflicts). Therefore, in order to formalize the study of the dynamics of international armed conflicts, the so-called Uppsala Conflict Data Program *(UCDP)* has been prepared since 2002 in close collaboration with researchers at the Department of Peace and Conflict Research at Uppsala University and the Departments of Sociology and Political Science and Geomatics at the Norwegian University of Science and Technology *(NTNU)* [24]. We will call here Armed Conflicts *(AC)* only to those defined in the *UCDP/PRIO* Dataset Codebook [57].

The number of AC as terrorist attacks worldwide by year is shown in Fig. 3 [57, 59]. The data reveal an endogeny in the frequency of attacks from 1970 until 1992. A period of decline is evident beginning in the wake of the Cold War's end and lasting roughly a dozen years [54]. For the past decade, however, there has been a exogenous rise in the number of terrorist attacks from just over a thousand in 2004 to almost 17,000 in 2014. The trends indicate some meaningful distinctions before and after the 9/11 Al-Qaeda attack. Since 9/11, these countries have experienced significantly more armed conflicts than they had previously [54]. It is also noteworthy, from the inserted picture, the hyper exogenous character of the September 11 attack.

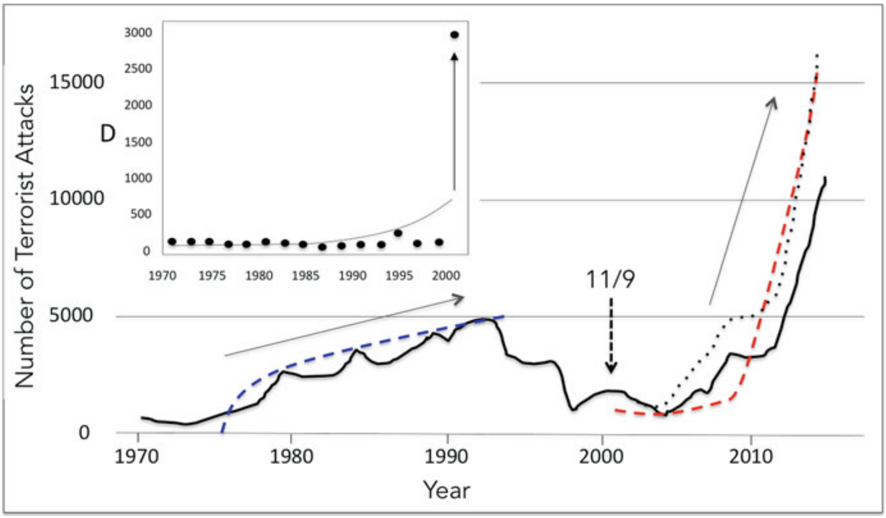
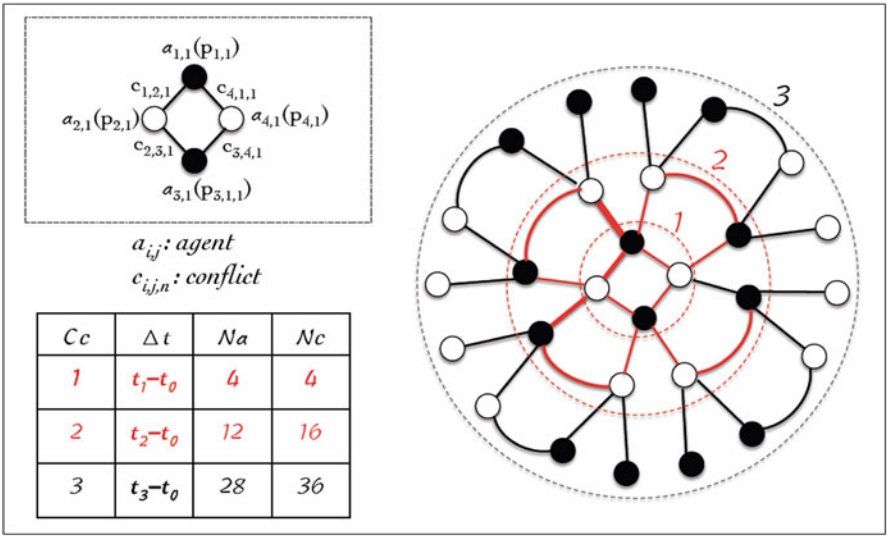


Fig. 3 Endogeny (blue) and exogeny (red) patterns in the total number of conflicts per year from terrorist attacks since 1970 until 2012. The exogenous pattern holds even when removing attacks in Iraq and Afghanistan (dashed curve). The smaller picture shows the GTD total number of deaths (D) per year from terrorist attacks against the USA state from 1970 until the Sep 11th 2001. This includes all victims and attackers who died as a direct result of the incident [59]



Cc	Δt	Na	Nc
1	$t_1 - t_0$	4	4
2	$t_2 - t_0$	12	16
3	$t_3 - t_0$	28	36

Fig. 4 The Agent-Conflict Network, $ACN(SP_3)$ with $n = 3$ containing 28 agents and 36 conflicts. The partial number of agents and conflicts for sub-cells are shown in the inserted table. The embedded small picture on the left shows the details of the SP_3 core configuration

3.1 A Prototype for Agents-Conflict Network (ACN)

In order to illustrate how, in practice, the non-homogeneous p-model is designed for describing Geopolitical Conflicts, we introduce the simplest Agents-Conflict Network (ACN) shown in Fig. 4. We assume that the network has a core with four agents: $a_{1,1}$, $a_{2,1}$, $a_{3,1}$, and $a_{4,1}$. This set of agents is called the first *conflict cell*: C_1. In C_1 the agents $a_{1,1}$ and $a_{2,1}$ are in conflict. Following the cascade model described in Fig. 3, $a_{3,1}$ is pro-agent $a_{1,1}$ while $a_{4,1}$ is pro-agent $a_{2,1}$. Then, $a_{3,1}$ and $a_{4,1}$ are in conflict too. In the simplest configuration each agent will be in conflict with two new agents giving rise to cell C_2 which will contain $N_{C2} = N_{C1} + 2N_{C1}$ agents, where N_{C1} is the number of agents in C_1.

In a war of great proportions not all the agents involved (in general states) are in conflict with all their enemies. Geographical and diplomatic limits impose this restriction. Note that in the ACN prototype this happens naturally due to the connection adopted in the circular topology.

This prototype is referred to here as the *Conflict Core SP3* (SP_3). In this prototype, agent $a_{1,1}$ is always a *superpower state*[1] in conflict with some nation (or faction) with status of state (but not a superpower) that is agent $a_{2,1}$. A convenient initial condition to non-homogeneous cascade is that pro-agents $a_{3,1}$ and $a_{4,1}$ are

[1]The concept is based on the global hegemony introduced by Lyman-Muller [19].

Table 1 Tree pragmatic examples of SP_3 conflict core

Event	Date	$a_{1,1}$	$a_{2,1}$	$a_{3,1}$	$a_{4,1}$	$C(\tau_1 = 15)$	Deaths
NKB	10/09/17	USA	NK	Japan	China	16	0
SMS	4/07/17	USA	Syria	EU	Russia	08	25
WTC	9/11/01	USA	Al-Qaeda	EU	ISIS	06	2996

also necessarily superpowers [39]. Three contemporary examples involving the USA as the agent $a_{1,1}$ are set forth in Table 1: North Korea Border (NKB), Shayrat Missile Strike (SMS), and World trade Center (WTC). In this table, the acronyms EU and ISIS are, respectively, for European Union and Islamic State of Iraq and Syria, and τ_1 is given in days.

The conflict between two agents is denoted as $c_{i,j,n}$, where n denotes the cell level C_n. Each agent $a_{i,j}$ is assigned a probability $p_{i,j}$ which measures its chance of being active in the conflict (that is, $c_{i,j,n} \neq 0$).

The energy injected into the core SP_3 is the source that materializes the conflicts: $c_{1,2,1}$, $c_{2,3,1}$, $c_{3,4,1}$, and $c_{4,1,1}$ for a time interval $\tau_1 = t_1 - t_0$, where t_0 is defined as the initial conflict time. For a given τ_n it is possible to estimate the amplitude $C(\tau_n)$ by counting the number of active and significant conflicts such that $p_{i,j} \geq p_c$, where p_c is a certain critical probability as input to the model.

For the SP_3 an extreme event occurs when $C(\tau_n) \geq N_{C_n} + 4$, where N_{C_n} is the number of **active** agents contained in cell C_n. This criterion imposes on the model the form of distribution of the injected energy. Let's say for SP_3 with $n = 3$ we have all layer conflicts $n = 3$ disabled and all others activated which results then in 16 conflicts. In this case $C(\tau_3) = 12 + 4 = 16$. It is an extreme event where the energy balance did not reach the outermost layer and there is no any extra external energy source for this. Therefore characterizing in this case a typical XE_{endo}. If there were an complementary external energy injection, in the avalanche structure, this enclave would be transferred to the N_3 agents more quickly thus characterizing a more abrupt and more intense event, then a typical case of XE_{exo}.

3.2 *The Prototype Simulation*

In this section, we introduce a bidimensional cellular automata (CA) to simulate the ACN prototype [2]. The 2DCA-ACN is a two-dimensional cellular space with discrete time step where each cell holds one state from a finite state set that changes following a local update rule which depends on the neighborhood state around each cell at the previous time step [30]. At the core, the two black cells represent, according to the notation used in Fig. 4, the agents $a_{1,1}$ and $a_{2,1}$ and the white ones the respective pro-agents $a_{3,1}$ and $a_{4,1}$. The neighborhoods strategy is a Von Neumann configuration [30] that is composed of the cell itself and the four cells situated at north, south, east, and west. Moreover, the pressure in this conflict space

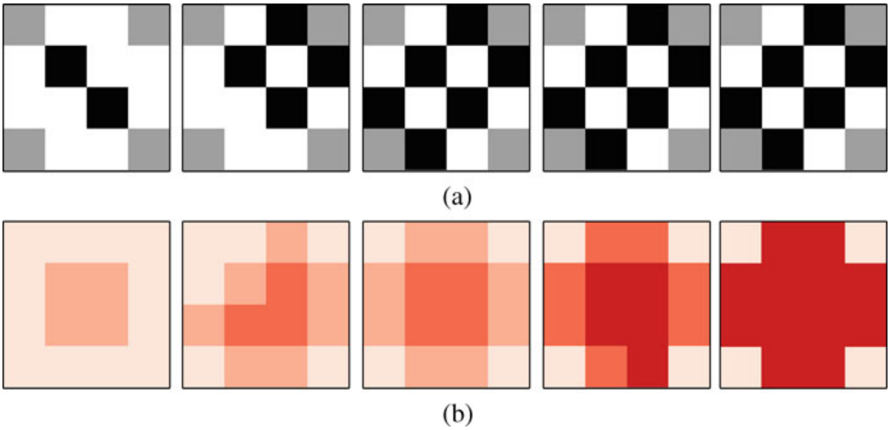


Fig. 5 An example of 2DCA-ACN simulation setting the parameter $P(A) = 0.5$ as the initial value to each activated cells. (**a**) Snapshots of the activated cells. (**b**) Evolution of the space conflict state represented by four red levels at each time step. The corresponding state with the intensity of red, in the ascending order, is given by: threats, strike, and war. The lighter color of the red levels does not draw any state, hence shown an inactive cell and is defined as level 0

only tends to grow. For the simulations to be considered in this article, the AC prototype is formed of only two-stage, that is $C_c = 2$: the initial state which is described as the catalyst iteration of the conflict space, while the second is characterized as a complete system, showing all allies of the two side of the conflict space, with a total agents $N_a = 12$ (the black and white cross-shaped area in Fig. 5) and a maximum number of conflicts of $N_c = 36$. Not that, to be compatible with the ACN topology, as a rule, there is no activation in the gray squares of the cellular space conflict. The time step follows the Von Neumann rule and is thus recurrent until the system converges to the maximum configuration of the second stage.

In this 2DCA-ACN, every cell holds a probability $P(A) \in [0, 1]$ of conflict with each neighborhood cell, a three-up-let state which is defined as (i) threats, (ii) strike, (iii) war and a counter to save the number of conflicts (i, ii, iii) that occurred. Through each state, we set as well an energy value $\mathcal{E}_1$, $\mathcal{E}_2$, and $\mathcal{E}_3$ to threats, strike, and war, respectively such that $\mathcal{E}_3 \gg \mathcal{E}_2 > \mathcal{E}_1$. It is assumed that only cells with threats or superior state can influence in the environment, we call this an *active cell*. Otherwise, the cell is inactive and not assumes any value. At the initial time, the configuration of the system is given by activating all cells located in the first stage, setting their state as a threat, and keeping the other cells inactive (the gray cells of the space conflict are always inactive). Furthermore, a cell cannot bring down your state and the geopolitical conflicts only expand if a cell in the first stage turns up the state to the second level.

The chance of happens a conflict (η) in a cell by the joint probability of conflict between the cell (i, j) and your neighbors $(i + \alpha, j + \beta)$ is given by

$$P(\eta) = \prod P(A_{i+\alpha,j+\beta}) \tag{3}$$

where α is the x-axis and β is the y-axis coordinates, which assume the following indices: $\{(0, 0), (0, -1), (-1, 0), (0, 1), (1, 0), (1, 1)\}$. In this case, each cell is independent so the state of the other cells does not influence in your own state. Thereafter, we use a Bernoulli distribution to sample the probability $P(\eta)$ and decide if a conflict (threats, strike, war) get success or failure, in other words, if the conflict will happen or not.

Moreover, if some conflict happened, the counter must be incremented to register this action. In this way, the probability of $P(A)$ must be up to date according to the number of conflict in a cell, which is defined by:

$$P(A) = \frac{P(A) \times F}{z} \tag{4}$$

where F counts for the amount of conflict in a cell and $z = P(A) \times F + P(\overline{A})$ is the normalized probability.

The model was developed with the programming language Lua, a simple pseudo-code of the conflicts procedure is detailed in Algorithm 1. In the procedure, the parameter p represents all activated cells in the system at a specific time t. After receiving the cells, a loop is used to iterate over each neighbor of the current cell p for computing the joint probability (line 4). Worth to emphasize that the update of parameters occurs at the same time in every activated cell and to calculate the new value of counter and $P(A)$ it is only necessary the previous values. Therefore, if x is succeeded, the next step updates both the counter and the probability of conflict (line 10, 11).

Algorithm 1 Cellular automaton to geopolitical conflicts

1: Set parameters;
2: **Input:** $P(A)_p$: initial probability of conflict
3: **procedure** CONFLICT(p)
4:     $\eta \leftarrow P(A)_p^{t-1}$;
5:     **for** $\forall q \in N(p)$ **do** ▷ Neighbors of the current cell
6:         **if** $State_q^{t-1}$ is active **then**
7:             $\eta \leftarrow \eta * P(A)_q^{t-1}$;
8:         **end if**
9:     **end for**
10:     **Compute** x $\sim Bernoulli(\eta)$;
11:     **Update** $Counter_p^t$ according x;
12:     **Update** $P(A)_p^t$ according x;
13: **end procedure**

Figure 5 shows the output for a 2DCA-ACN. The space conflict is shown at time = 10, 60, 70, 80, 160. The initial time is defined as the first stage for the agents: $\{(1, 1), (1, 2), (2, 1), (2, 2)\}$ and every agent assumes the parameter $P(A) = 0.5$. While Fig. 5a shows the activated cells, Fig. 5b represents the state of each cell by means of four red color levels, such that, the level 1 illustrates the initial conflict state as a *threat* until the level 3 which is the conflict state *war*. Along the evolution of the conflict space a mean energy of the *state* in each cell at time t is registered, where the t is equivalent 15 days passed according to the UCDP data (see Sect. 4 and Appendix 1).

We find that the model is able to simulate both endogenous (XE_{endo}) and exogenous behavior (XE_{exo}) according to a specific initial value in the parameter probability of conflict $P(A)$. Figure 6 (Up) illustrates an endogenous case by initializing $P(A)$ with random probability for every cell activated at some time t. In general, the simulations showed that one can obtain similar results as well when $P(A)$ is defining, in average, with low probability. On the other hand, if $P(A)$ admit high probabilities ≈ 1, then an exogenous pattern XE_{exo} occurs in the state conflict space as shown in Fig. 6 (Bottom).

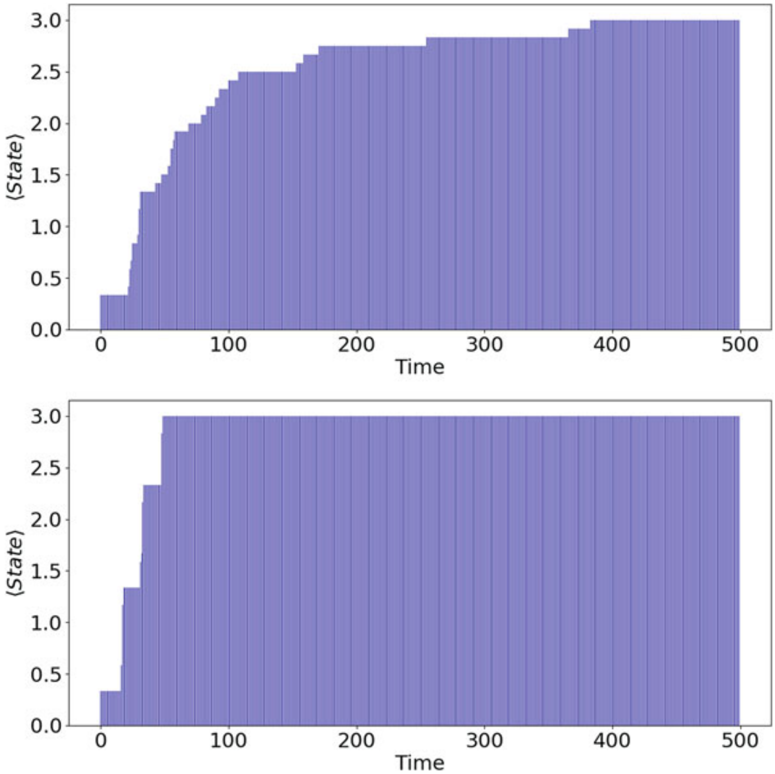


Fig. 6 **Up**: The average state of activated cells designing an endogenous behavior by simulating the model with $P(A)$ as a random probability. **Bottom**: The average state of activated cells illustrating an exogenous case when $P(A) = 0.95$

4 Building a World War Time Series

Looking through current international affairs and conflicts in the IACM dataset, we have designed new scheme to understand conflict intensity based on causalities [25]. The counts of armed conflicts are performed each 15 days. International Armed conflict data when plotted on $log - C(\tau) \times \tau$ scale distinct levels can be categorized as:

(i) *Level W* (War): $C_W(\tau) \gg 3\sigma$ (σ is the standard deviation of $C(\tau)$). Using the notation $C(15) = D_{15} = N_D$: number of deaths in the interval $\tau = 15$ days.

- *stability*: $N_D < 10^2$ on log scale. It has almost no fluctuation, continuous smooth unit vector.
- *conflicts*: $10^2 \leq N_D < 10^3$ on log scale. This is interpreted as one of the parties having conflicts with the other involved in the battle. But no use or threats of any missiles or nuclear weapons.
- *cold war*: $10^3 \leq N_D < 10^4$ on log scale. High production and large number of nuclear weapons tests. There are high counts of threats (conflicts).
- *warm war*: $N_D \geq 10^4$ on log scale. High production and large number of nuclear weapons tests. There are high counts of threats (conflicts). One of the parties uses the missiles. Threats of use of nuclear weapons are high (conflicts).
- *war or hot war*: $N_D \geq 10^5$ on log scale. Both parties use the missiles and nuclear weapons.

(ii) *Level S* (Strike): $C_S(\tau) \geq 3\sigma$ using $C(30) = N_S$ for UCDP monthly counting of armed attacks (strikes) (deaths are not computed in this index) [17]. The time series is shown in Fig. 7.

(iii) *Level T* (Threats): $C_T(\tau) \simeq \sigma$ using $C(\tau)_{p-model} = N_T$. This level can be also called *Level N* from *noise*.

To inspect an international conflict as an extreme event, we are interested in finding whether data is endogenous or requires some thrust and be categorized as exogenous. To analyze endogenous and exogenous patterns in *IACM*, a complex systems model has been built by inducing endogenous and exogenous *P-model* time series as a noise. This is equivalent to the complex daily threats among the agents and pro-agents in conflict involving international affairs conveyed by the official media (see Fig. 8, Appendix 1). The main cause of this component of the signal is political instability due to adverse regime. Actually from our understanding it works as a non-homogeneous turbulent-like information cascade, the underlying process which drives the energy until the state of extreme event [49–52]. War is a matter of making decisions in a very complex system from where the underlying turbulent-like fluctuations follow the patterns as shown in Fig. 3.

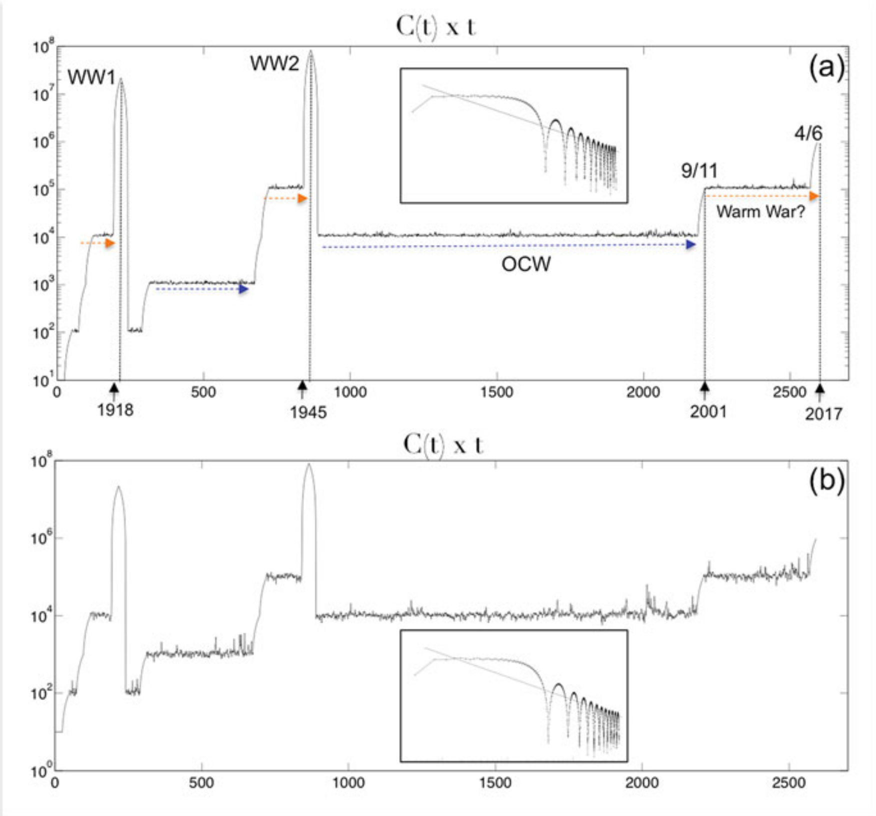


Fig. 7 The $C(t)$ times series for the interstate armed conflict model starting from the first World War conflict and ending at the USA missiles launched on Syria on 6 April 2017. The time series resolution is composed of 2592 points due to a 15 days sampling rate. (**a**) this model is based on the exogenous noise component σ_{XXe} and (**b**) based on the endogenous noise component σ_{DXe}. The respective PSDs are shown using embedded smaller pictures

Considering the three IAC counting components the model for the overall signal is defined as follows:

$$C(\tau) = \omega_D log N_D + \omega_S log N_S + \omega_T log N_T \tag{5}$$

Figure 7 shows the global (endogenous and exogenous) time series generated by Eq. (5). By consistency of conditional standard deviation, the set of weights are: $\omega_D = 10^{-1}$, $\omega_S = 10^{-2}$, and $\omega_T = 10^{-3}$.

The importance of this time series model, considering the results obtained with the prototype that describes a possible underlying process discussed in the previous section, is to allow the application of forecasting tools for the study of a possible armed conflict that can reach global proportions. In this direction, we are already working on supervised learning methods in artificial intelligence, such as the artificial neural networks (ANNs) and the support vector machine (SVM) which are suitable for nonlinear time series prediction [8, 13, 29, 32].

5 Concluding Remarks

Data mining in the *UCPD/PRIO* dataset has inspired a more careful study on the fluctuation patterns of interstate armed conflict (IAC). Our approach leads to a multifractal p-model originally designed to simulate the highly intermittent spatial fluctuations of the kinetic energy dissipation in non-homogeneous turbulent-like dynamics. There exists a great potential for this approach through the exploration of the features of complex systems that make them distinct (diversity, memory, cross-scale interactions, sensitivity to environmental variability). The great challenge, however, remains to find generalities in the model dynamics to improve understanding and prediction. For example, the meaning of the evolution of the *state conflict space* defined here.

Based on this challenge, in this work, a mathematical and computational treatment has been proposed whose results show some consistency with the real data. The cascade interpretation of energy for non-homogeneous turbulence besides being consistent with the dynamics of complex social systems allowed to develop a prototype of multi-agents for which a simulation with cellular automata was performed. The simulation is validated from the main characteristics studied in this approach to AIC that are the occurrence of extreme endogenous and exogenous events from threats, attacks, and wars. An important question into this context, considering the results, is: what are the real causes of exogenous extreme events? That is, how should the high values of conflict probabilities of the model be interpreted in real life?

The occurrence of a XE_{exo} means that some important factor is not being considered in the dynamics of the system. Therefore, possible causes of exogeny are the following: existence and action of powerful and invisible terrorist cells; infiltrators and heavily camouflaged agents, and, finally, the existence of clandestine nuclear programs for high-destruction attacks. On the other hand, the most perverse aspect of endogeny is the possibility of protocol conflicts, that is, those devised and commissioned by undemocratic agreements between fake enemies.

Finally, from a practical point of view, we can say that geopolitical conflicts, in special the IAC, have become more frequent and intense maybe due to the increasing of exogeny in the conflict system. From the theoretical point of view, this probable increasing exogenous dynamics could gradually suppress smaller armed conflict and simultaneously forced the system to release tensions through increasingly severe and frequent systemic armed conflict. Is it a self-organized criticality process that should be discussed within the geopolitical scope? Is it possible that the superpowers, for perverse reasons, are interested in carrying out a great protocol war? Exogenous behaviors are less likely since they can result in extreme events that can lead to an armed conflict of world proportions (world war) whose practical sociological results are of no interest to any of the agents involved. In this case, the result would be a global disaster with low resilience thus compromising the permanence of humanity on this planet. Anyway, no kind of war is welcome for most. Thus, this type of study challenges the geopolitical systems to create mechanisms of transparency that allow the population and the press to follow closely the great decisions taken by the most powerful leaders. Only then we will have the great power to prevent major social disasters.

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Appendix 1: The UCDP Data Base

The Uppsala Conflict Data Program (UCDP) database [57] provides one of the most accurate and extensive information on armed conflicts including attributes like conflict intensity based on total number of battle-related deaths; number of conflicts (see Fig. 8); conflict type; details of warring party including geopolitical information; period with specific start and end date, etc. This database is updated annually and considered well-used data-sources on global armed conflicts. Its definition of armed conflict[2] is becoming a standard in how conflicts are systematically defined and studied. Conflict with minimum of D **battle-related deaths** per period τ and in which one of the warring party is government of a state is recorded as an *Interstate Armed Conflict* (IAC) [17]. UCDP DataBase (UDB) categorizes *IAC* in different intensity levels based on the total battle-related causalities:

- *Not active*: $D < 25$ per year.
- *Minor*: $D \geq 25$ per year but fewer than in the extreme event period.
- *Intermediate*: $25 \ll D < 1000$ total accumulated of at least 1000 deaths, but fewer than 1000 in any given year.
- *War*: $D \geq 1000$ per year.

[2]Based on the UDB the IAC is here defined as: contested incompatibility that concerns government and/or territory where there is a probability of using armed force between two parties, of which at least one is the government of a state.

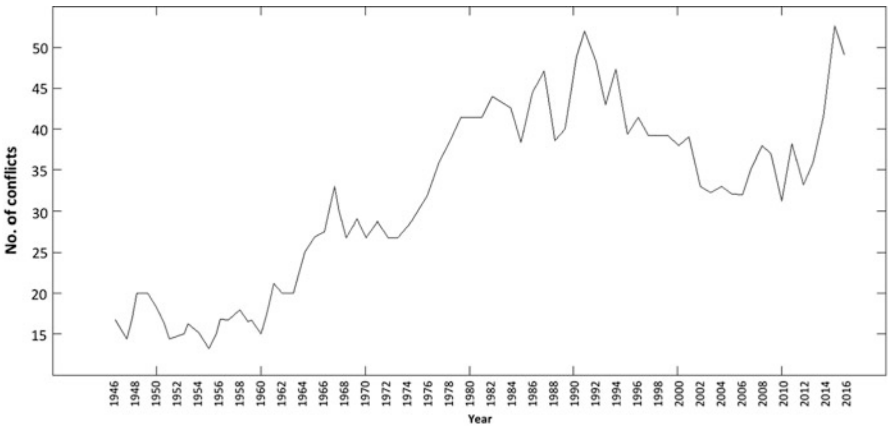

Fig. 8 UCDP monthly counting of armed attacks which is used as the component N_A in our time series model

Appendix 2: Power Laws for Endogenous and Exogenous Time Series

The systemic difference between endogeny and exogeny in abrupt events has been interpreted as a scaling process by Sornette–Deschtres–Gilbert–Ageon (SDGA) [55], where internal perturbations give rise to endogenous extreme events (XE_{endo}) which is characterized, as shown in Fig. 9a, by smoother average continuous fluctuations that increases slowly and after reaching its highest peak and gradually reduces by itself. Differently, an exogenous extreme event (XE_{exo}) results from a preponderant external perturbation and can be characterized by a sudden peak followed by unexpected rapid drop in the fluctuations (Fig. 9b).

The SDGA model is based on the book sales rank. While the book's selling rate, which has a XE_{endo} pattern, only relies on the advertising provided by the common sales system (basically, the publisher's advertising and, especially, the cascade of information between the readers and likely readers), the sales rate of the book with XE_{exo} pattern counted on an unusual systemic outsider high cost advertisement via a famous newspaper or TV broadcast interview.

According to the SDGA a time series can be modeled based on *social epidemic process* where in the beginning, first (*mother*) agent notices the book in advertisement or news or by chance and initiates buy at time t_i. Subsequent (*daughter*) generations of agents are build at different time t resulting in an epidemic that can be modeled by a memory kernel $\phi(t - t_i)$. The net sale is the sum of $1/f$ noise processes following a power law distribution that accounts for XE_{endo}, and impulsive distribution associated with XE_{exo}. The time series can be described by a conditional Poisson branching process given by

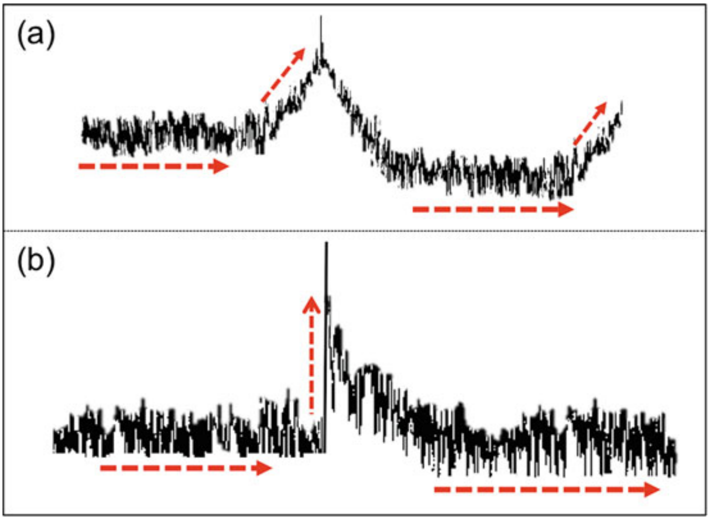

Fig. 9 Typical time series for (**a**) XE_{endo} and (**b**) XE_{exo}, according to the SDGA scaling approach

$$\lambda(t) = R(t) + \sum_{i/_1 \leq t} \mu_i \phi(t - t_i) \tag{6}$$

where μ_i is number of potential agents influenced by the agent i who bought earlier at time t_i. $R(t)$ is the rate of sales initiated spontaneously without influence from other previous agents.

For our generic complex systems scenario, the key idea in the SDGA approach is the invariance of the epidemic model but as a non-homogeneous network of potential daughter generations which can be considered through different values of branching ratio. The ensemble average yields a *branching ratio*, n, that signifies the average number of conflicts triggered by any *mother Agent* within her contact network and rely upon the network topology and impact of the systemic dissipative behavior. Authors considered the sub-critical regime $n < 1$ in order to ensure stationarity which accounts for efficient coarse-grained nature of the complex nonlinear dynamics. The exogenous response function is obtained from Laplace transform of the Green function $K(t)$ of the ensemble average.

According to Sornette [55] a *bare propagator* as $\phi(t - t_i) \sim 1/t^{(1+\theta)}$ with $0 < \theta < 1$ corresponds to long-range memory process which provides information on the conflicts propagation:

$$C_{exo}(t) \equiv K(t) \sim 1/(t - t_c)^{1-\theta}. \tag{7}$$

It provides information about the average number of agents influenced by one agent through any possible direct descent or ancestry. And thus average number of conflicts triggered by one agent can be given as:

$$\int_0^\infty K(t)dt = n/(1-n). \tag{8}$$

Continuous stochastic time series with spontaneous peaks indicates the lack of exogenous shock. Such series can be interpreted as an interaction between external factors over small-scale and enlarged effect of widespread cascade of social influences. This mechanism can explain peak in endogenous time series. Considering results for stochastic processes with finite variance and covariance for average growth of processes prior and later to the peak and applying to $\lambda(t)$ defined in Eq. (5) one get:

$$C_{endo}(t) \sim 1/|t-t_c|^{1-2\theta}. \tag{9}$$

Equations (7) and (9) agree with the prediction that XE_{exo} should occur faster with exponent $1-\theta$ compared to XE_{endo} with exponent $1-2\theta$. Therefore, after characterizing the power laws $1/(t-t_c)^\beta$ with highest correlation coefficient [55], the scaling interpretation presents two different universality classes characterizing XE_{endo} with β as $1-2\theta \approx 0.4$ and XE_{exo} with β as $1-\theta \approx 0.7$. These are compatible values with Eqs. (7) and (9) with the choice of $\theta = 0.3 \pm 0.1$.

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