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ORIGINAL PAPER

Self-organized criticality of climate change

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Abstract Self-organized criticality (SOC) of three climatic factors (average daily temperature, vapor pressure, and relative humidity) was studied by analyzing climate records from 1961 to 2011 in Yanqi County, northwest China. Firstly, we investigated the frequency-size distribution of three climatic factors and found that they were well approximated by power-law distribution, which suggested that climatic factor might be a manifestation of self-organized criticality. Furthermore, we introduced a new numerical sandpile model with decay coefficient to reveal inherent dynamic mechanism of climatic factor. Only changing the number value of decay coefficient of climatic factors, this model would give a good simulation of three climatic factors' statistical characteristics. This study showed that it was the self-organized criticality of the climate change that results in the temporal variation of climatic factors and the occurrence of large-scale climate change events triggered by SOC behavior of the minor climatic factors. So, we believed that SOC characteristics would have practical implications for climate prediction.

1 Introduction

Power-law distribution has been found in many actual systems and phenomena, such as solar flares (Lu and Hamilton 1991; Boffetta et al. 1999; Wheatland 2000), family names (Miyazima et al. 2000), earthquake (Carlson and Langer 1989), computational linguistics (Abney 2011), World Wide Web (Barabasi and Albert 1999; Huberman and Adamic 1999; Adamic and Huberman 2000; Albert et al. 1999; Bornholdt and Ebel 2001), lung inflation (Suki et al. 1994), DNA (Kim and Park 2011; Jeong et al. 2000), and traffic flow (Shang et al. 2008; Atzori et al. 2006). Self-organized criticality (SOC), introduced by Bak et al. (1987, 1988) and Bak and Paczuski (1993), was intended to explain the universality of $1/f$ noises and fractal in the nature. Irreversible dynamics would drive the system into a critical state without the fine tuning of parameters (Song et al. 2001). When the system reaches the critical state, the "frequency-size" distribution of energy dissipation events satisfies a power-law relation. The SOC idea is illustrated by computer models that have slow driving or energy input and rare, avalanche-like dissipation events that are instantaneous on the time scale of driving. These models include the sandpile model with landslides (Paczuski and Bak 1993; Iverson 1997; Hergarten and Neugebauer 1998), air pollution model (Shi et al. 2008; Shi and Liu 2009), slide-block model with earthquakes (Carlson and Langer 1989; Olami et al. 1992; Malamud and Turcotte 1999), forest-fire model with forest fires (Grassberger and Kantz 1991; Drossel and Schwabl 1992; Paczuski and Bak 1997), etc. These models can explain the frequency-size distributions of these nature systems.

Climatologists have long been interested in nonlinear dynamics and fractal aspects behind climate change phenomena (Xu et al. 2009, 2010). Some recent studies showed that a lot of climatic factor concentrations time series are characterized by a long-range correlation, $1/f$ noise, and scale invariance (Govindan et al. 2001; Tsonis et al. 1999; Chen et al. 2007; Bunde et al. 2004; Feldstein 2000; Mann and Lees 1996). Some studies suggested that SOC might be a possible mechanism underlying climate change processes, such as carbon cycle (Cronise et al. 1996; Lichtenegger and Schappacher 2011; Yu 2006) and rainfall (Pinho and Andrade 1998; Aegerter 2003; Andrade et al. 1998; Peters

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and Christensen 2006; Peters and Neelin 2006) with some empirical evidences. To date, a model which can illuminate SOC behavior of other climatic factors such as temperature and vapor pressure has been rarely seen in literatures. Do these climatic factors exhibit SOC behavior?

In this paper, we first analyzed the frequency-size distribution of three climatic factors (average daily vapor pressure, temperature and relative humidity). Furthermore, we put forward a numerical sandpile model with decay coefficient to illuminate SOC of climatic factors. We found that this model could reveal a common inherent dynamic mechanism of three climatic factors. Based on these studies, we tried to provide some suggestions to the actual climate prediction.

2 Study area and data

Yanqi County (41°45′~42°20′ N, 85°13′~86°44′ E) is located in the abdominal region of Yanqi Basin, across Kuruktag above the fold belt and the South Tianshan fold belt. Yanqi County is surrounded by many mountains and is the main location in the heart of the Yanqi Basin with a major axis of NWW basin extending to the diamond, relatively flat terrain (Fig. 1). Within the county, the northwest protrudes and is higher than the southeast and slightly skewed. The county possesses rich water resources, and the Kaidu River is the largest river that flows through Hejing, Yanqi, and Bohu County and at last flows into Bosten Lake. This area has a typical desert climate of the warm temperate zone with an average annual temperature of 8.2 °C, with extremely high and low temperatures of 38 and −35 °C, respectively. Average annual precipitation is 74.4 mm, with greatly uneven distribution of precipitation within any single year. More than 80 % of the total annual precipitation falls between May and September, while less than 20 %, from October to the next April. Moreover, flora in this region mainly includes the century Asia component, ancient Mediterranean Sea component, and so on.

Data used in this study include average daily vapor pressure, temperature, and relative humidity from 1 January 1961 to 31 December 2011, in Yanqi County. These data all come from the Information Center of Meteorological Office in Xinjiang Uygur Autonomous Region, so the accuracy and precision of the data can be ensured.

3 Scaling relationships

Cumulative frequency-size distributions associated with many natural systems exhibit power-law scaling, which is called the typical "critical" dynamical behavior found in SOC systems such as earthquakes, landslide, and forest fire (Grassberger and Kantz 1991; Drossel and Schwabl 1992; Turcotte and Malamud 2004). A power law applied to a cumulative distribution can be expressed as follows:

$$N = cr^{-\lambda} \tag{1}$$

where N is the cumulative number of events per unit time with size greater than or equal to the magnitude (r), λ is the scaling exponent, and c is a constant.

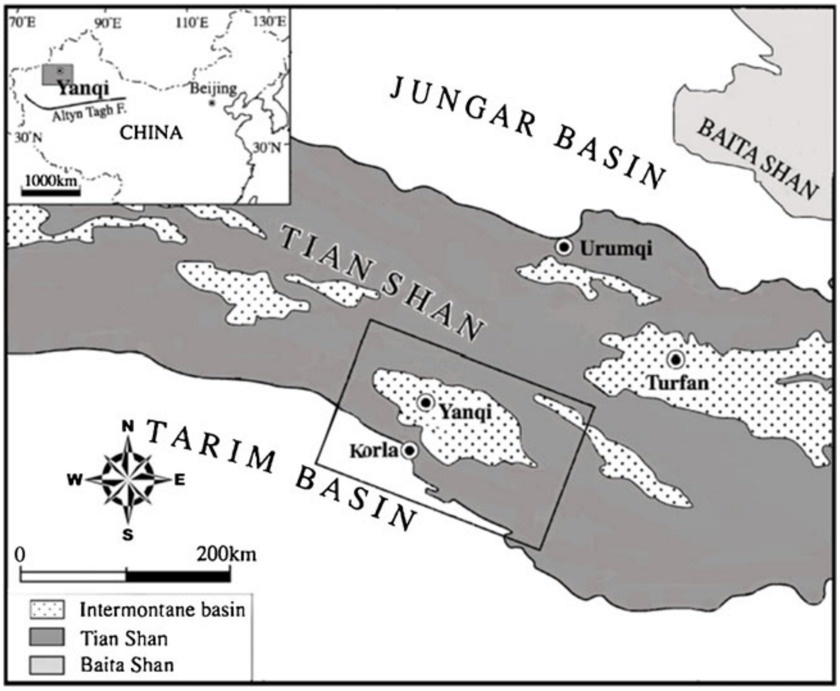

Fig. 1 Topographic map of Yanqi County, northwest China

Following the sandpile analogy, we defined the formation of the climatic factor as an avalanche event and the magnitudes of various climatic factors as avalanche sizes in a granular pile.

Figures 2, 3, and 4 show the number density of temperature, vapor pressure, and relative humidity change events per year, respectively. The results are similar to the Gutenberg–Richter law (Gutenberg and Richter 1944) in the earthquakes study. However, temperature, vapor pressure, and relative humidity also exhibit differences in power-law behaviors. Their scaling exponents are 6.87, 5.37, and 8.98, respectively, while their scaling regime extends over about 0.8, 0.8, and 0.4 orders of magnitude, respectively. This implies that a typical scale of change events does not exit, and scale invariance prevails. In the scaling regions, there is an inherent dynamical connection between small and high events of climate change. We note that the power law breaks down in smaller climatic factor magnitude regions. We think that low monitoring frequency of climatic factors result in the low-size tail of the frequency distribution. Shi and Liu (2009) had found the similar phenomenon in air pollution.

4 The model

By following an analogy to sandpile, we note the similarity to air pollution and rainfall process (Shi et al. 2008; Aegerter 2003; Peters and Christensen 2006) in the study from the qualitative view of SOC. We consider that the power-law scaling in these climatic factors is equivalent to that of avalanche size evolution in SOC system. Therefore, the proper sandpile model can be used to simulate the statistical characteristic of climatic factors.

For the creation of real long-term climate change patterns, we believe that the degradation effect of climatic factors should play a central role. Based on the above motivation, we established a model for the climatic factor change process on a lattice and simulated the formation of climate change patterns.

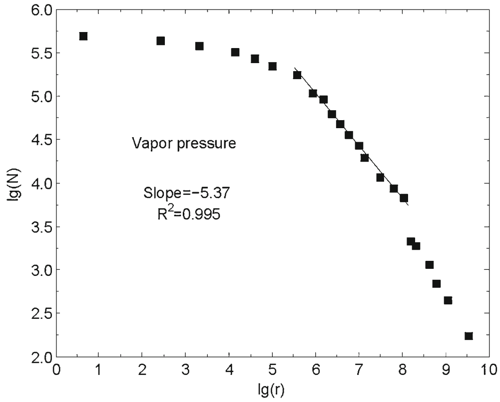

Fig. 3 The number density of vapor pressure change events per year N, with size greater than or equal to r, versus change event size r on a double logarithmic scale. The data are consistent with a power-law $N \propto cr^{-\lambda}$, $\lambda \approx 5.37$ (*solid line*) over at about 0.8 order of magnitude scales

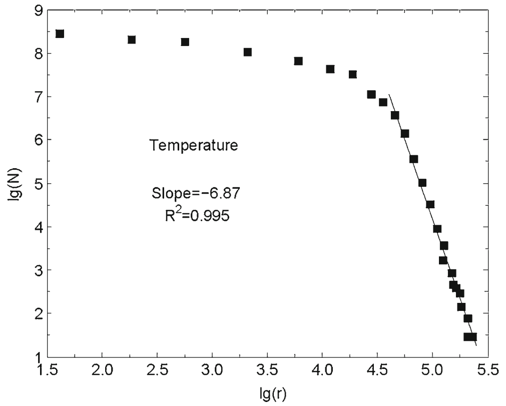

Fig. 2 The number density of temperature change events per year N, with size greater than or equal to r, versus change event size r on a double logarithmic scale. The data are consistent with a power-law $N \propto cr^{-\lambda}$, $\lambda \approx 6.87$ (*solid line*) over at about 0.8 order of magnitude scales

The model is defined on a square lattice of size $L \times L$ with open boundaries in two dimensions. Variables $h(i,j)$ represent amounts of the climatic factors at the site (i,j), which is similar to height of the sandpile. The continuously increasing temperature, vapor pressure, and relative humidity are regarded as the sands continuously dropping on a lattice. Temperature, vapor pressure, and relative humidity can be added to the lattice by the following procedure:

Step 1 A sand is randomly added to a site. The height of the added sand column is β, as to three climatic factors, β values correspond to 60, 50, and 40, respectively, which represent the climatic factor of unit volume which is β. This process corresponds to a minor climatic factor.

$$h(i,j) = h(i,j) + \beta \qquad (2)$$

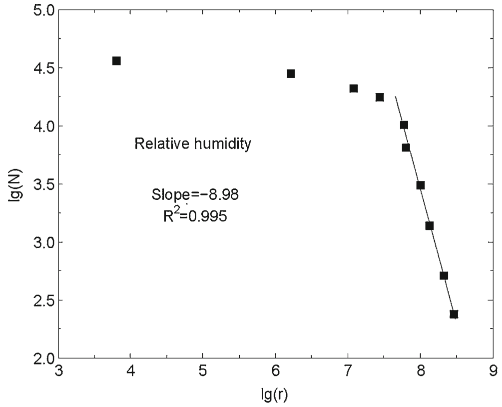

Fig. 4 The number density of relative humidity change events per year N, with size greater than or equal to r, versus change event size r on a double logarithmic scale. The data are consistent with a power-law $N \propto cr^{-\lambda}$, $\lambda \approx 8.98$ (*solid line*) over at about 0.4 order of magnitude scales

In order to approach the actual process of climatic factor change, we presume that sands are randomly added to 1 % of all sites at a time, and a sand may fill in for a site just right.

Step 2 A site is active or critical when the height of a site becomes greater than or equal to a predefined threshold value h_c, which h_c values correspond to 200, 150, and 100 for temperature, vapor pressure, and relative humidity, respectively. The active site will burst into a toppling activity. The relaxation rule is as follows:

$$h(i,j)\rightarrow h(i,j)+\beta \tag{3}$$

$$h(i\pm 1,j)\rightarrow h(i\pm 1,j)+[h(i,j)+\beta-\gamma]\times 0.36 \tag{4}$$

$$h(i,j\pm 1)\rightarrow h(i,j\pm 1)+[h(i,j)+\beta-\gamma]\times 0.36 \tag{5}$$

If a neighbor of site (*i,j*) becomes unstable due to the addition of this toppling, it also topples, and the avalanche stops when reaching a new stable configuration, namely, all $h(i,j)<h_c$. During an avalanche, there are no new sands added to the system. Avalanche size (*s*) is defined as the total number of toppling during an avalanche. The boundaries of the system are open. That is to say, sands are allowed to leave the system through the boundary.

The relaxation rule represents the movements and transformation process of climatic factors without considering the condition of other factors affected. During climatic factor changing, water and energy in atmosphere will loss owing to evaporation, solar radiation, human factors, etc. In this model, we presume that 1 % of water and energy will lose at four directions, respectively, when climate change sand topples to its four adjacent neighbor sites. At the same time, the site of a climatic factor will reserve some energy which the index is γ, which γ values correspond to 20, 15, and 10 for temperature, vapor pressure, and relative humidity, respectively. So, these processes are done by reducing the height at position (*i,j*) to γ and by increasing the height at positions ($i\pm1,j$) and ($i,j\pm1$) by $[h(i,j)+(\beta-\gamma)]\times(30-1\ \%)$.

Step 3 Climatic factor change will decay with time owing to self-purification. In order to simulate this process, we presume that degradation of climatic factors follows the first level of decaying kinetics. After step 2, amounts of the climatic factors at all sites will decay to e^{-k} of the original level.

$$h(i,j)\rightarrow h(i,j)\times e^{-k} \tag{6}$$

The *k* values of different climatic factors are closely related to their own characteristics in the same meteorological and geographical conditions.

Step 4 After all lattice sites are stable, we repeat the steps 1–3 by adding new sand to the system. The probability distribution function $P(s)$ of avalanche sizes will be measured once after continuing the adding and toppling processes every time. If climatic factor change is an example of a SOC process, we expect $P(s)\propto s^{-\alpha}$, where α is the exponent of toppling number for avalanches.

5 Results and discussion

The nonequilibrium steady state is defined by the constant average height of the sandpile at which the current of influx of the sand to the system is equal to the current of outflux of the sand at the open boundary. In order to achieve this steady state, the first 10^6 avalanches are skipped. The simulated data are generated on a square lattice of size $\beta\times\beta$ in runs of 10^7 avalanches.

We emphasize that the *k* values of different climatic factors are closely related to their own characteristics in the same meteorological and geographical conditions. In the spirit of SOC, we do not want to introduce further external parameters. We analyze the effects of *k* values on climatic factors SOC.

We found that when $k=0.009$, for the size distribution of avalanches, the climatic factors and pile model can give a good agreement with the monitored temperature data shown in Fig. 2. The simulated result of avalanche size distribution is shown in Fig. 5. As can be seen from Fig. 5, power-law scaling is obtained for almost 0.8 order of magnitude with a scaling exponent of $\alpha_1=6.86$.

When $k=0.008$, the simulated result of avalanche size distribution is shown in Fig. 6. The power-law scaling is obtained for almost 0.6 order of magnitude, with a scaling exponent of $\alpha_2=5.31$. Compared to Fig. 3, we found that the

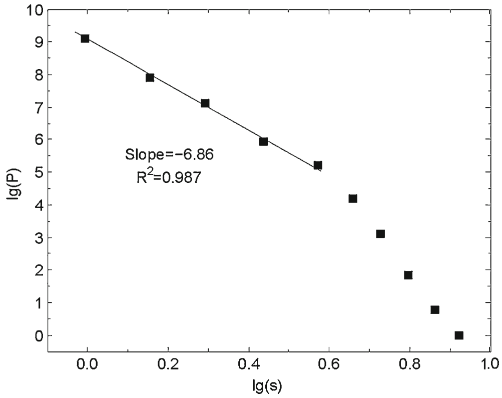

Fig. 5 Avalanche size distribution for the climatic factor sand model when $k=0.009$. It follows a power law, with an exponent of $\alpha_1=6.86$ (*solid line*), which is consistent with that of the size distribution of temperature change events in Fig. 2

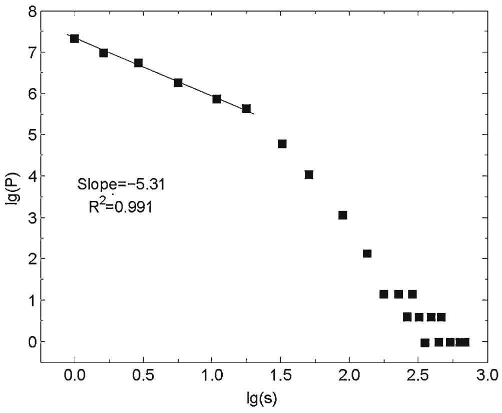

Fig. 6 Avalanche size distribution for the climatic factor sand model when k=0.008. It follows a power law, with an exponent of α_2=5.31 (*solid line*), which is consistent with that of the size distribution of vapor pressure change events in Fig. 3

simulation of the model is in good quantitative agreement with the monitored vapor pressure indexes data.

When k=0.015, the simulated result of avalanche size distribution is shown in Fig. 7. The power-law scaling is obtained for almost 0.3 order of magnitude, with a scaling exponent of α_3=8.94. The simulation of the model again is in good quantitative agreement with the monitored relative humidity indexes data shown in Fig. 4.

In this model, only changing the number value of decay coefficient k, the frequency-size distributions of various climatic factors can be simulated, and all results are consistent with the actual data.

Based on the simulated result, we assure that the climatic factor acts as dynamically self-organized systems, and it is SOC of the climatic factors that results in the temporal variation of climatic factors. This maybe indicates that the change of minor climatic factors, such as temperature, precipitation, and atmospheric motion, also can result in high events of climate change by SOC behaviors. In addition, we note that the model is based on calm weather. In the future work, the effect of other factors, such as atmospheric circulation, sunshine duration, and geographic location, will be investigated to improve the model.

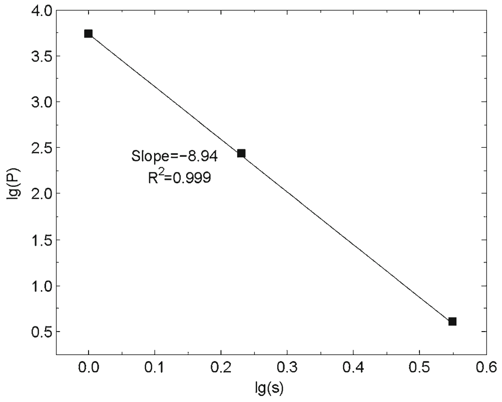

Fig. 7 Avalanche size distribution for the climatic factor sand model when k=0.015. It follows a power law, with an exponent of α_3=8.94 (*solid line*), which is consistent with that of the size distribution of relative humidity change events in Fig. 4

In SOC models, the dissipation always plays many important roles, e.g., determining the scaling behavior (Drossel 2000) in the Bak–Tang–Wiesenfeld (BTW) sandpile model, destroying the universality class or criticality in the Olami–Feder–Christensen (OFC) model (Olami et al. 1992), fixing the total energy to discuss the source of SOC (Chessa et al. 1998; Vespignani et al. 2000), etc. In general, the dissipation is either through the boundary or bulk. The BTW sandpile (Bak et al. 1987), Manna sandpile (Manna 1991), Olso rice pile model (Christensen et al. 1996), etc., are prototypical for boundary dissipation, whereas the OFC earthquake (Olami et al. 1992) and the fixed energy sandpile (Chessa et al. 1998; Vespignani et al. 2000) involve bulk dissipation. The dissipation is, however, decided by three aspects: the boundary, spatial toppling process, and temporal decaying process in our climate change sand model. So, this model in a physical prototype maybe represents a new sandpile model. By changing the parameters k of model slightly, we uncover an abundant dynamic pattern of climatic factors sandpile model, showing that chaos plays a fundamental role in the dynamics of the climate change system. This conclusion accords with Vieira's opinion (Vieira 2004) that avalanches in sandpiles are a chaotic phenomenon. The further study of this model in physics maybe helps us to understand the role of the dissipation in SOC.

6 Conclusions

In this paper, we found that scale-free power-law behaviors could govern the statistics of three climatic factors (average daily temperature, vapor pressure, and relative humidity) over some range of event size scales. A new numerical sandpile model with decay coefficient was constructed to describe frequency-size distributions of climatic factors and to reveal inherent dynamic mechanism of climatic factor process. In this model, only changing the number value of decay coefficient of climatic factors, the frequency–intensity distribution of various climatic factors can be simulated, and all the results are consistent with the actual monitored data.

Our findings suggest that climate change is an excellent self-organized critical process. One consequence is that the measured frequency of occurrence of small climate change events can be used to estimate the frequency of occurrence of large change events. The model shows that the minor climatic factors change can trigger the occurrence of large change events by SOC behavior. This argument suggests that the change of minor climatic factors, such as evaporation, precipitation, and atmospheric motion, also can result in high events of climate change by SOC behaviors. The new insights into climate change will greatly contribute to making policies on climate change management.

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