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# Scale invariant behavior of cropping area losses

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ABSTRACT

This paper shows how crop losses, display Self-Organized Critical Behavior, which implies that under a wide range of circumstances, these losses exhibit a power-law dependence on frequency in the affected area whose order of magnitude approximates those reported for extreme climate events. Self-Organized Critical Behavior has been observed in many extreme climate events, as well as in the density and distribution of pests linked to crop production. Empirical proof is provided by showing that the frequency-size distribution of the cropland loss fits the Pareto and the Weibull models with scaling exponents that are statistically similar to the expected value. In addition, the test included comparisons of the expected value and the predicted value of the scaling exponents among different subsystems and among systems of the same universality class. Results show that the Pareto model fits the heavy-tailed distribution of losses mostly caused by extreme climate events, while the Weibull model fits the whole distribution, including small events. The analyses show that crop losses adopt Self-Organized Critical Behavior regardless of the growing season and the water provision method (irrigated or rainfed). Irrigated systems show more stable behavior than rainfed systems, which display higher variability. The estimation is robust not only for calculating model parameters but also for testing the proximity to a power-law-like relationship.

A long-term risk index by growing season and water provision method is derived as an application of this power-law behavior. The index is flexible, comparable between geographical units regardless of their size and provides an indirect measure of the probability of losing a cropping area of a given size.

## 1. Introduction

Cropping areas anywhere in the world face a wide range of risks, from those inherent to any productive activity (e.g. market price volatility, financing, and the economic, social and institutional framework), to risks directly related to the production system, such as those driven by differences in the composition of inputs, pests, diseases, fires, and crop management regimes. The negative effects of these sources of risk can be mitigated in one way or another through a broad array of financial products, as well as through the appropriate use of crop protection measures (Barnett and Mahul, 2007). However, crop losses occur mostly because despite preventive practices, agricultural systems are dependent on the climate and its variations, since they operate under uncontrolled environmental conditions. In all cases, the loss has a direct impact in reducing production along the value chain including backward (seeds, fertilizers, etc.) and forward (processing, distribution, markets and retailers) linkages, affecting the wellbeing of people, particularly the rural poor (Nelson et al., 2009).

Crop losses may be caused by biotic and abiotic environmental factors which reduce crop performance, resulting in a lower actual yield than the attainable yield for specific conditions. Some estimates reveal that losses triggered by diseases, animal pests, and weeds range between 20 and 40% of the yield that would be attained in their absence (Savary et al., 2006; Oerke, 2006). Furthermore, losses derived from extreme climate events can be so severe that the whole crop can be lost causing damages even to the agricultural infrastructure (FAO, 2015). FAO estimates that nearly 25% of the monetary losses caused by extreme meteorological events (floods, droughts, hurricanes, typhoons and cyclones) are concentrated in the agricultural sector, and within this sector, the crop subsector absorbs over 42% of the total damage and losses caused by disasters (FAO, 2015). Direct damages include partial or total destruction of infrastructure, assets, standing crops, farm tools and equipment. This percentage share varies significantly according to the type of event (disaster), its magnitude and the geographic location, among other factors (FAO, 2015). Nevertheless, it is recognized that, by far, droughts constitute the type of disaster with the highest share of total damage in agriculture at the global level.

Recent projections show that climate change is likely to increase the frequency and intensity of extreme weather events in several world regions (Pachauri, 2008). Such changes will be more severe in tropical

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and semi-arid developing countries, where projections suggest reductions in agricultural production within the 5–10% range (Fischer et al., 2005) with strong regional differences (Parry et al., 2004).

The occurrence and impact of severe perturbations (biotic or abiotic) in cropping areas are difficult to predict, even if the impact results in the total loss of the crop. The problem turns even more difficult if we consider the variability and complexity of agricultural systems, their location specificity, as well as the lack of proper meteorological or socio-economic information to develop a forecasting tool (Morton, 2007).

Given the multiplicity of factors causing crop losses and the difficulty to incorporate all this information into a single model to predict them, alternative approaches to analyze such complex systems should be considered. A perspective known as Self-Organized Criticality has been used recently to model this type of complex systems driven by energy inputs (drivers) that reach a state characterized by scale-free behavior. Measurement of such a state fluctuates around a marginally stable value which can be used to characterize the system. The classic example consists of making a pile of grains of sand; the pile is only stable if an avalanche of these grains does not form (event). A measurement of the system can be the number of grains in the pile before an avalanche is generated or the grains in the avalanche, which vary around a more or less stable value. This number does not only depend on the characteristics of the grains, but also on the conditions of the medium, environment and the individual who is forming the pile; however, its value is marginally stable, which is the main feature of a process or event that presents a Self-Organized Critical Behavior (SOCB). Extrapolating the example of the pile of grains to agricultural systems, the cropping area could represent the grains in the pile before the avalanche and the crop losses would be analogous to the grains in the avalanche after an event has occurred.

This framework of analysis has several advantages since it concentrates in a single model the general behavior of a complex system, regardless of the condition where it occurs. In the past decades, various models have been developed to describe the power-law scaling found in complex systems (Marković and Gros, 2014). Examples can be found in the literature of the frequency-size relationship of natural hazards (Kadanoff et al., 1989; Pelletier et al., 1997; Malamud and Turcotte, 1999), and of the complex ecological (Wu and Marceau, 2002), physical and financial systems (Mills and Markellos, 2008; Chave and Levin, 2003). All of them follow the basic idea that a complex system following a SOCB will spontaneously self-organize, under general conditions, into a state which is a transition between two different regimes and without the need for external intervention or tuning (Marković and Gros, 2014).

Agricultural systems are complex systems. They depend on many factors interacting simultaneously, such as the climate and its variations, the performance of the agricultural system, the capacities of the farmer, the conditions of product and factor markets, or the presence of pests or other disturbances (fires, extreme climate events, etc.), among others. Consequently, crop losses constitute complex systems as well, since the interaction of all these factors makes it difficult to predict them or even to identify a mechanism to estimate the occurrence and its magnitude in a relative scale.

This article pursues the objective of testing the hypothesis that crop losses, measured as the cropping area loss, follow a power-law distribution; in other words, they might constitute a critically self-organized event. The test is important since it opens the possibility to describe with a single model the general pattern of crop losses, regardless of social, economic, technological and cultural conditions. A model with these attributes can be used to estimate the risk of agricultural regions. Such estimates, based on general principles, become necessary for policy makers who require this information to identify appropriate policy instruments to increase production in agricultural regions, as well as improving the target of those instruments related to the mitigation of agricultural risks (FAO et al., 2017).

The test is implemented with data from Mexico during the period of 1980–2014; however, the model and its applications can be extended to any region in the world, since the model just requires information of the cropping area losses per period. The document has been divided as follows: In the following section, the principles of Self-Organized Critical Behavior (SOCB) are briefly described, together with the methodology for testing the power-law relationship and the data description. Section 3 shows the results of the tests followed by a description of a risk index based on the findings, in Section 4. Section 5 presents a discussion on the results, while the last section presents some concluding remarks.

## 2. Material and methods

### 2.1. Model

Different authors have already shown that some disturbances affecting crops follow a power-law distribution, which makes plausible the hypothesis that the cropping surface affected by these and other events also displays SOCB behavior. For instance, the rainfall distribution measured as the number of precipitation events per year has an exponential relationship with the water column released (water volume per surface unit). Moreover, the duration of rain events and the time between events are unique for each region, and therefore the relationships between the number of events and the water column are also unique to each region (Veneziano and Furcolo, 2002; Peters and Christensen, 2002; Peters and Neelin, 2006; Wang and Huang, 2012). Analysis of accurate precipitation data has revealed that the power relationship that describes the rainfall events also describes the number of droughts versus their duration, which leads to the hypothesis that extreme meteorological events might indeed behave as processes with Self-Organized Critical Behavior (Peters et al., 2001; García-Marín et al., 2008; Bogachev and Bunde, 2012; Wang and Huang, 2012; García-Marín et al., 2013; Medina-Cobo et al., 2016). Other results show that cycles in the size of pest and disease populations largely depend on climate cycles. Johansen (1994) has shown that the dispersal pattern of pests reflects SOCB, while Lockwood and Lockwood (1997) have presented evidence of this behavior in the size of insect populations.

The usual test for determining whether a process, system or set of events (observable in a specific dimension) follows SOCB is to test its scaling behavior. The easiest way to do it is to estimate the power-law frequency distribution exponent of the observable event (size, area, duration, etc.), making sure that the distribution of events to be analyzed fits a simple exponential model and that the magnitude of the estimated exponent falls within the expected range (White et al., 2008; Clauset et al., 2009). The usual relationship to be tested is:

$$f(x) \sim \alpha\, x^{\lambda} \tag{1}$$

where $x$, is the magnitude of the observed event (e.g. size, area or duration), $\alpha$ is a parameter, $\lambda$ is the power-law frequency distribution exponent (scaling exponent) and $f(x)$ is a probability density function (*pdf*), also known as the scaling function.

Marković and Gros (2014) synthetize the research on scale-free models, and they show that analytical estimates (in different SOCB-type observable events) for the scaling exponents are similar among quantities and only vary according to the scaling function. If the quantity observed is area, a simple scaling function as model (1) provides scaling exponents in the order of $-\,{}^{3}\!/_{2}$, as has been documented in several references (Bak et al., 1988; Malamud and Turcotte, 1999).

In all cases the observed events are considered to exhibit a heavy-tailed distribution, in other words, distributions whose probability of observing extremely large values is more likely than it would be for an exponentially distributed variable (Adler et al., 1998). For the case of simple functions, as model (1), the density function $f(x)$ usually adopts the simplest heavy tailed form, similar to the Pareto or power function