

Correlation dimension and phase space contraction via extreme value theory

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Correlation dimension and phase space contraction via extreme value theory

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We show how to obtain theoretical and numerical estimates of correlation dimension and phase space contraction by using the extreme value theory. The maxima of suitable observables sampled along the trajectory of a chaotic dynamical system converge asymptotically to classical extreme value laws where: (i) the inverse of the scale parameter gives the correlation dimension and (ii) the extremal index is associated with the rate of phase space contraction for backward iteration, which in dimension 1 and 2, is closely related to the positive Lyapunov exponent and in higher dimensions is related to the metric entropy. We call it the Dynamical Extremal Index. Numerical estimates are straightforward to obtain as they imply just a simple fit to a univariate distribution. Numerical tests range from low dimensional maps, to generalized Henon maps and climate data. The estimates of the indicators are particularly robust even with relatively short time series. *Published by AIP Publishing*. https://doi.org/10.1063/1.5027386

This study uses the link between extreme value laws and dynamical systems theory to show that important dynamical quantities as the correlation dimension, the entropy, and the Lyapunov exponents can be obtained by fitting observables computed along a trajectory of chaotic systems. All this information is contained in a newly defined Dynamical Extreme Index. Besides being mathematically well defined, it is almost numerically effortless to get as (i) it does not require the specification of any additional parameter (e.g., embedding dimension, decorrelation time); (ii) it does not suffer from the so-called curse of dimensionality. A numerical code for its computation is provided.

AQ2 31 I. INTRODUCTION

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Since its introduction by Grassberger and Procaccia, 1,2 the correlation dimension (CD) has been used as a powerful indicator for the description of the fractal structure of invariant sets in dynamical systems. Similarly, the Lyapunov exponents and the entropy^{3,4} provide an indication of the relevant time scales associated with the dynamics and the predictability horizon of the system. Given the importance of these quantities, there exists an increasing body of literature on how to estimate CD, Lyapunov exponents, and entropy. It has been shown that reliable estimates of CD can be obtained with a relatively short time series.⁵ Instead, the computations of Lyapunov exponents and entropy are still challenging because the existing methodologies require as input additional parameters as the dimension of the phase space and the relevant time scale of the dynamics (e.g., the decorrelation time). Calculations are then limited to the top Lyapunov exponent and the reliability of estimates from the time series of experimental phenomena is often questioned. We defer the reader to the monographs 7,8 and to the articles 9,10 for recent advancements on the various statistical tools to investigate the nonlinear time series.

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The extreme value theory (EVT) has been used to characterize the evolution of chaotic systems. 11,12 It is possible to obtain dynamical properties in phase space (fractal dimension or stability) by exploiting the limiting theorems of the extreme value theory. The main idea is: (i) to replace the stochastic processes used in the statistical framework with a trajectory of a chaotic dynamical system and (ii) to study the convergence of maxima of suitable observables to the classical extreme value laws. The parameters of the EVT provide estimates of dynamical properties of the system. This connection between EVT and the dynamical properties of chaotic systems is rich not only from a theoretical but also from a numerical perspective. Indeed, the estimates of local properties obtained with EVT do not require the introduction of additional parameters and they are easy to implement numerically. They have been used to get insights into the dynamical behavior of atmospheric flows in Refs. 13–15. In Ref. 16, it has been shown that the numerical algorithm based on EVT provide reliable estimates of the dimension of high dimensional systems up to phase spaces with thousands of dimensions. It is therefore desirable to estimate other key dynamical quantities in the EVT framework.

The purpose of this communication is to show that the correlation dimension and the EVT are intimately related: the CD arises by studying the distribution of the maxima of a new suitable observable evaluated along the orbit of a chaotic system. Moreover, an exponent of the limit law, the extremal index, is related, for hyperbolic attractors, to the positive Lyapunov exponent in dimension two and to the metric entropy in higher dimensions. The idea of the relationship between EVT and CD comes from a previous

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work¹⁷ where we used the extreme value theory to detect and quantify the onset of synchronization in coupled map lattices. The relationship between the extremal index and the 86 Lyapunov exponent and the entropy is new and is particu-88 larly striking for maps with piecewise constant jacobian. In the general case, we derive a formula whose validity is confirmed by numerical experiments. We also explain the rela-90 tion between our extremal index, the local dimensions, and 91 the phase space contraction. In the rest of the paper, we will 92 name it as the DEI, the dynamical extremal index. We want to point out that our DEI is a well defined quantity that can 94 be used as a new indicator for the sensitivity associated with local hyperbolicity. We will present the theoretical results in AQ3 97 Sec. II: some of those results can be obtained by generalizing the techniques introduced in Ref. 17; we will also address 98 the need to develop a more appropriate theory of EVT for diffeomorphisms in higher dimensions. We will then provide 100 101 several examples of classical conceptual low-dimensional dynamical systems. We will discuss the implications of our 102 results on higher dimensional systems and the possibility to 103 apply them to more a general time series. As an example, we 104 105 will compute the indicators on climate data and explain how they provide relevant physical information on the atmo-106 spheric circulation over the North Atlantic. 107

II. THEORETICAL RESULTS

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A. A brief presentation of the extreme value theory and a new observable

Let (M, μ, T) be dynamical systems given by a map T acting on the metric compact space M with distance $d(\cdot,\cdot)$ and preserving the Borel measure μ . Usually, M will be a compact subset of some \mathbb{R}^n and d a distance equivalent to the standard one. Let us take the direct product $(M \times M)$ $\mu \times \mu, T \times T$), and denote with $(x, y) \in M \times M$, a couple of point in the Cartesian product $(M \times M)$. We then introduce the observable $\psi(x,y) = -\log d(x,y)$, and consider the process $\{\psi \cap (T^j \times T^j)\}_{j>0}$, and the maximum of the sequence $\mathcal{M}_n(x,y) = \max\{\psi(x,y), \psi(Tx,Ty), ..., \psi(T^{n-1}x,T^{n-1}y)\}$ and finally its distribution $\mathbb{P}(\mathcal{M}_n \leq u_n)$, where $\mathbb{P} = \mu \times \mu$ is the underlying probability and u_n is a suitable scaling function tending to infinity and which we are going to define. Suppose that for a given positive number τ we can find a sequence of numbers u_n such that $n\mathbb{P}(\psi \ge u_n) \to \tau, n \to \infty$. We say, that the process $\{\psi \circ (T^j \times T^j)\}_{j \ge 0}$ satisfies an extreme value law of Gumbel's type if there is a number $\theta \in (0, 1]$, the extremal index, such that $\mathbb{P}(\mathcal{M}_n \leq u_n) \to e^{-\theta \tau}$, $n \to \infty$. We now introduce the diagonal neighborhood S_n in the product space: $S_n = \{(x,y), d(x,y) \le e^{-u_n}\}$. By substituting the expression of ψ in $\mathbb{P}(\psi \geq u_n)$, we have

$$\mathbb{P}(\psi \ge u_n) = \mathbb{P}((x, y) \in S_n) = \int_M \mu(B(x, e^{-u_n})) d\mu(x),$$
(2.1)

where B(x, a) denotes the ball of radius a centered on x. (Actually, we got the equality of the right hand side in the limit of large n when the two small corners of S_n become negligible.) The quantity $\int_M \mu(B(x,r)) d\mu(x)$ scales like r^{D_2}

and the exponent D_2 is called the *correlation dimension* and 136 it characterizes the fractal structure of the support of μ ; a 137 more formal, from the mathematical point of view, definition 138 of this fact is given in Ref. 18, Sec. 17, and references 139 therein. (A precise definition consists in taking the limsup 140 and liminf of the ratio of the logarithm with $\log{(1/r)}$.) By 141 injecting successively into (2.1), we have therefore that for 142 large n

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$$u_n \sim \frac{-\log \tau}{D_2} + \frac{\log n}{D_2} := \frac{z}{a_n} + b_n,$$
 (2.2)

where $\tau=e^{-z}$, $a_n=D_2$ and $b_n=\frac{\log n}{D_2}$. For numerical purposes, distribution functions like $\mathbb{P}(\mathcal{M}_n\leq z)$ are modelled, 145 for n sufficiently large, by the so-called *generalized extreme* 146 value (GEV) distribution which is a function depending upon 147 three parameters $\xi\in\mathbb{R}, \kappa\in\mathbb{R}, \sigma>0$ and such that: 148 $F_{\text{GEV}}(z;\kappa,\sigma,\xi)=\exp\left\{-[1+\xi(\frac{z-\kappa}{\sigma})]^{-1/\xi}\right\}$.

The parameter ξ is called the tail index; when its value 150 is 0, the GEV corresponds to the Gumbel type. The parame- 151 ter κ is called the location parameter and σ is the scale 152 parameter: for *n* large, the scaling constant a_n is close to σ^{-1} 153 and b_n is close to κ . Therefore, if we could fit a limit law of 154 Gumbel's type with suitable normalizing parameters a_n and 155 b_n , we immediately get the correlation dimension. Such a 156 technique was previously used with a different observable, 157 and it allowed to get the so-called information dimension 158 $D_1(x)$, another fractal dimension which provides the scaling 159 of the measure of a ball around a given point x, see Ref. 19 160 and references therein. Although the information dimension 161 depends on the point x, its value is the same for almost all $\frac{162}{1}$ the choices of x with respect to the invariant measure and 163 such an averaged valued, simply D_1 , is larger or equal to D_2 , 164 see Ref. 20 for an account on the different fractal dimen- 165 sions. In particular, if we denote with d_H the Hausdorff 166 dimension, we have $D_2 \le D_1 \le d_H$.

B. The spectral approach with the new observable for conformal repellers

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Before showing our numerical simulations for the computation of the CD, let us argue how we get a Gumbel's type 171 asymptotic distribution with an extremal index θ of dynamical meaning. First, we consider one-dimensional dynamical 173 systems generated by uniformly expanding maps with an 174 invariant set which could be a Cantor set and equipped with 175 mixing Gibbs measures. These systems are better known as 176 conformal repellers,—see for instance²¹ for a recent contri- 177 bution—whose measures are characterized by a potential φ 178 of type $\varphi(x) = -\beta \log |T'(x)|$, where T' denotes the derivative of T and $\beta \in \mathbb{R}$. If we denote them as μ_{β} , they are given 180 by $h_{\beta}\nu_{\beta}$, where the density h_{β} and the *conformal* measure ν_{β} 181 are, respectively, the eigenfunctions of the transfer operator 182 (Perron-Fröbenius) and of its dual, both with eigenvalue 183 $\lambda_{\beta} = e^{Q(\beta)}$, being $Q(\beta)$ the topological pressure. We remind 184 that the transfer operator \mathcal{P}_T for the map T is defined, for an 185 observable f in some suitable Banach space \mathcal{B} —for instance 186 the space of Lipschitz continuous functions—by the duality 187 relation: $\int \mathcal{P}_T f d\nu_\beta = \lambda_\beta \int f d\nu_\beta$. We defer to the monograph ²² 188

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189 for an introduction to thermodynamic formalism. The conformal measure verifies the property $\nu_{\beta}(TA) = \lambda_{\beta} \int_{A} e^{-\varphi} d\nu_{\beta}$, where T is one-to-one over the measurable set A. A powerful method to investigate the distribution of our process $\{\psi \circ (T^j \times T^j)\}_{j \ge 0}$ consists in perturbing the transfer opera-193 tor \mathcal{P} of the direct product $T \times T$. The key observation is that by repeatedly using the duality relation, we can write $\mathbb{P}(\mathcal{M}_n \leq u_n) = \lambda_{\beta}^{-2n} \int \int \tilde{\mathcal{P}}_n^n(h_{\beta}(x)h_{\beta}(y)) d\nu_{\beta}(x) d\nu_{\beta}(y), \text{ where }$ the perturbed operator $\tilde{\mathcal{P}}_n$ is defined by acting on observables $\in \mathcal{B}$, as $\tilde{\mathcal{P}}_n(f) = \mathcal{P}(f\mathbf{1}_{S_n^c})$, and $S_n = \{(x,y); d(x,y)\}$ $\leq e^{-u_n}$ When *n* tends to infinity, the characteristic function 199 of the complement of S_n , $\mathbf{1}_{S_n^c}$, goes to the identity and the 200 operators \mathcal{P} and $\tilde{\mathcal{P}}_n$ converge to each other in \mathcal{B} . If the 201 unperturbed operator \mathcal{P} has a spectral gap, it allows expo-202 nential mixing for the observables in \mathcal{B} . This compensate the 203 lack of independence of the process $\{\psi \circ (T^j \times T^j)\}_{j \ge 0}$. The 204 same is true for the operator \tilde{P}_n and the maximal, isolated, 205 eigenvalue of \mathcal{P} , λ_{β}^2 , is close to that of $\tilde{\mathcal{P}}_n$, $\tilde{\lambda}_{\beta,n}^{(2)}$. More precisely: $\tilde{\lambda}_{\beta,n}^{(2)} \sim \lambda_{\beta}^2 - (1 - \lambda_{\beta}^2 q_0) \mathbb{P}(S_n)$, where now $\mathbb{P} = \mu_{\beta}$ $\times \mu_{\beta}$. We will define the factor q_0 in a moment. The operator $\tilde{\mathcal{P}}_n$ now decomposes as the sum of a projection along the one dimensional eigenspace associated with the eigenvalue $\tilde{\lambda}_{\beta,n}^{(2)}$ and an operator with a spectral radius exponentially decreas-211 ing to zero and which can be neglected in the limit of large 212 *n*. This allows us to write $\mathbb{P}(\mathcal{M}_n \leq u_n) \sim \lambda_{\beta}^{-2n} \tilde{\lambda}_{\beta,n}^{(2)n} \int \int h_{\beta}(x)$ $h_{\beta}(y)d\nu_{\beta,n}(x)d\nu_{\beta,n}(y)$, where $\nu_{\beta,n}$ is the conformal measure for the perturbed operator and the double integral on the right hand side converges to 1 for $n \to \infty$. Finally, we get by approximating $\tilde{\lambda}_{\beta,n}^{(2)}$ as above: $\mathbb{P}(\mathcal{M}_n \leq u_n)$ $\sim \left[1 - \frac{(1 - \lambda_{\beta}^2 q_0) \mathbb{P}(S_n)}{\lambda_{\beta}^2}\right]^n \sim \exp\left[-\frac{(1 - \lambda_{\beta}^2 q_0) \mathbb{P}(S_n)}{\lambda_{\beta}^2}n\right]$. We now remind that we are under the assumption that $n\mathbb{P}(\psi \geq u_n)$ $= n\mathbb{P}(S_n) \to \tau, n \to \infty$. This lead to the Gumbel law $e^{-\theta \tau}$

$$\theta = \frac{1 - \lambda_{\beta}^{-2} q_0}{\lambda_{\beta}^2}.$$
 (2.3)

The term q_0 is obtained by the previous perturbation theory under the assumption that the diagonal in the product space is left invariant by the direct product of the two maps. In par-224 225 ticular, we have

provided that the dynamical extremal index θ is defined as

$$q_0 = \lim_{n \to \infty} \frac{\mathbb{P}(S_n \cap \bar{T}^{-1}S_n)}{\mathbb{P}(S_n)},\tag{2.4}$$

provided that the limit exists. The technique just described was first proposed by Keller²³ as an alternative way to get 227 EVT for systems with exponential mixing and it is based on 228 a perturbative result by Keller and Liverani.²⁴ We defer to Ref. 23 and to our paper¹⁷ for a detailed presentation of that 230 theory. It can be applied to conformal mixing repellers and it provides the preceding estimates, namely the asymptotic scaling for the maximal eigenvalue. We would like to point out that with our choice for the observable ψ , the perturba- 234 tive approach just sketched gives the Gumbel's law in a very direct and natural manner.

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The computation of q_0 proceeds now as in Ref. 17 with 237 a substantial difference: the nature of the conformal measure 238 does not imply necessarily that the ratio $\frac{\nu_{\beta}(B(Tx,r))}{\nu_{\beta}(B(x,r))}$ is constant, $_{239}$ which happened when the conformal measure was Lebesgue. 240 This difficulty could be partially overcome by supposing that 241 the potential is constant, otherwise we could bound q_0 from 242 above and below with (close) approximations of the poten- 243 tial. By assuming that the latter is constant and equal to $\bar{\varphi}$ 244 and also that the density h_{β} does not vary too much, we get 245 that q_0 is of order $e^{\bar{\varphi}}$ and therefore

$$\theta \sim \frac{1 - \lambda_{\beta}^{-2} e^{\bar{\phi}}}{\lambda_{\beta}^{2}}.$$
 (2.5)

It is worth mentioning that whenever the conformal measure 247 is Lebesgue ($\beta = 1$), the above computation can be made rig- 248 orous as in Proposition (5.3) in Ref. 17 and it gives

$$\theta = 1 - \frac{\int_{M} \frac{h^{2}(x)}{|T'(x)|} dx}{\int_{M} h^{2}(x) dx},$$
(2.6)

where h is the density of the invariant measure: we defer to 250 our paper 17 for the assumptions on the system which permit 251 to get such a result. In particular, those systems contain con- 252 formal repellers with finitely many branches and absolutely 253 continuous conformal measures. Notice that by introducing 254 the invariant measure $\mu = hdm$, we could identically write

$$\theta = 1 - \frac{\int_{M} h(x)e^{-\log|T'(x)|}d\mu(x)}{\int_{M} h(x)d\mu(x)}.$$
 (2.7)

If the derivative does not change too much, we get 256 $\theta \sim 1 - e^{-\Lambda_{\mu}}$, where Λ_{μ} is the positive Lyapunov exponent 257 of the measure μ . Alternatively, if the density h could be 258 considered constant, we can bound (2.7) by Jensen's inequal- 259

$$\theta \sim 1 - \int_{M} \frac{1}{|T'(x)|} d\mu(x) \le 1 - e^{-\int_{M} \log |T'(x)| d\mu(x)} = 1 - e^{-\Lambda_{\mu}}.$$

In both cases, the DEI θ is related to the positive Lyapunov 261 exponent: this analogy will be pursued in Sec. II C.

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C. Attractors and high dimensional systems

For invertible maps generating attractors endowed with 264 the SRB measure, the computation of the dynamical 265 extremal index is less straightforward; we should stress that 266 a spectral theory of extreme value for (invertible) uniformly 267 hyperbolic maps is still missing. Suppose we take an hyper- 268 bolic diffeomorphisms T preserving the ergodic SRB mea- 269 sure \mathcal{L} . Then, the quantity q_0 in (2.4) becomes

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 $q_0 = \lim_{n \to \infty} \frac{\int d\mathcal{L}(x) \int \mathbf{1}_{S_n}(x, T^{-1}y) \mathbf{1}_{S_n}(Tx, y) d\mathcal{L}(y)}{\int d\mathcal{L}(x) \int \mathbf{1}_{S_n}(x, y) d\mathcal{L}(y)}.$

When we iterate backward the points $y \in B(Tx, e^{-u_n})$, we should keep only those points whose preimage is at a distance at most e^{-u_n} from x. Those preimages form a set Q(x)273 which is obtained by squeezing the ball $B(Tx, e^{-u_n})$ along the 274 unstable manifolds. Let us suppose that the tangent expand-275 ing subspace $\Sigma_n(Tx)$ at x has dimension d. Then the measure 276 of Q(x), and therefore, by the forward invariance of the measure, of its image in $B(Tx, e^{-u_n})$ will be of order 278 $|\det(DT(x)|_u)|^{-1} \mathcal{L}(B(Tx, e^{-u_n})), \text{ where } DT(x)|_u \text{ is the deriv-}$ 279 ative of T restricted to $\Sigma_u(x)$. We remember in fact that the 280 conditional SRB measure on the unstable manifolds is 281 smooth. This immediately gives q_0 of order 282

$$q_0 \sim \frac{\int d\mathcal{L}(x) |\det(DT(x)|_u)|^{-1} \mathcal{L}(B(T(x), e^{-u_n}))}{\int d\mathcal{L}(x) \mathcal{L}(B(x, e^{-u_n}))}.$$
 (2.9)

We see that q_0 contains information about the dimension through the scaling of the denominator; we are now interested in the contribution of the other term in the numerator. 285 286 In this regard, we first remind that, for SRB measures, we can use the Pesin's formula²⁵ 287

$$\int d\mathcal{L}(x)|\det(DT(x)|_u)| = \sum_{j=1}^d \Lambda_j^+ = h_{\mathcal{L}},$$

where Λ_i^+ is the positive Lyapunov exponents with multiplicity one, and $h_{\mathcal{L}}$ is the metricentropy of the SRB measure. 289 We now proceed under two assumptions as we did at the end AQ7 291 of Sec. IIB. Let us first assume that the derivative along the unstable subspaces does not vary too much. Then, we could estimate the DEI as

$$\theta \sim 1 - e^{-h_{\mathcal{L}}}. (2.10)$$

For d = 1, we can replace the entropy with the (unique) posi-294 tive Lyapunov exponent $\Lambda_{\mathcal{L}}$; in the following, we will simply write it as Λ_+ . 296

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The other assumption exploits the fact that for these system, and for \mathcal{L} -almost all points x we have, by Young's theorem, ²⁶ that $\lim_{r\to 0} \frac{\log \mathcal{L}(B(x,r))}{\log r} = D_1$, where D_1 is the information dimension. Hence, we could guess that $\mathcal{L}(B(x,e^{-u_n})) \sim e^{-u_n D_1}$ and therefore forget about the dependence on the variable x. This is generally false since the multiplicative factor in the previous scaling could depend on x. Indeed, when we integrate $\mathcal{L}(B(x,e^{-u_n}))$, we get D_2 which could be different from D_1 . If we suppose that the dependence on x of the prefactors is negligible, which means that we are considering a homogenous fractal invariant set with $D_1 \sim D_2$, then we have for the DEI

$$\begin{split} \theta &\sim 1 - \int \! d\mathcal{L} |\mathrm{det}(DT(x)|_u)|^{-1} \leq 1 - e^{-\int d\mathcal{L}(x) |\mathrm{det}(DT(x)|_u)|} \\ &= 1 - e^{-h_{\mathcal{L}}}, \end{split} \tag{2.11}$$

where the derivative is *not* supposed to be constant and $\frac{309}{2}$ where we have used again the Jensen's inequality to estab- 310

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lish the upper bound.

Those two approximations are very crude; we are in fact 312 either neglecting the contributions of the prefactors in the 313 local scaling of the balls in (2.9), or not taking into account 314 the geometric factors when the ball $B(Tx, e^{-u_n})$ is squeezed 315 at a distance e^{-u_n} from x. Moreover, the variation of the 316 derivative, especially sensible in the non-uniformly hyper- 317 bolic setting, could give large differences in the determina- 318 tion of the DEI, as we experience for instance for the Hénon 319 map, see below. The preceding relation is pretty well satis- 320 fied for maps with one-dimensional unstable subspace and 321 (piecewise) constant jacobian, like the Baker transformation, 322 the Lozi map, and the solenoid. For the algebraic automor- 323 phism of the torus (cat's map), a simple argument allows us 324 to improve the previous rate just by taking into account the 325 geometric factors. Surprisingly, relation (2.11) is pretty well 326 satisfied in the example below of the generalized Hénon 327 maps, where the unstable subspace has dimension larger 328 than one, i.e., we have more than one positive Lyapunov 329 exponent. In conclusion, our index θ traces in a satisfactory 330 way the entropy. The eventual deviations are due to the vari- 331 ation of the derivative and the local scaling of balls in (2.9). 332 Although these effects are difficult to compute analytically, 333 the DEI θ is relatively easy to compute numerically and it 334 furnishes a new indicator for the local instability in chaotic 335 systems.

III. NUMERICAL COMPUTATIONS

The numerical computations presented in the remaining 338 of this work are performed by using the numerical algo- 339 rithms and codes detailed in the supplementary material. The 340 stability of the results is checked against different l,n,m,s. In 341 particular, we perform two sets of simulations. The first set 342 of accurate simulations consist of l = 100 trajectories, with 343 $n=10^6$ iterations, $m=10^3$ blocks of $s=10^3$ length each. 344 The second set of l = 100 simulations consists of short series 345 of $n = 10^4$ iterations, with $s = m = 10^2$. This second set is 346 useful to check whether the technique is reliable also for 347 short time series. Except where specified, we use $\tilde{s} = 0.99$ 348 for the following computations. However, results are stable 349 when considering different quantiles ranging from 0.97 350 $<\tilde{s}<0.999$. 351

A. Low dimensional maps

We begin the numerical computations with several 353 examples on low dimensional maps. A summary of the 354 results for all maps analysed is reported in Table I. For a few 355 maps, we report the model equations in the supplementary 356 material to streamline the exposition.

- Let us begin with the Bernoulli Shift map T(x) = 3x-mod 358 1. For this system, $D_2 = 1$ and $\theta = 1 - 1/3 = 2/3$. The 359 numerical estimates (Table I) are coherent with the theo- 360 retical values for both accurate and short simulations.
- We now consider the Gauss map $T(x) = \frac{1}{x} \mod 1$ defined 362 on the unit interval. Although, strictly speaking, this map 363

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TABLE I. Estimates of correlation dimension D_2 and dynamical extremal index (DEI) θ obtained with l = 100 trajectories, consisting of $n = 10^6$ iterations or $n = 10^4$ iterations. The maxima of $\psi(x, y)$ are extracted in the block of $s = 10^3$ and $s = 10^2$ length, for a total of $m = 10^3$ or $m = 10^2$ blocks. The quantile for the estimate of the DEI is $\tilde{s} = 0.99$. For the Arnold Cat's map, the convergence to theoretical value is lower and the estimates are provided only for $\tilde{s} = 0.99999$ and $n = 10^7$.

Map	D ₂ (classical)	$D_2 (n = 10^6)$	$D_2 (n = 10^4)$	θ (from Lyapunov)	$\theta \ (n=10^6)$	$\theta (n=10^4)$
Bernoulli's shifts	1	1.00 ± 0.02	1.01 ± 0.14	0.667	0.668 ± 0.004	0.69 ± 0.04
Gauss map	1	1.00 ± 0.03	0.96 ± 0.16	0.773	0.773 ± 0.005	0.78 ± 0.04
Cantor IFS	0.667	0.64 ± 0.01	0.59 ± 0.13	0.5	0.502 ± 0.005	0.50 ± 0.05
Baker map	1.41	1.46 ± 0.02	1.42 ± 0.25	0.47	0.49 ± 0.02	0.50 ± 0.04
Lozi map	1.38	1.39 ± 0.11	1.29 ± 0.25	0.37	0.37 ± 0.01	0.37 ± 0.05
Henon map	1.22	1.24 ± 0.03	1.13 ± 0.25	0.34	0.43 ± 0.01	0.43 ± 0.06
Solenoid $a = 1/3$	1.6309	1.64 ± 0.04	1.55 ± 0.17	0.5	0.51 ± 0.01	0.59 ± 0.03
Solenoid $a = 1/4$	1.5	1.52 ± 0.03	1.57 ± 0.20	0.5	0.51 ± 0.01	0.53 ± 0.03
Arnold Cat's map	1.987	2.00 ± 0.06		0.51	0.53 ± 0.06	

- does not fit the assumptions in Ref. 17 since in the latter paper, we consider maps with finitely many branches, we still try formula (2.6). For the Gauss map, the density is explicit and reads $h(x) = \frac{1}{\log 2} \frac{1}{1+x}$. The integral in (2.6) can be easily computed and gives $\theta = 4 \log(2) - 2 \sim 0.77$, whereas D_2 is expected to be 1. The numerical estimates are coherent with the theoretical values (Table I).
- Returning to a map with constant slope 3, we now look at the transformation generating the classical ternary Cantor set. In order to compute numerically the GEV function, one should access the invariant Cantor set, which is of zero Lebesgue measure. We need therefore to use the backward iterates of the map (otherwise almost all the forward orbits will fall into the holes), and the measures allowing us to compute the time averages are the so-called balanced measures, given suitable weights to the preimages of the map: see our article, Ref. 27 Sec. 3.2.2 for a description of such measures. For the ternary Cantor set and choosing equal weights 1/2 for the two preimages, it is easy to check that such a balanced measure coincides with the Gibbs measure with $\beta = \log 2/\log 3$ which is the Hausdorff dimension of the invariant set. The measure $\mu_{d\mu}$ is called *uniform*, see Ref. 20, Sec. 3. The potential φ will be equal to $-\log 2$ and $\lambda = 1$, since by Bowen's formula $Q(d_H) = 0$. Therefore, for the ternary Cantor set, we get a DEI equal to 0.5 which is perfectly confirmed by the numerical simulations (Table I).
- For the Lozi map: $x_{n+1} = a|x_n| + y_n + 1$, $y_{n+1} = bx_n$, a = 1.7, b = 0.5, Λ_+ is of order 0, 47, 28 which gives, with our approximation, a DEI of order $\theta = 0.37$. Previous numerical computations for D_2 gave $D_2 \sim 1.38^{29}$ Our computations (Table I) are coherent with the theoretical values.
- For the Hénon map $x_{n+1} = ax_n^2 + y_n + 1$, $y_{n+1} = bx_n$, a = 1.4, b = 0.3, Λ_+ is of order 0, 42, 28 which gives, with our approximation, a DEI of order $\theta = 0.34$. Previous numerical computations for D_2 gave $D_2 \sim 1.22$. The GEV computations give $D_2 = 1.24 \pm 0.11$ but $\theta = 0.43$ ± 0.01 for $n = 10^6$ (See Table I for the results with $n = 10^4$ iterations). The discrepancy of the DEI estimate does not get any better with the increase of \tilde{s} or n. As said before, we do not expect θ to coincide with the estimate 0.34 due to the variation of the derivative and the nonuniform hyperbolicity of the map.

- Let us consider the cat's map with the associated matrix 408 $\begin{pmatrix} 1 \\ 2 \end{pmatrix}$. The stable and unstable manifolds for such a $\begin{pmatrix} 409 \\ 409 \end{pmatrix}$ map are orthogonal, so we could suppose that the pre- 410 image of the ball $B(Tx, e^{-u_n})$ will intersect the ball 411 $B(x, e^{-u_n})$ in a rectangle R(x) centered at x and with the 412 shortest side of length $(\lambda_+)^{-1}e^{-u_n}$, where $\lambda_+ = \frac{3+\sqrt{5}}{2}$ is the 413 eigenvalue larger than 1 corresponding to the unstable 414 direction. An elementary calculation shows immediately 415 that $q_0 \sim \mathcal{L}(R(x))/\mathcal{L}(B(x, e^{-u_n}))$ is approximately given by 416 $\frac{4}{\pi}(\lambda_{+})^{-1}$ which gives an extremal index as 0.51. Previous 417 numerical computations for D_2 gave $D_2 \sim 1.987.^{29}$ The 418 numerical computation with the GEV fitting gives 419 $D_2 = 2.00 \pm 0.06$ and $\theta = 0.552 \pm 0.005$ for $n = 10^6$. 420 In order to investigate the discrepancy with our theoretical 421 estimate, we raised the quantile from $\tilde{s} = 0.99$ to 422 $\tilde{s} = 0.999$, i.e., we select more extreme clusters. The estimates for this case are $\theta = 0.54 \pm 0.02$, more compatible 424 with the theoretical one. Finally, if we consider longer tra- 425 jectories ($n = 10^7$ iterates) with an even higher quantile 426 $(\tilde{s} = 0.9999)$, we get $\theta = 0.53 \pm 0.06$, which is even closer 427 to the theoretical guess.
- We now consider the baker's map (see supplementary 429 material); it depends on three parameters α , γ_a , and γ_b . The 430 positive Lyapunov exponent is given by Ref. 20, Eq. 431

$$\Lambda_{+} = \alpha \log \frac{1}{\alpha} + (1 - \alpha) \log \frac{1}{1 - \alpha}.$$

With the value $\alpha = 1/3$, $\gamma_a = 1/5$, $\gamma_b = 1/4$, we get $\Lambda_+ \sim 0$, 433 64 which gives, with our approximation, an extremal 434 index of order 0, 47. In the paper, Ref. 20 Eq. (5.18), we 435 gave an implicit formula expressing D_2 as a function of α 436 and with respect to the SRB measure. For $\alpha = 1/3$, this 437 estimate reads $D_2 \simeq 1.41$. The GEV estimates are given in 438 Table I and are consistent with the theory.

• We next consider an attractor embedded in \mathbb{R}^3 , the socalled solenoid, see supplementary material; it depends 441 upon the parameter $a \in (0, 0.5)$. The attractor is foliated 442 by one-dimensional unstable manifolds, while each meridional disk is a two-dimensional stable manifold each of 444 which intersecting the attractor over a Cantor set. The 445 Lyapunov exponents are

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$$\Lambda_- = \log a < 0, \quad \Lambda_+ = \log 2,$$

447 while the Hausdorff dimension d_H is given by the formula³⁰

$$d_H = 1 + \frac{\log 2}{-\log a}.$$

The numerical computations for the solenoid provide a further test of the validity of the numerical algorithm and are provided in Table I.

B. High dimensional generalized Hénon maps

We now analyze the generalized Hénon maps defined in Ref. 31 and further analyzed in Ref. 32. They are defined as

$$x_{n+1}(1) = ax_n(d-1)^2 - bx_n(d)$$
 $x_{n+1}(i) = x_n(i-1)$. (3.1)

When the parameter a=1.76, the number of positive Lyapunov exponents is d-1; we could therefore test our relation (2.11) by computing the entropy $h_{\mathcal{L}}$ as the sum of positive Lyapunov exponents (see Table II in Ref. 32) for a given d. We also perform the computation of the dimension D_2 and compare it to the Kaplan-Yorke dimension D_{KY} given in Ref. 32; we used such a dimension because we did not find an explicit computation of D_2 in the literature. The good agreement between our numerical results (Fig. 1) confirm the validity of Eq. (2.10) with the caveat that an exact correspondence cannot be derived for the geometric factor that stretch balls in phase space in different dimensions: the origin of this discrepancy has been discussed in detail at the end of Sec. II C.

C. Application to atmospheric data

We now consider an application to atmospheric data.
The purpose of this application is to show that the applicability of the technique on real data provides results that have a

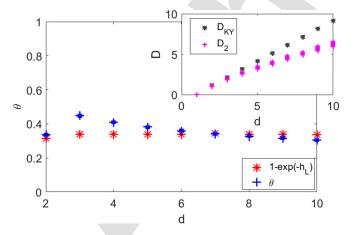


FIG. 1. Estimates of the dynamical extremal index θ and correlation dimension D_2 (inset) obtained for the Generalized Henon maps [Eq. (3.1)] in different dimensions d. The values represent the estimates obtained taking 30 couples of trajectories, iterated for $n=10^6$ iterations. Each couple is displayed using a single marker, but the uncertainty is so small that the difference between couples is hardly recognizable. The quantile used for the estimation is $\tilde{s}=0.98$. The results are compared to those obtained using the Kaplan-Yorke dimension D_{KY} and the entropy $h_{\mathcal{L}}$. This map has d-1 positive Lyapunov exponents.

coherent interpretation in terms of the underlying physics of 472 the systems. In order to provide evidence of the robustness 473 of our results, we will study several trajectories of a climate 474 models which incorporate observations of the past 110 years, 475 and compute θ and D_2 for several sub-periods showing that 476 the results are numerically stable. We study the atmospheric 477 circulation over the North Atlantic and focus on a single field 478 that represents its major features: the sea-level pressure 479 (SLP). 33,34 Indeed, it has been shown that SLP fields can be 480 used to study teleconnection patterns as well as storm track 481 activity and atmospheric blocking. 35,36 The trajectories of 482 our dynamical systems are successions of SLP fields 483 extracted with daily frequency from the ERA-20 CM reanal- 484 ysis project over the period 1900–2010.³⁷ The ERA-20 CM 485 consists of 10 members ensemble of a (climate) model 486 whose task is to reconstruct at best the 1900-2010 atmo- 487 spheric dynamics by constraining the model to include the 488 information from available surface observations. Each mem- 489 ber of the ERA 20 CM is therefore a slightly perturbed 490 reconstruction of the atmospheric dynamics in the past 491 110 years. The choice of the North Atlantic domain (80° W 492 \leq Long. \leq 50° E, 22.5° N \leq Lat. \leq 70° N) is motivated by 493 the better observational coverage over the region in the first 494 part of the analysis period compared to other regions of the 495 globe. 38 Before presenting the results for D_2 and θ , we would 496 like to stress that (i) our analysis will only be representative 497 of the North-Atlantic domain and D_2 will be a proxy of the 498 active degrees of freedom of the atmospheric circulation in 499 this area. Therefore, our results cannot be used to estimate 500 the dimension of the full atmospheric climate attractor. (ii) 501 Previous results 15,39,40 have shown that the estimates 502 obtained for the daily dimensions are robust with respect to 503 the changes in the datasets, resolution of the climate models, 504 and are linearly insensitive to the size of the domain. This 505 gives us confidence on the applicability of the numerical 506 algorithm described in this paper for climate data since it is 507 largely based on those used in Refs. 15, 39, and 40.

The results for D_2 and θ on the SLP fields of the ERA- 509 20 CM ensemble are presented in Fig. 2. For each estimate, 510 we fix the reference trajectory x as the first member (M1) of 511 the ERA-20 CM ensemble because this is always considered 512 as the reference simulation, while y is alternatively set as the 513Mith member with i = 2, 3, ..., 10. The dependence of the 514 results on the reference member are tested in the supplemen- 515 tary material Fig. S1. To test the robustness of the results, we 516 provide four estimates of D_2 and θ : (i) using the full data in 517 the period 1900-2010, (ii) using 1900-1955 data, (iii) using 518 1900–1928 data, and (iv) considering only the first 14 years 519 (1900-1914) of data. For each member, the results are 520 reported in Fig. 2. The ensemble averages of D_2 and θ for 521 the different periods are instead reported in Table II. 522 Estimates are consistent for different periods and the value 523 of $D_2 \simeq 9$ found on average, is slightly lower than the esti- 524 mates of d_H found in Ref. 15 (we remind that $D_2 < d_H$). The 525 value of D_2 roughly corresponds to the number of spatial 526 degrees of freedom active in a North-Atlantic SLP field as 527 explained in Ref. 15. Indeed, the domain used for this analysis can host about 9 large spatial structures reparted between 529 3 and 4 extratropical cyclones at time and the same number 530

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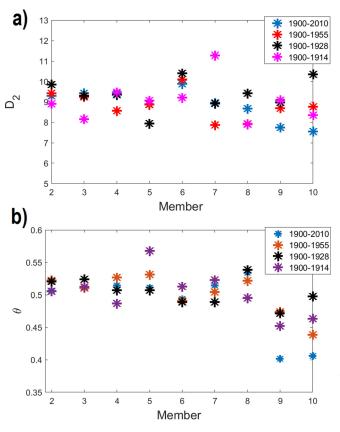


FIG. 2. Estimates of correlation dimension D_2 (a) and extremal index θ (b) obtained for daily sea-level pressure maps for four different periods in the ERA-20 CM reanalysis. The values represent the estimates obtained taking as reference trajectory x the member M1 and as y, the remaining 9 ensemble members.

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of anticyclones (see the textbook of Holton, ⁴¹ for estimates of the typical size of these objects). θ is, in fact, the inverse of the average time the two trajectories x and y cluster together. The value of the DEI $\theta = 0.5$ corresponds therefore to a contraction of the phase space associated with a timescale between 2 and 3 days. This is the typical decay rate of baroclinic eddies associated with the low pressure systems observed in SLP fields (see again the textbook by Holton⁴¹ for the decay rates). We finally notice that our formula (2.11)gives for the entropy the value log 2. In Fig. S2, we show a moving window computation of D_2 and θ . No clear trend emerges that could be attributed to anthropogenic forcing. This result is consistent with those found for d_H in Ref. 39. We remark however some differences in the variability of

TABLE II. Estimates of correlation dimension D_2 and extremal index θ obtained for daily sea-level pressure maps for four different periods of the ERA-20 CM reanalysis. The values represent average over the 9 ensemble members and uncertainty is expressed as the standard deviation of the ensemble mean.

Period	D_2	θ
1900-2010	8.9 ± 0.8	0.48 ± 0.05
1900-1955	8.8 ± 0.7	0.50 ± 0.03
1900-1928	9.4 ± 0.8	0.50 ± 0.02
1900-1914	9.0 ± 1.0	0.50 ± 0.03

the indicators among the members. In particular, M9 and 545 M10 have a minimum of θ around 1960. This could be due 546 to the different boundary conditions applied to the members 547 and detailed in Ref. 37.

D. Additive noise

In our previous papers, 17,42,43 we have analyzed the 550 effect of additive noise on the parameters of the extreme 551 value laws. It consists in defining a family of maps $T_{\varepsilon} = T$ 552 $+ \varepsilon \xi$ with ξ a random variable sampled from some distribu- 553 tion G (we will take here the uniform distribution on 554 some small ball of radius ε around 0). The iteration of the 555 single map T will be now replaced by the concatenation 556 $T_{\xi_n} \cap T_{\xi_{n-1}} \cdots \cap T_{\xi_1}$ and the evaluation of an observable 557 computed along this orbit will be given by the probability 558 measure $\mathbb P$ which is the product of $\mathbb G^{\mathbb N}$ with the so-called 559 stationary measure μ_S , verifying, for any real measurable 560 bounded function f: $\int f d\mu_s = \int f \circ T_{\tilde{e}} d\mu_s$: see Ref. 19 561 Chap. 7, for a general introduction to the matter. In the afore- 562 mentioned papers, Refs. 42 and 43, we have shown analyti- 563 cally that for dynamical systems perturbed additively, the 564 extremal index $\theta = 1$, no matter what the intensity of the 565 noise is. The proof was supported by numerical experiments, 566 using also different noise types. The extremal index is a 567 parameter that quantifies the amount of clustering, the stickiness of the trajectory in phase space. In our setting, cluster- 569 ing happens in the presence of invariant sets, which are 570 periodic points in Ref. 42. By looking at formula (2.4), we 571 see that we estimate the proportion of the neighborhood of 572 the invariant set returning to itself; as we argued above, that 573 estimate gives information on the rate of backward volume 574 contraction in the unstable direction. Since the noise gener- 575 ally destructs these invariants sets, we expect the extremal 576 index be equal to 1 or quickly approaching 1 when the noise 577 increases. This is confirmed by the numerical experiments 578 reported in Fig. 3 where the value of θ is plotted against the 579 intensity of the noise ε for three maps: $3x \mod 1$ map, the 580 Baker map, and the Lozi map. In all cases, indeed $\theta \to 1$ for 581 large enough noise. However, with respect to the observables 582 discussed in Ref. 42, we find some remarkable differences 583 on the intensity of the noise needed to observe changes of 584 the extremal index from the deterministic values: whereas in 585 Ref. 42, we observed significant deviation from the deter- 586 ministic behavior for very small noise intensities ($\varepsilon \ge 10^{-4}$), 587 here we need $\varepsilon \geq 10^{-2}$, i.e., only large noise amplitudes per- 588 turb the estimates of D_2 and θ . This difference can be easily 589 explained: in Ref. 42, the extremal index was used to explore 590 the local stability at periodic fixed points, where the dynam- 591 ics is deeply affected even by a small noise. Here, instead, 592 the extremal index tracks a global property that it is stable 593 with respect to small stochastic perturbations. We underline 594 that, for the Lozi map, we cannot obtain estimates of θ for 595 noise larger than 0.1 because the dynamics fall out the basin 596 of attraction.

IV. DISCUSSION AND CONCLUSIONS

Using the extreme value theory, we have introduced a 599 new and efficient way to compute the correlation dimension 600

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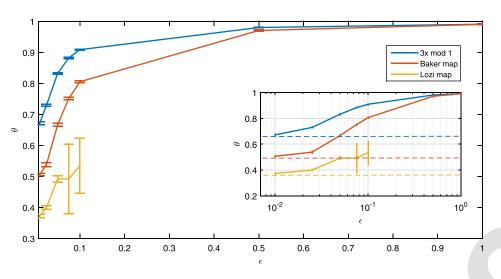


FIG. 3. Dynamical extremal index θ vs intensity of the additive noise ε for three different maps: $3 \times \text{ mod } 1$ (blue), Baker map (red), and Lozi map (orange). The error bar indicates the standard deviation of the sample of l = 100 trajectories, each consisting of $n = 10^6$ iterations. The quantile for the estimate of the extremal index is $\tilde{s} = 0.99$. The inset shows the same data in the semilog scale, with the deterministic values represented by the dotted lines.

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 D_2 . Moreover, for higher dimensional maps, we introduced the quantity q_0 , related to the expectation of the inverse of the determinant of the derivative along the expanding subspace. Therefore, the extremal index $\theta = 1 - q_0$ is a measure of the average rate of phase space contraction for backward iteration. Although this quantity slightly differs from the entropy or from the positive Lyapunov exponent when the expanding subspace has dimension one, it provides an important piece of information on the dynamics of the system. In fact it can be linked to the global predictability and therefore considered as a new indicator of the local instability in chaotic systems. We would like also to emphasize that both θ and D_2 can be computed simultaneously just by looking at the GEV function and this makes our method quite rapid and economically efficient from a numerical point of view. We have shown that even for a short time series of only of 10⁴ iterations, the estimates are robust and consistent with the theoretical expectations. We have also presented a first application of these indicators to climate data proving that the indicators are useful to infer the spatial number of degrees of freedom and the typical time scales of the atmospheric dynamics on the North Atlantic region. Finally, we have observed their sensitivity to the different boundary conditions imposed for the climate simulations analyzed. This implies that the indicators could be useful in characterizing and comparing also different climate datasets as those analyzed in international campaigns.

Our interpretation of θ together with that on the correlation dimension D_2 could be useful also to analyze the times series arising from the evolution of chaotic systems. Indeed, these quantities are particularly straightforward to obtain from numerical computations. Moreover, the results obtained can also be used to detect the embedding dimension, namely by replacing the sample of data with delay vectors of variable lengths; we stress that computing the GEV with those delay vectors will allow us to get exactly the embedding dimension. We mean to develop further this approach in a future paper.

Finally, the computation of the DEI could be helpful to distinguish purely stochastic sequences for which the extremal index should approach 1, see Sec. IIID, from dynamical systems with an underlying chaotic behavior even in the presence of small stochastic perturbations. Again, 643 these further applications of our approach with EVT will be 644 the objects of forthcoming investigations. 645

SUPPLEMENTARY MATERIAL

See supplementary material for: (i) the algorithm for the 647 estimation of the correlation dimension D_2 and the 648 Dynamical Extremal Index (DEI) θ , (ii) a commented 649 numerical MATLAB code for such estimation, (iii) the 650 model equations for the maps used, and (iv) the supplemen- 651 tary figures.

ACKNOWLEDGMENTS

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