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A century of nonlinearity in the geosciences

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6	Key Points:
7	• Nonlinear concepts and methods have greatly expanded the range of problems we can address

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- There is still only a small but increasing number of nonlinear methodologies
- Prediction is a great test of our mathematical and physical understanding

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11 Abstract

This paper provides a thumbnail sketch of the evolution of nonlinear ideas in the mathematics and physics of the geosciences, broadly construed, over the last hundred or so years. It emphasizes the mathematical concepts and methods, and outlines simple ex-

¹⁵ amples of how they were, are, and maybe will be applied to the solid Earth — i.e., the

¹⁶ crust, mantle, and core — and its fluid envelopes — i.e., the atmosphere and oceans.

Plain-Language Summary. Nonlinearity has become a buzzword, along with chaos,
 complexity, fractals, networks, tipping points, turbulence, and other concepts associated
 with modern science. We outline here what it all means and how it has affected the progress
 of the geosciences over the past century, mostly over the last six decades or so.

1 Introduction and Motivation

As we are celebrating 100 years since the founding of the American Geophysical Union (AGU), it appears of interest to consider the way that nonlinear concepts and methods have modified the way that we are practicing the geosciences today and may practice them over the next century.

While nonlinear approaches have rapidly expanded over the last half century, it is 26 clear that their roots go back much further. One of the oldest nonlinear problems in the 27 geosciences is certainly drawing a right angle on the face of the Earth, e.g., between a 28 meridian and a parallel: this problem is equivalent to solving the Diophantine equation 29 $a^2+b^2=c^2$. It is conjectured that the ancient Egyptians applied this equivalence, com-30 monly called Pythagoras's theorem, to build their pharaonic projects, from the basis up; 31 specifically, that they used the simplest solution — namely (a, b, c) = (3, 4, 5) — by ty-32 ing 12 = 3+4+5 equidistant knots into a rope, and used it in order to build the great 33 pyramids of Gizeh, and many other temples, palaces and tombs (e.g., Cooke, 2011). 34

But that is, of course, not what we all have in mind when discussing nonlinearity 35 in the sciences in general and in the geosciences in particular. Linear approaches dom-36 inated the physical sciences in the 19th century; the explosion of a variety of method-37 ologies that deviate from them is well illustrated by the saying, often attributed to Stanis-38 law Ulam (Gleick, 1987), that linear dynamics is akin to elephant zoology, or words to 39 that effect. What we mean by tracing back the rapid rise of nonlinear dynamics, non-40 linear sciences or what not to some time after World War II, is the following fact: ac-41 cording to the well-known story of the lamppost, and of attempts to find the forlorn keys 42 in its circle of light, a superb development of methods for solving linear algebraic and 43 differential equations in the 19th century led to great emphasis on solving problems for-44 mulated in terms of such equations in the first half of the 20th century. 45

Basically, linear problems are easily separable, and hence solvable, due to the superposition principle, projection onto orthonormal bases, and so on. Thus, many such problems were solved over the last 200 years, most often analytically, i.e., with pencil and paper or with very rudimentary computational devices. And these methods are still of great use to us, in deriving and determining the properties of tangent linear equations, adjoint operators, and many other mathematical approximations of real-world problems.

It is the rise of more-and-more powerful computational devices after World War 52 II that changed our way of thinking about what the solution to the mathematical for-53 mulation of a physical problem really is, i.e., not necessarily an analytical expression but 54 an algorithm for obtaining information about such a solution with prescribed accuracy. 55 The improvement in observational methods — in the geosciences and elsewhere, whether 56 in vitro, i.e., in the lab, or in vivo, i.e. outdoors— has also contributed greatly to our 57 appetite for going beyond linear approximation to model, simulate, understand, and pre-58 dict the complexity of the phenomena under study. 59

The nonlinear way of thinking about problems, in the geosciences and many other 60 sciences — physical sciences in general, biosciences, socio-economic sciences — still needs 61 to operate within the circles of light projected into the night of our ignorance by a cer-62 tain number of lampposts. These lampposts include the theory of dynamical systems, 63 statistical mechanics, scale invariances, the theory of localized coherent structures, and 64 several others. Some lampposts that have been added or whose light circle has expanded 65 in the last decade or so are network theory and the theory of non-autonomous and ran-66 dom dynamical systems. 67

The remainder of this paper will examine some of these lampposts and their respective circles of light, following Ghil, Kimoto, and Neelin (1991) and Ghil (2001). In the next section, we outline with a broad brush how linear results provided first insights into the behavior of fluid motions, around the turn of the 19th into the 20th century, and how nonlinear ones completed our knowledge after World War II.

⁷³ Sections 3 and 4 examine in somewhat greater detail the dynamical systems and ⁷⁴ the scale invariance lamppost, respectively. Each section starts with a sketch of the ba-⁷⁵ sic concepts and methods, in Secs. 3.1 and 4.1, respectively; each then follows up with ⁷⁶ some key applications. Thus, in Secs. 3.2 we discuss the mechanics of vacillation, mul-⁷⁷ tiple weather regimes in the atmosphere, and multiple flow regimes in the oceans, while ⁷⁸ in Sec. 4.2 we cover succintly fractals in dynamical systems, as well as scale invariance ⁷⁹ in general three-dimensional (3-D), two-dimensional (2-D) and geostrophic turbulence.

A few additional lampposts are examined in Sec. 5, each subsection starting again with theoretical foundations, followed by selected applications. Section 5.1 covers network theory, including both topology and dynamics, in particular that associated with Boolean delay equations; the applications illustrated are to earthquake and climate networks. In Section 5.2 we discuss fluctuation-dissipation theory, outlining both the classical theory for thermodynamic equilibrium and the more recent out-of-equilibrium generalizations, and emphasizing applications to climate response.

In Sec. 5.3, we cover the extension of dynamical systems theory to nonautonomous and random dynamical systems; the applications are the stochastically perturbed Lorenz (1963a) model and the oceans' wind-driven circulation subject to time-varying wind stress. This subsection ends with an introduction to climate sensitivity and the use of Wasserstein distance to generalize the traditional concept of equilibrium sensitivity.

Section 6 presents two meanings of prediction as touchstones of progress in the non-92 linear geosciences: (i) forecasting, i.e. prediction in time of the quantitative realization 93 of known phenomena; and (ii) theoretical prediction of qualitatively new phenomena. The 94 former meaning is illustrated by forecasting atmospheric and oceanic phenomena on longer 95 and longer time scales, from days through seasons and on to several decades. The lat-96 ter one is presented in the context of predicting an ice-covered Earth by simple energy 97 balance models and leading to the current arguments about a snowball Earth. Section 7 98 concludes this review paper with a brief coda. qq

¹⁰⁰ 2 From Linear to Nonlinear Thinking: A Quick Review

A paradigmatic success of linear concepts and methods at the beginning of the 20th century is the explanation by Lord Rayleigh (1916) of the striking patterns found in the thermal convection experiments of James Thomson (1882) and of Henri Bénard (1900). The word "paradigm" is used here advisedly in the sense of Thomas Kuhn (1962): it is easy to see how the transition from a linear — and for quite a while very successful mode of thinking to a nonlinear one is not just an evolutive generalization but a genuine revolution.

In the next section, we will consider a few key traits of the nonlinear mode of think-108 ing. In many applications to the physical sciences, like fluid dynamics, the linear mode 109 involves linearizing the equation of motion about a suitably symmetric steady state, most 110 often a state of rest (Rayleigh, 1916, p. 534). The stability of the resulting linear oper-111 ator is examined and the spatial pattern of the most rapidly growing unstable mode can 112 then be compared to observations. While Lord Rayleigh only examined a rectangular 113 domain, subsequent work led to the study of convective rolls and hexagons as the most 114 often occurring spatial patterns near equilibrium (e.g., Busse, 1978; Krishnamurti, 1973). 115 It is interesting, though, that Rayleigh (1916, pp. 529–530) does describe the irregular 116 transitions between two types of flow regimes. Pursuing an explanation thereof was clearly 117 beyond the reach of the linear methodology available to him. 118

Be that as it may, linear methodology led to many other successes during the first half of the 20th century, in explaining flow patterns observed in the laboratory, in industry, and in nature. Thus, when we see parallel cloud streaks in the sky, we know that they are the result of either Rayleigh-Bénard or Kelvin-Hemholtz instability. Possibly the crowning success of this approach was the discovery of a truly 3-D instability of great importance for atmospheric and oceanic flows, namely baroclinic instability, by Jule G. Charney (1947) and, independently, by Eric T. Eady (1949).

Charney's and Eady's results on baroclinic instability and variations thereupon man-126 aged to explain various features of the initial stages of development of mid-latitude storms 127 in the atmosphere and of mesoscale meanders in the oceans. But they could not explain 128 the finite-amplitude interactions between separate storms nor help very much in predict-129 ing weather beyond 1–2 days. In fact, Eady (1949, pp. 51–52) already had a pretty clear 130 vision of the difference between theoretically identifying recognizable initial patterns in 131 a storm's development and "the formidable task facing theoretical meteorology — that 132 of discovering the nature of and determining quantitatively [sic] all the forecastable reg-133 ularities of a permanently unstable (i.e., permanently turbulent) system." It is here that 134 the paradigmatic jump from linear to nonlinear concepts and methods has to occur. 135

¹³⁶ 3 The dynamical systems lamppost

3.1 The theory

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The mathematical theory of dynamical systems deals with modeling the behavior 138 of systems that evolve on long time scales. Sufficiently long, that is, for assuming that 139 solutions of the models exist for all times, from $-\infty$ to $+\infty$. This theory does not dis-140 tinguish, in principle, linear from nonlinear systems but has much to say about the lat-141 ter; it does not distinguish either between natural systems — whether physical, biolog-142 ical or socio-economical — and human-made systems but we will be interested here in 143 the natural ones. Some basic facts of nonlinear life are outlined below, from the dynam-144 ical systems perspective, following Ghil et al. (1991). 145

The equations of continuum mechanics are nonlinear. Surprisingly many phenomena
 can be explained by linearization about a particular fixed basic state. Many more can not; see Sec. 2 above.

2. Behavior of solutions to the nonlinear equations changes qualitatively only at isolated
points in phase-parameter space, called bifurcation points. Behavior along a single branch
of solutions, between such points, is modified only quantitatively and can be explored
by linearization about the basic state, which changes as the parameters change. That
is, nonlinear dynamics is much like linear dynamics, only more so (Ghil & Childress, 1987;
Lorenz, 1963a, 1963b).

Bifurcation trees lead from the simplest, most symmetric states, to highly complex
 and realistic ones, with much lower symmetry in either space or time or both. These trees

can be explored partially by analytic methods (Jin & Ghil, 1990; Jordan & Smith, 2007)

and more fully by numerical ones, such as pseudo-arclength continuation (Dijkstra, 2005; 158 Legras & Ghil, 1985). 159 4. The truly nonlinear behavior near bifurcation points involves robust transitions, of 160 great generality, between single and multiple fixed points (saddle-node, pitchfork and trans-161 verse bifurcations), fixed points and limit cycles (Hopf bifurcation), limit cycles and strange 162 attractors ("routes to chaos": Eckmann, 1981; Guckenheimer & Holmes, 1983). As the 163 complexity of the behavior increases, its predictability decreases (Ghil, 2001). 164 5. Behavior in the most realistic, chaotic regime can be described by the ergodic the-165 ory of dynamical systems. In this regime, statistical information similar to, but more de-166 tailed than for truly random behavior, can be extracted and used for predictive purposes 167 (Eckmann & Ruelle, 1985; Ghil & Robertson, 2000; Mo & Ghil, 1987). 168 6. Chaos and strange attractors are not restricted to low-order systems. They can be 169 shown to exist for the full equations governing continuum mechanics (Constantin, Foias, 170 Nicolaenko, & Temam, 1989; Temam, 2000). The detailed exploration of finite- but high-171 dimensional attractors is in full swing (Dijkstra, 2005; Ghil, 2017; Legras & Ghil, 1985). 172 7. Single time series (Takens, 1981) and single numbers derived from them (e.g., Grass-173 berger, 1983) have been used to describe chaotic behavior. This very simple and straight-174 forward use of a nonlinear concept has attracted considerable attention to determinis-175 tically chaotic dynamics, including in the geosciences (Nicolis & Nicolis, 1984; Tsonis & 176 Elsner, 1988). The use of single time series, while exciting in theory, is not very promis-177 ing when the series are short and noisy (Ruelle, 1990; Smith, 1988). The increasing avail-178 ability of a large number of similar series at different points in space, combined with phys-179 ical insight, is compensating more and more for the shortcomings of each individual time 180 series in describing the complexity of many phenomena in the geosciences, as well as ad-181

vancing their prediction (Ghil et al., 2002).

3.2 Some results

The mechanics of vacillation. Two steps beyond linear theory, in the direction already outlined by Eady (1949), were taken by Edward N. Lorenz (1963a, 1963b). The first was stimulated by the work on convection mentioned in Sec. 2 above, and revisited by Barry Saltzman (1962). This step yielded the paradigmatic strange attractor of Lorenz (1963a), too well known to be reviewed here yet another time; see Sparrow (1982), Guckenheimer and Holmes (1983), Ghil and Childress (1987, Sec. 5.4), and McWilliams (2019) in this issue. It showed the road to understanding deterministic chaos in a low-dimensional case.

The second step was going beyond the linear theory of baroclinic instability and 191 was stimulated by the rotating-annulus experiments with differential heating of David Fultz 192 (e.g., Fultz et al., 1959) and Raymond Hide (Hide & Mason, 1975, and references therein); 193 see also Ghil, Read, and Smith (2010). In this step, Lorenz (1963b) showed how to pro-194 ceed from the initial baroclinic instability of Charney (1947), via successive bifurcations, 195 to the so-called index cycle of atmospheric mid-latitude variability. Namias (1950) de-196 scribed this cycle of the zonal index as a recurrence of changes in intensity of the pre-197 vailing westerlies, with a rough periodicity of 4–6 weeks. 198

Lorenz (1963b, Fig. 3) reproduced key features of this phenomenon — such as the changes in strength, latitude and meandering of the westerly jet — by associating them with the tilted-trough vacillation in the rotating annulus experiments. The corresponding bifurcation tree appears as Fig. 5.8 in Ghil and Childress (1987).

Multiple weather regimes. Charney (1947) and Eady (1949) followed the linear approach
outlined in Secs. 1 and 2 and assumed small perturbations about a stationary mid-latitude
state of zonally symmetric flow. But observational meteorologists knew already that predominantly zonal flow is only one of the mid-latitudes' persistent states, and that episodes
of so-called blocked flow — with large deviations from zonality — can persist for fairly
long times (e.g., Baur, 1947; Namias, 1968). 'Long' here is defined as longer than the life

cycle of a typical mid-latitude storm, which is 5–7 days, while blocking events can last for up to a month (e.g., Dole & Gordon, 1983); see also Ghil and Childress (1987, Fig. 6.1).

Charney and DeVore (1979) studied a low-order barotropic model with merely three 211 modes in a β -channel — i.e., in a rectangular domain on a tangent plane to the sphere 212 (e.g., Gill, 1982; Pedlosky, 1987) — that had two stable stationary solutions: one with 213 features similar to zonal flow, the other resembling blocked flow; see the bifurcation di-214 agram in Ghil and Childress (1987, Fig. 6.5). Charney, Shukla, and Mo (1981) and Benzi, 215 Malguzzi, Speranza, and Sutera (1986) provided observational evidence for the existence 216 217 of blocked-vs.-zonal bimodality in the Northern Hemisphere extratropics, while Mo and Ghil (1987) also found bimodality in the Southern Hemisphere extratropics. The latter 218 bistability involved different amplitudes and phases of a dominant wavenumber-three, 219 quasi-stationary wave; a third quasi-stationary pattern, of regional rather than hemispheric 220 extent, was called by Mo and Ghil (1987) the Pacific–South-American (PSA) pattern. 221

Legras and Ghil (1985) showed that, using just 25 modes of a barotropic model on 222 the sphere, one could go well beyond two stable fixed points, to obtain not only more 223 realistic zonal and blocked flow, but also stable limit cycles and deterministically chaotic 224 behavior. In the latter regime, depending on the Rossby number Ro that determines the 225 relative importance of the planet's rotation (see Sec. 4.2 for further details), it is either 226 a zonal, a blocked or an intermittent regime that dominates. In the presence of inter-227 mittency, the relative time spent in zonal and blocked episodes changes smoothly as Ro 228 increases (Ghil & Childress, 1987, Fig. 6.14). Weeks et al. (1997, Fig. 5B) used a barotropic 229 rotating annulus with topography and found that the dependence of persistence times 230 of zonal vs. blocked flow on the experiment's Rossby number exhibited marked similar-231 ities to the numerical results of Legras and Ghil (1985). 232

The existence of several weather regimes in the Northern Hemisphere's atmosphere 233 is statistically pretty well established now by a number of distinct clustering methods 234 and their application to several data sets; see, for instance, Table 1 in Ghil, Groth, Kon-235 drashov, and Robertson (2018) and references therein. Even so, the exact number of such 236 regimes supported by the data, as well as their description and dynamical explanation, 237 remains a matter of debate. Moreover, high-resolution numerical weather prediction (NWP) 238 models — which are otherwise quite skillful at predicting weather a few days in advance 239 still have difficulties in predicting the onset of blocking and transitions between it and 240 zonal flow (Dawson & Palmer, 2014). 241

Multiple flow regimes in the oceans. The horizontal extent of storms in the atmosphere and of eddies in the oceans is given by the Rossby radius of deformation R (Ghil & Childress, 1987; Gill, 1982; Pedlosky, 1987) that determines the so-called synoptic scale. Because of the differences in stratification between the two fluid media, $R_{\rm oc} \simeq 100$ km \ll $R_{\rm atm} \simeq 1000$ km. Thus, when first discovered, oceanic eddies have been erroneously called "mesoscale eddies," since 100 km is termed the mesoscale in the atmosphere. Be that as it may, the name has stuck (e.g., McWilliams, 2011).

While the diameter of oceanic eddies is much smaller than that of the atmospheric 249 ones, their life cycle is much longer: months rather than days. Thus, low-frequency vari-250 ability (LFV) in the oceans is on the scale of years-to-decades, while in the atmosphere 251 it is subseasonal-to-seasonal, 10-100 days. In the oceans, one tends to distinguish be-252 tween two types of causes of LFV: the wind-driven circulation and the thermohaline or 253 meridional-overturning circulation (THC or MOC). The former is predominantly in a 254 horizontal plane, driven by atmospheric momentum fluxes, and contributes to the inter-255 annual LFV of the oceans, while the latter is predominantly in a meridional plane, driven 256 by buoyancy fluxes and contributes to the interdecadal LFV (Dijkstra & Ghil, 2005). 257

Important contributions to the nonlinear understanding of oceanic LFV are roughly contemporaneous to, or even earlier than, the pioneering contributions of Lorenz (1963a,

1963b) for the atmosphere. Henry Stommel (1961) obtained two stable stationary so-260 lutions in a simple two-box model of the THC. He was originally interested in the sea-261 sonal reversal of local THCs, such as in the Red Sea or the Eastern Mediterranean (Stom-262 mel, 1961, p. 225) but did note on p. 228 that "One wonders whether other quite dif-263 ferent states of flow are permissible in the ocean $\left| \dots \right|$ and if such a system might jump 264 into one of these with a sufficient perturbation. If so, the system is inherently frought 265 with possibilities for speculation about climatic change." Speculations on this matter 266 continue apace, and some of the relevant research is reviewed in Dijkstra and Ghil (2005, 267 Sec. 3). 268

George Veronis (1963) considered the wind-driven ocean circulation in a rectangular basin on the β -plane, subject to time-independent wind stress, and truncating the expansion of the barotropic, single-layer streamfunction at four sine modes. He obtained two stable steady states, as well as a limit cycle for various parameter values.

Jiang, Jin, and Ghil (1995) introduced a different expansion of the shallow-water equations in the same geometry, with an exponential multiplier in the zonal, x-direction to allow for a western boundary current, as well as carrying out numerical integrations on an eddy-permitting grid with $\Delta x = \Delta y = 20$ km. They obtained exact steady states, as well as exactly periodic solutions (Fig. 1) for the numerical integrations that used 15 000 grid variables. These authors also showed that the generation of the nearly mirror-symmetric steady states in the numerical integrations was well captured by the perturbed pitchfork bifurcation of their highly idealized, intermediate-order model.



Figure 1. Snapshots from an exactly periodic relaxation oscillation of the Jiang et al. (1995) model; see also Fig. 7 (black and white) there. Color indicates contours of the model's upperlayer thickness, with warm colors for the subtropical gyre and cold ones for the subpolar one; black lines indicate contours of potential vorticity, with a modified Rossby wave propagating across the basin. Courtesy of Shi Jiang.

The periodic solutions became more and more anharmonic and sawtooth-shaped 280 as the time-constant wind stress intensity was increased, and finally led to aperiodic, in-281 termittent solutions. This transition to chaos can be followed in Fig. 2 via a homoclinic 282 bifurcation for a quasi-geostrophic (QG) model with a resolution of $\Delta x = \Delta y = 10$ km. 283 Dijkstra and Ghil (2005, Sec. 2) provide further details on this particular model, as part 284 of an entire hierarchy of increasingly detailed and realistic models that confirm its re-285 sults, and many additional references. Concerning geostrophy and its effect on turbu-286 287 lent fluid behavior, see Sec. 4.2 below.

Overall, the line of work outlined in the preceding paragraphs has provided fairly 288 convincing evidence that intrinsic oceanic LFV, even in the absence of variable atmo-289 spheric forcing, is an important source of interannual climate variability. Detailed con-290 frontation of model results with recent reanalysis data for both atmosphere and oceans 291 supports these ideas, at least in the case of the North Atlantic basin (Groth, Feliks, Kon-292 drashov, & Ghil, 2017), where this mechanism also provides a possible explanation of 293 the North Atlantic Oscillation (NAO) and of its approximate 7-8-year periodicity. The 294 situation for time-dependent wind forcing will be discussed in Sec. 5.3. 295



Figure 2. Generic bifurcation diagram for the barotropic QG model of the double-gyre problem: the asymmetry of the solution is plotted versus the intensity of the wind stress τ . The streamfunction field $\psi = \psi(x, y)$ is plotted for a steady-state solution associated with each of the three branches; positive values in red and negative ones in blue. After Simonnet et al. (2005).

Bifurcations and tipping points. In the applications covered herein, we have limited ourselves to classical bifurcations (e.g., Arnol'd, 2012; Guckenheimer & Holmes, 1983), which
go back to the work of Leonhard Euler (1757) on buckling of a beam (e.g., Timoshenko
& Gere, 1961). Recently, the interest in bifurcations in the geosciences has greatly increased due to the introduction of the concept of tipping points from the social sciences
(Gladwell, 2000; Lenton et al., 2008). Clearly, a tipping point sounds a lot more threatening than a bifurcation point, especially when dealing with an earthquake or a dramatic

³⁰³ and irreversible climate change.

Aside from their rhetorical impact, though, tipping points generalize classical bifurcations when considering open, rather than closed systems. In fact, there are three

³⁰⁶ kinds of tipping points under consideration recently for open systems (Ashwin, Wiec-

- ³⁰⁷ zorek, Vitolo, & Cox, 2012):
- (i) B-Tipping or Bifurcation-due tipping slow change in a parameter leads to the system's passage through a classical bifurcation;
- (ii) N-Tipping or Noise-induced tipping random fluctuations lead to the system's cross ing an attractor basin boundary;
- ³¹² (iii) R-Tipping or Rate-induced tipping rapid changes lead to the system's losing track
- of a slow change in its attractors.
- ³¹⁴ We will have more to say about open systems and their attractors in Sec. 5.3.

315 4 The Scale Invariance Lampost

The light of this lamppost has to do with insights about patterns that appear to keep their spatial structure at increasing magnification. Such spatial patterns — like the Cantor set on the line and the Peano curve in the plane — were well known by the late 19th century (e.g., Sagan, 2012) but their pervasiveness in nature and connection to a system's evolution in time only became evident in the second half of the 20th century.

321 4.1 The theory

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Probably the best-known set with strange properties that arise by an iterative construction is the Cantor ternary set. Consider the closed unit interval $C_0 = [0, 1]$ of length $\ell_0 = 1$ on the real line \mathbb{R} and remove the open middle third (1/3, 2/3), which leaves the set $C_1 = (C_0/3) \cup (2/3 + C_0/3) = [0, 1/3] \cup [2/3, 1]$ of length $\ell_1 = 2/3$. Removing inductively the open middle third of the two closed intervals left, then of the four ones left at the next stage and so on, one gets

$$\mathcal{C}_n = \frac{\mathcal{C}_{n-1}}{3} \cup \left(\frac{2}{3} + \frac{\mathcal{C}_{n-1}}{3}\right),\tag{1}$$

of length $\ell_n = (2/3)\ell_{n-1} = (2/3)^n$. This construction is perfectly self-similar and scale invariant.

Clearly $\ell_n \to 0$, so that the limit set $\mathcal{C}_{\infty} = \mathcal{C}$ has length $\ell_{\infty} = 0$. But the deep 331 result is that there is a one-to-one correspondence between the points in the set $\mathcal C$ of zero 332 Lebesgue measure and those in the unit interval \mathcal{C}_0 , i.e., the two sets have the same un-333 countable cardinality $|\mathcal{C}| = |\mathcal{C}_0|$, which equals also the transfinite cardinality \aleph_1 of the 334 real line itself. The former result was stated by Georg Cantor (1887) without proof; the 335 modern proof is based on what became known as the Cantor-Schröder-Bernstein the-336 orem, with Felix Bernstein and Ernst Schröder having almost simultaneously given two 337 different proofs in 1897, as did Felix Dedekind. The 2-D generalization of the Cantor set 338 in the plane \mathbb{R}^2 is called the Sierpiński (1916) carpet; see Fig. 3. 339

Many mathematicians at the time were not comfortable with transfinite numbers 340 nor with statements like the inequality $\aleph_0 < \aleph_1$, where \aleph_0 is the cardinality of natu-341 ral, integer and rational numbers, among other countable sets. Nor did physicists in the 342 late 19th century appreciate functions that were not continuously differentiable every-343 where. This inequality and the absence of any cardinals between \aleph_0 and \aleph_1 depended 344 on difficult issues raised by the axiomatization of mathematics (e.g., Suppes, 1972) that 345 were not that palatable for most mathematicians and almost all physicists. This fact tran-346 spires even in Cantor's choice of journal for his 1887 paper, namely a philosophical rather 347 than a standard mathematical one. 348



Figure 3. The 6th-level iteration for obtaining the Sierpiński carpet on the unit square $[0, 1] \times [0, 1]$. The carpet has topological dimension $d_{\rm T} = 1$ but Hausdorff dimension $d_{\rm H} \simeq 1.893 < 2$. From Wikimedia, public domain.

The situation was as bad or worse with respect to functions that were not continuously differentiable anywhere. Bernard Bolzano and Augustin-Louis Cauchy had given early definitions of continuity in 1817 and 1823, respectively, and Karl Weierstrass had given the better-known ($\epsilon - \delta$) definition a few decades later. As discussed in Sec. 2, physicists were extensively using ordinary and partial differential equations (ODEs and PDEs) around the turn of the 19th into the 20th century and lack of continuous differentiability was considered a mathematical oddity of little use in studying natural phenomena.

Benoît Mandelbrot (1967) had an important role in stressing that this was not so. 356 Hugo Steinhaus (1954) had already discussed what we now call fractional dimension, when 357 Lewis Fry Richardson (1961) pointed out the "coastline paradox" and provided the polyg-358 onal method for correctly overcoming this paradox; see also Hunt (1998). Essentially, 359 the length L of a coastline, river (e.g., Steinhaus's Vistula) or geographic border depends 360 on the scale G used to approximate it by a polygon. Based on several examples avail-361 able at the time, Richardson (1961, Fig. 17) proposed the approximation $L(G) = \kappa G^{1-D}$. 362 where κ is a constant and $D \geq 1$ is the fractional dimension; the latter equals unity if 363 the curve is smooth. Quite recently, Losa, Ristanović, Ristanović, Zaletel, and Beltraminelli 364 (2016) found "[...] that among many fractal analysis techniques, only Richardson's method 365 enables correct calculation of the length of an object's border or irregular line." 366

The basic ingredients of Mandelbrot's development of fractal concepts and methods became available in the early 20th century. First, Felix Hausdorff (1918) provided a generalization of dimension that allowed one to evaluate it for the kinds of odd sets we discussed above, cf. Fig. 3; it is now called the Haussdorf dimension and it can take on noninteger values. Second, the same year, Gaston Julia (1918) considered a class of iteratively defined sets in the complex plane C that have the right oddity.

Speaking loosely, for a given holomorphic (i.e., complex analytic) function f(z), with 373 z = x + iy, the Julia set $\mathcal{J}(f)$ and the Fatou (1919) set $\mathcal{F}(f)$ are complements of each 374 other, with $\mathcal{J}(f)$ being the set of points on which repeated iterations of $z \to f(z)$ di-375 verge, while on $\mathcal{F}(f)$ these iterations behave similarly. In other words, f is regular on 376 $\mathcal{F}(f)$ and chaotic on $\mathcal{J}(f)$. As for the Cantor set \mathcal{C} above, we only outline here the sim-377 plest case, namely that of quadratic polynomials, written as $f_c(z) = z^2 + c$, with $c \in$ 378 \mathbb{C} . It is this case that Benoît Mandelbrot (2013, and references therein) made famous 379 in the late 20^{th} century. 380

For c = 0, the Julia set is simply the unit circle |z = 1|, and the two Fatou sets are its interior and exterior, with iterations that converge to 0 and ∞ , respectively. In general, though, the Julia set $\mathcal{J}(f_c)$ is much more complicated and Mandelbrot (1977) introduced the term "fractals" for such complicated sets. A beautiful illustration of the self-similarity that characterizes many fractals is given by the Mandelbrot set $\mathcal{M}(f)$, defined as the set of points c in the complex plane for which the iterates

$$\{z_{n+1}(c) = f(z_n; c); n = 0, \ldots\}$$

stay bounded as n increases, when starting at $z_0 = 0$. The most often studied and cited 381 case is that of $f(z;c) = f_c(z) = z^2 + c$. 382 While there is no definitive consensus on how best to define a fractal, there are two 383 key ingredients: (i) a degree of self-similarity and (ii) a Hausdorff dimension $d_{\rm H}$ that ex-384 ceeds the classical, topological dimension $d_{\rm T}$. The rigorous mathematical definition of 385 the latter is also laborious, but its integer values are obvious for the usual Euclidean spaces, 386 namely $d_{\mathrm{T}} = n$ for \mathbb{R}^{n} ; the former is often an irrational number, although a "fractal 387 dimension," while often used, is an obvious misnomer: it is the set that is a fractal, while 388 the dimension is a simple scalar in all cases, and a fraction in many. 389

Both Julia sets, defined for a fixed c as z varies, and Mandelbrot sets, defined for a fixed $z_0 = 0$ as c varies, have fascinating properties and there are interesting connections between the two. Peitgen and Richter (2013) provide both mathematical substance and beautiful illustrations on these topics. Figure 4 illustrates just one such case, but for this set, the scale invariance is more qualitative: things look roughly the same rather than exactly the same at different scales.

4.2 Some results

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Fractals in dynamical systems. A number of factors concurred in the second half of the 20th century to greatly increase the circle of light of this lamppost, as well as the interest in it. First, there was the increase of interest in dynamical systems and their applications, as reviewed in Secs. 2 and 3 herein. Next, like in the case of dynamical systems, it was the great progress in computing power and storage capacity.

It's great fun computing Julia or Mandelbrot sets on your laptop, as it is computing the strange attractor of the Lorenz (1963a) model. Moreover, this attractor is a fractal for a broad range of parameter values, i.e. when you drill through it perpendicular
to the tangent manifold, anywhere except at the origin, you get a Cantor-like set.

The dimensions of the attractor, for the standard nondimensional parameter values illustrated in the original Lorenz (1963a) paper — namely the Rayleigh number $\rho =$ 28, the Prandtl number $\sigma = 10$ and the wavenumber $\beta = 8/3$ — are $d_{\rm H} = 2.06 \pm$ 0.01 > 2 = $d_{\rm T}$ and its volume is zero, as for the Cantor set. Please see, again, Sparrow (1982), Guckenheimer and Holmes (1983), Ghil and Childress (1987, Sec. 5.4), and McWilliams (2019) in this issue for further details.

While several metric dimensions have been defined for dynamical systems (e.g., Farmer,
Ott, & Yorke, 1983), a particularly useful one is the Lyapunov dimension. It is given by
the Lyapunov spectrum of the undelying system and is also called the Kaplan-Yorke dimension (Kaplan & Yorke, 1979):

$$d_{\rm KY} \equiv k + \sum_{j=1}^{k} \frac{\lambda_j}{\lambda_{k+1}} \,; \tag{2}$$

here k is the maximum integer such that the sum of the k largest exponents is still nonnegative. We shall return to the Lyapunov spectrum in Sec. 6 below. Leonov, Kuznetsov, Korzhemanova, and Kusakin (2016) obtained the following remarkable formula for the



(c) $100 \times$ magnification.

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(d) $2000 \times$ magnification.

Figure 4. Mandelbrot set, with c_r on the abscissa and c_i on the ordinate. The white rectangles indicate the domain of the zoom in the next panel. From Nadim Ghaznavi, under the Creative Commons Attribution-Share Alike licence https://creativecommons.org/licenses/by-sa/3.0/deed.en.

$$d_{420}$$
 Lyapunov dimension d_{KY} of the global attractor of the Lorenz (1963a) model:

$$d_{\rm KY} = 3 - \frac{2(\sigma + \beta + 1)}{\sigma + 1 + ((\sigma - 1)^2 + 4\rho\sigma)^{1/2}} < 3.$$
(3)

Fractals in turbulence. Of course, it is one thing to describe numerically and study mathematically fractals in dynamical systems and quite another thing to do so in natural phenomena. As already indicated in Sec. 1, the improvement in making and in analyzing observations, with their rapidly increasing number and accuracy, has also greatly accelerated the uses of scale invariance in the natural environment.

⁴²⁷ A particularly stimulating example is given by turbulence in general and by geo-⁴²⁸ physical turbulence more specifically. Turbulent flow arises in many areas of engineer-⁴²⁹ ing, as well as in nature, from blood flow to galactic evolution. Its presence and inten-⁴³⁰ sity is characterized by the Reynolds number $R \equiv UL/\nu$, where U, L and ν are a char-⁴³¹ acteristic velocity, length and kinematic viscosity of the flow and the fluid: the higher ⁴³² U or L and the smaller ν , the more turbulent the flow.

Understanding and predicting turbulent behavior is probably the hardest problem in continuum physics. Compared to huge progress throughout the 20th century in quantum and relativistic physics, progress in turbulence studies has been more moderate.

⁴³⁶ In fact, in the opening article of the Annual Reviews of Fluid Mechanics, Sydney ⁴³⁷ Goldstein (1969) attributes to Sir Horace Lamb the following statement "I am an old

man now, and when I die and go to Heaven there are two matters on which I hope for 438 enlightenment. One is quantum electrodynamics, and the other is the turbulent motion 439 of fluids. And about the former I am really rather optimistic." The "old man," of course, 440 was a leader in fluid dynamics at the turn of the 19th into the 20th century and the au-441 thor of the Lamb (1932) book on which the generation of S. Goldstein, Ludwig Prandtl 442 and Theodor von Kármán had grown up. Goldstein's comment on this quote is, "Lamb 443 was correct on two scores. All who knew him agreed that it was Heaven that he would 444 go to, and he was right to be more optimistic about quantum electrodynamics than tur-445 bulence." Goldstein's prediction still holds exactly 50 years later. 446

Rapid progress of technology still obliged engineers and other practitioners to find empirical results even in the absence of deeper understanding of the causes of turbulence and the behavior of turbulent flows. In particular, once the crucial role of boundary layers in mediating the transition between the fairly frictionless flow far from a wall and the necessity of a viscous fluid to be at rest at the boundary was understood, several empirical formulas were developed. Schlichting and Gersten (2016, and earlier editions) are a good source for this important subfield of turbulent fluid dynamics.

Thus, assumptions about the phenomena at play that appear at first sight rather strong, along with dimensional analysis (e.g., Barenblatt, 1996), lead to the well-known "law of the wall." Let U be the (nearly constant) velocity outside the boundary layer, $\tau_{\rm w}$ the shear stress at the solid surface, y the distance perpendicular to the surface, $u_{\tau} =$ $(\tau_{\rm w}/\rho)^{1/2}$, with ρ the density of the fluid, μ its molecular viscosity, and $\nu = \mu/\rho$ its kinematic viscosity. The law is then given by $U/u_{\tau} = f((u_{\tau}y)/\nu)$ and it holds for the "inner layer" $y \leq 0.2\delta$, where δ is the total thickness of the boundary layer.

Based on work variously attributed to Lev Landau in the former Soviet Union and
to L. Prandtl and Th. von Kármán in the western literature, the form of the function *f* above is logarithmic, resulting in the log-law

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$$\frac{U}{u_{\tau}} = \frac{1}{\kappa} \ln \frac{u_{\tau} y}{\nu} + C; \qquad (4)$$

see Bradshaw and Huang (1995, and references therein). Extensive experimental work shows that Eq. (4) holds for $\kappa \simeq 0.41$ and $C \simeq 5.0$, provided the pressure gradient parallel to the wall is not too large, within the region $30\nu/u_{\tau} \leq y \leq 0.1\delta$. The goodness of fit of the log-law above decreases as the pressure gradient increases and one approaches separation of the boundary layer.

Such semi-empirical relations, based on physical approximations and dimensional
 analysis, served practitioners well. Still, there was an increasing need for fundamental
 understanding of the complexities involved in turbulent flows.

A truly major step forward was due to the development of the concept of energy cascade and the statistical theory of turbulence. In his pioneering study of numerical weather prediction, L. F. Richardson (1922, p. 66) formulated the key idea of a turbulent cascade via the verse "Big whirls have little whirls that feed on their velocity, and little whirls have lesser whirls and so on to viscosity—in the molecular sense."

This idea was refined first by distinguishing between the largest scales in a fluid 478 that are most energetic and are affected by the geometry of the domain, and the small-479 est ones, at which energy input from nonlinear interactions and the energy drain from 480 viscous dissipation are in exact balance. The latter have high frequency and are locally 481 isotropic and homogeneous (e.g., Batchelor, 1953). In between these two scales, geomet-482 ric and directional information is lost in the A. N. Kolmogorov (1941) inertial cascade, 483 between the large scales L and the Kolmogorov scale $\ell_{\rm K}$, provided the Reynolds num-484 ber R is sufficiently high. 485

The value of $\ell_{\rm K}$ is given again merely by dimensional arguments and the physical assumption that the statistics of the small scales are universally and uniquely determined by the rate of energy dissipation ϵ and the kinematic viscosity ν , as $R \to \infty$,

$$\ell_{\rm K} = \left(\nu^3/\epsilon\right)^{1/4}.$$

Between L and $\ell_{\rm K}$, instabilities break up the larger eddies into smaller ones that interact nonlinearly, while viscous effects are negligible. Once more, these assumptions and dimensional analysis lead — for scalar wavenumbers $k = 2\pi/r$ and $L > r > \ell_{\rm K}$, where $r = |\mathbf{r}|$ and \mathbf{r} is the distance in the physical space \mathbb{R}^3 — to the kinetic-energy spectrum E = E(k), namely

$$E(k) = C\epsilon^{2/3}k^p,\tag{5}$$

with p = -5/3 and C a presumably universal constant.

Frisch (1995) presents this statistical theory of 3-D turbulence elegantly and reviews 493 the experimental evidence, which confirms broadly the theory. This so-called direct energy cascade appears in Fig. 5(a). There are two related difficulties, though. First, to 495 cite again Goldstein (1969), "[...] distinguished mathematical statisticians, some of whom 496 had hopes of contributing to the theory of turbulence, [when] they saw the physical, rather 497 than mathematical, nature of Kolmogorov's contribution [...] decided that such research 498 was not for them." Indeed, to this day — and in spite of considerable progress in the 499 mathematical theory of the Navier-Stokes equations that govern fluid dynamics (e.g., Temam, 500 2001) — there is no rigorous derivation of the Kolmogorov (-5/3) law.



Figure 5. Energy and enstrophy cascades in (a) three-dimensional (3-D) and (b) twodimensional (2-D) turbulence. The latter panel also characterizes the dual cascades in QG turbulence. Courtesy of Niklas Boers.

Second, the Kolmogorov (1941) theory implicitly assumes that 3-D turbulence is statistically self-similar at different scales in the inertial range. Thus the flow velocity increments $\delta \mathbf{u}(r) = \mathbf{u}(\mathbf{x} + \mathbf{r}) - \mathbf{u}(\mathbf{x})$, when scaled by $\lambda > 0$, should behave as $\delta \mathbf{u}(r) \simeq$ $\lambda^{\beta} \delta \mathbf{u}(r)$, with β independent of r, where \simeq stands for equality in distribution. It follows that the structure functions of order n, i.e. the n^{th} -order statistical moments of the flow velocity increments $\delta \mathbf{u}$, should scale as

$$\left\langle \left(\delta \mathbf{u}(r) \right)^n \right\rangle = C_n (\epsilon r)^{n/3},$$
(6)

where the brackets denote the statistical average, and the C_n are universal constants.

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More generally, given 1 < |p| < 3 in Eq. (5), one can show that the second-order structure function, i.e. n = 2 in Eq. (6) behaves like r^{p-1} . Since the latter is easier to measure accurately, $\langle (\delta \mathbf{u}(r))^2 \rangle \propto r^{2/3}$ implies that p = 5/3, confirming Kolmogorov (1941) theory. In fact, experimental differences are of the order of 2 % (Mathieu & Scott, 2000). So far, so good.

Higher-order structure functions, though, deviate more and more from the scaling 515 predicted by Eq. (6), as they become a sublinear function of n, and the constants C_n are 516 far from universal, according to both laboratory and numerical experiments. The main 517 reason for the observed deviations is the lack of homogeneity in the turbulent flow field, 518 in either time or space; this feature of turbulence is referred to as intermittency and Man-519 delbrot (1969) highlighted its role: he conjectured that, as $R \to \infty$, the dissipation of 520 the energy, far from being uniform, tends to concentrate on a fractal set with $d_{\rm H} < 3$. 521 Lagrangian coherent structures play an important role in reducing dissipation, produc-522 ing intermittency in turbulent flows, and increasing their predictability (e.g., Haller, 2015). 523

Geophysical turbulence. Large-scale atmospheric and oceanic flows are characterized by the key role of rotation and shallowness (e.g., Ghil & Childress, 1987; Gill, 1982; Pedlosky, 1987). The theoretical study of such flows is referred to as geophysical fluid dynamics (GFD) and an important tool in this study is the QG approximation; see Ghil and Childress (1987, Ch. 4) for a succint introduction.

Shallowness is due to the small aspect ratio $\delta \equiv H/L \ll 1$, where H is the characteristic height — with $H \simeq 10$ km in the atmosphere and even smaller in the oceans — and L the characteristic horizontal extent, with $L \simeq 10^3$ km in the atmosphere and $L \simeq 10^2$ km in the oceans. The dominant role of planetary rotation is due to the smallness of the Rossby number $Ro \equiv U/fL \ll 1$, where U is a characteristic horizontal velocity, $f = 2\Omega \sin \phi$ is the Coriolis parameter that measures the local angular velocity, while Ω is the planet's angular velocity of rotation around its axis and ϕ the latitude.

QG flows are hydrostatic, i.e., vertical accelerations are negligible due to the flows'
shallowness, and they are dominated by geostrophic balance between the Coriolis force
and the pressure gradient. These two features result in QG flows being 2-D to a good
first approximation, which suggests that geostrophic turbulence should also have 2-D features (e.g., Cushman-Roisin & Beckers, 2011; McWilliams, 2011; Salmon, 1998). We start
by rapidly reviewing the differences between 2-D and 3-D turbulence.

The key difference is the existence of two quadratic invariants, enstrophy and kinetic energy, rather than energy alone; see the references in Charney (1971, pp. 1087-1088), with enstrophy Z being the mean-squared vorticity. In 3-D turbulence, the conservation of the kinetic energy E(k) leads to the direct cascade from large to small scales, cf. Eq. (5), as illustrated in Fig. 5; the slope of the E(k) spectrum over the inertial range $L \leq k \leq \ell_{\rm K}$ equals approximately -5/3.

In 2-D turbulence, the existence of the two separate, positive-definite quadratic invariants, kinetic energy E and enstrophy Z(k), leads to two cascades. Indeed, Fjørtoft (1953) showed that an energy transfer from k to $k+\Delta k$ must, to conserve Z(k), be accompanied by a larger transfer of energy to $k-\Delta k$; this follows, essentially, from $Z(k) \propto$ $k^2 E(k)$. Based on this crucial fact, Kraichnan (1967) showed that, in 2-D turbulent flows, there are two inertial ranges: one with a reverse energy cascade and zero enstrophy flux, between L and L_{*}, the other with a direct enstrophy cascade and zero energy flux, between L_{*} and $\ell_{\rm K}$. The slope of the energy spectrum in the former is (-5/3), and it is (-3) in the latter, as illustrated in Fig. 5(b).

⁵⁵⁷ Charney (1971) noted atmospheric observations (e.g., Wiin-Nielsen, 1967) and nu-⁵⁵⁸ merical simulations (e.g., Manabe, Smagorinsky, Holloway, & Stone, 1970) of a k_z^{-3} en-⁵⁵⁹ ergy spectrum, where $7 \le k_z \le 20$ is the zonal wavenumber, with a corresponding range ⁵⁶⁰ of linear scales from 1 500 to 4 000 km. He emphasized, though, that the previously ac-⁵⁶¹ cepted analogies between 2-D and QG flows are not really sufficient to argue for a sim-⁵⁶² ilarity of the turbulent physics, given the fact that the baroclinic instability that injects ⁵⁶³ energy at $L_* \simeq 10^3$ km is highly 3-D.

Charney (1971) argued that a deeper reason for the k_z^{-3} spectrum is the possibil-564 ity, in geostrophic turbulence, to combine its two quadratic invariants into a single one, 565 which he termed "pseudo-potential vorticity," following previous work of his own. In 1971, 566 no sufficiently accurate observations or simulations were available for distinguishing among 567 several hypotheses for the atmospheric spectrum beyond $k_z = 20$. As such observations 568 did become available, Nastrom and Gage (1985) showed that (i) all the way down to 2.6 km, 569 there are no spectral gaps; and (ii) in fact, the k_z^{-3} spectrum associated with the k_z^{-3} 570 enstrophy cascade is followed by yet another (-5/3) slope, as the flow becomes 3-D at 571 the smallest scales; see Fig. 6.



Figure 6. Wavenumber spectra of zonal and meridional velocity composited from three groups of flight segments of different lengths; these groups were selected from over 6 000 commercial aircraft flights. The three types of symbols (blue, red, and yellow) show results from each group. The least-square-fitted straight lines indicate slopes of (-3) and (-5/3). The meridional wind spectra are shifted one decade to the right for greater legibility. The actual observational results show the typical deviations from straight lines in log-log coordinates. After Nastrom and Gage (1985).

Subsequent work, reviewed by Rhines (1979), Salmon (1998), and McWilliams (2011), among others, has greatly refined understanding of both atmospheric and oceanic turbulence, including the role of intermittency in deviating from simple -5/3 and -3 laws. The interest of GFD practitioners for 2-D turbulence, combined with the computationally much easier task of carrying out high-resolution, high-*R* calculations in 2-D led to an important discovery linking localized coherent structures with intermittency and increased predictability (Legras, Santangelo, & Benzi, 1988; McWilliams, 1984).

These structures were shown to be stable nonlinear solutions of the 2-D Euler equations. They represent, therewith, a depletion of nonlinearity in the turbulent flow field, locally inhibit the direct enstrophy cascade, and can survive for long times. As a result, the predictability time of large-scale dynamics increases, being no longer limited as much by the small-scale fluctuations; see the recent review of Haller (2015).

Sakuma and Ghil (1991) also reviewed some of the pertinent GFD literature, as well as proving stability for such localized coherent structures in the shallow-water equations, and emphasizing the analogies with magnetohydrodynamics (MHD). These analogies arise from the similarity between the role of the magnetic field vector **B** in the latter and the angular rotation vector Ω in GFD (e.g., Ghil & Childress, 1987; Hide, 1989).

Helicity **H** is an additional quadratic invariant in both 3-D and 2-D turbulence (Chorin, 2013, and references therein) but it is not sign-definite, and hence does not have the same effect as enstrophy on balancing energy transfers. Still, it does give rise to both inverse and dual cascades, which are important in GFD as well as in MHD. Helicity dynamics and bidirectional cascades are discussed in this issue by Pouquet, Stawarz, Rosenberg, and Marino (2019). A particularly important application is to astrophysics in general and to the solar wind in particular (e.g., Pouquet, Marino, Mininni, & Rosenberg, 2017).

597 5 A Few More Lampposts

So far we have covered, to the extent allowed by the constraints of this special issue, some fundamental concepts, methods and results of dynamical systems theory in Sec. 3 and of scale invariance in Sec. 4. We will sketch now, even more briefly, the skeleton of three additional lampposts that increasingly are helping shed some light on nonlinear effects in the geosciences.

5.1 The network lamppost

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We live in a world that is more and more dependent on networks of computing devices, as well as of people. Network theory thus is playing a bigger role in both understanding and modifying this world. Its applications extend to a rapidly growing number of areas, which include of course the geosciences.

Arguably, it is the Burridge and Knopoff (1967) model of friction along a fault that 608 is the first and still one of the most important models of this kind in the geosciences. The 609 model consists of a string of blocks connected by springs and can also be thought of as 610 a modification of the Fermi, Pasta, Ulam, and Tsingou (1955) model with differing non-611 linear spring laws and the addition of nonlinear friction forces. It provided an understand-612 ing of the gradual accumulation and sudden release of potential energy associated with 613 slow pre-seismic build-up and rapid displacement along an earthquake fault. The Burridge-614 Knopoff model, by its simple-model explanation of a baffling phenomenon, played a role 615 in nonlinear solid-Earth studies that resembles that of the Lorenz (1963a) model in non-616 linear atmospheric studies. 617

Network theory. More generally, network theory is a field of graph theory. A graph is
 an object with nodes that are connected by edges. The nodes and edges have certain at tributes, e.g. the physics at each node may be described by an ODE, while the link be-

tween two nodes may correspond to couplings between their ODEs. Such a network could

then correspond to the method of lines being applied to a PDE (e.g., Schiesser, 2012).



Figure 7. Schematic diagram of the network classes studied by Colon and Ghil (2017). (a)– (g) Simple network motifs: (a) linear networks; (b) trees; (c) isolated loops; (d) and (e) two interacting loops, connected through a pivotal node; (f) and (g) three interacting loops. (h)–(k) More complex classes of directed graphs, with n = 100 nodes and connectivity c = 4: (h) directed Erdős–Rényi (ER) networks; (i) scale-free networks with the specific, production-network distribution of in- and out-degree based on the Fujiwara and Aoyama (2010) dataset; (j) random acyclic (RA) networks in which production moves upward; and (k) a network of two interdependent RA networks — in the network at left, production moves upward, while it moves downward in the one at right. From Colon and Ghil (2017).

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A much simpler network could be a geometrically linear one, each of its nodes having an identical Boolean expression attached to it, while being instantaneously connected to neighboring nodes. Such a network is called a cellular automaton (e.g., Von Neumann, 1951; Wolfram, 1983). For illustration purposes, Fig. 7 shows a number of network classes recently studied by Colon and Ghil (2017).

A graph may be undirected, meaning that there is no distinction between the two 629 nodes associated with each edge, or its edges may be directed from one node to another. 630 The latter can be the case of river networks (Zaliapin, Foufoula-Georgiou, & Ghil, 2010, 631 and references therein), supplier–producer networks (e.g., Colon & Ghil, 2017; Fujiwara 632 & Aoyama, 2010), and many others (e.g., Albert & Barabási, 2002; Newman, 2010). A 633 good example of the former is an Ising model on a 2-D lattice in statistical mechanics 634 (e.g., Onsager, 1944) or a forest fire model of lesser (Malamud, Morein, & Turcotte, 1998) 635 or greater (Spyratos, Bourgeron, & Ghil, 2007) complexity. 636

The topology of a network can be described by its adjacency matrix $\mathbf{A} = (a_{ij})$, where the entry a_{ij} equals 1 or 0 depending on whether an edge does exist between the nodes *i* and *j* or not. Much of network theory concentrates on various topological features, and on measures of centrality (Albert & Barabási, 2002; Newman, 2010, and references therein). Each of these measures aims to rank nodes by their importance, and they differ in how this importance is defined.

⁶⁴³ The simplest measure of centrality is the number of edges that it participates in, ⁶⁴⁴ which is called the degree k. For directed graphs, one also distinguishes between the in-⁶⁴⁵ and out-degree. The distribution of degrees can be uniform, e.g., $k \equiv 1$ for either a linear graph or a simple cycle and $k \equiv 2$ for a braid (e.g., Coluzzi, Ghil, Hallegatte, & Weisbuch, 2011); it can be fully connected, $k \equiv N - 1$, where N is the number of nodes; it can be fully random, in which case the mean degree is $z = \bar{k} > N/2$; or it can be scale-free, i.e. it obeys a power law, with $p(k) \simeq k^{-\alpha}$, with $\alpha > 0$.

The dynamics on a network depends on the mathematical description of the state of each node, its set of linked neighbors, and on the nature of the links, i.e., on the coupling between the nodes. The state of each node can be described by a time series of realor Boolean-valued variables; such time series, in turn, can either be provided by observations or be the result of evolution equations, be they systems of ODEs, PDEs or of Boolean equations. The links, as previously mentioned, can be directed or not; they can also change in time in an evolving network.

Network applications, I: Boolean delay equations (BDEs). We will give here an appli cation to earthquake modeling and prediction. First, we introduce the framework of Boolean
 delay equations (BDEs) to describe the state of the nodes and the nature of the links.

A system of BDEs is a semi-discrete dynamical model with Boolean-valued variables that evolve in continuous time (Dee & Ghil, 1984; Ghil & Mullhaupt, 1985). The place occupied by BDEs in the world of dynamical systems is illustrated in Fig. 8.

Systems of BDEs can be classified into conservative or dissipative, in a manner that
parallels the classification of ODEs or PDEs. Solutions to certain conservative BDEs exhibit growth of complexity in time; such BDEs can be seen therefore as metaphors for
biological evolution or human history. Dissipative BDEs are structurally stable and exhibit multiple equilibria and limit cycles, as well as more complex, fractal solution sets,
such as Devil's staircases and "fractal sunbursts" (Ghil, Zaliapin, & Coluzzi, 2008, and
references therein).



Figure 8. Schematic diagram of the distinct classes of dynamical systems, in terms of the state x and time t. Note the links: the discretization of time t can be achieved by the Poincaré map (P-map) or a time-one map, leading from Flows to Maps. The opposite connection is achieved by suspension. To go from Maps to Automata one has to discretize the statetion and smoothing lead in the opposite direction. Similar connections lead from BDEs to Automata and to Flows, respectively. Please see the glossary in Table A.1 for acronyms. Modified after Mullhaupt (1984).

More generally, Fig. 8 raises the question of which one of the various types of dynamical systems therein apprehends best the complexities of the world surrounding us? Clearly, the amount of detail provided by each increases as we move from the **Automata** at the bottom to the **Flows** at the top of the rhomboid in the figure.

Thus, one level at which one can read the figure is as an illustration of the hier-673 archy of models discussed further in Sec. 6. But there is also another way of reading it. 674 In fact, each one of the downward-pointing arrows between a class of models and an ad-675 jacent one below it represents a perfectly self-consistent simplification, obtained as one 676 discretizes either time t or space x. We all know how to obtain an ordinary or partial 677 difference equation (O ΔE or P ΔE) from an ODE or PDE respectively, by discretizing 678 time. The extent to which the solutions of the $O\Delta E$ so obtained converge to those of the 679 corresponding ODE depend on certain stability and consistency properties of the ODE's 680 right-hand side (e.g., Isaacson & Keller, 2012). 681

In the case of a P-map, topological properties are preserved as one goes from a Flow to a Map, and maps are easier to study. Under certain technical assumptions dealing with smoothness and one-to-oneness, one gets most of what one wants from studying the map, since the suspension that goes back from the Map one has studied to the Flow can be proven to have the right properties. For instance, a periodic solution of the Flow will appear as a point in the Map and vice-versa.

Can similar equivalence results be proven for other pairs of arrows in Fig. 8? There exists numerical evidence, at least, to suggest that it might be true under suitable circumstances. Two such examples of, at least partial, equivalences are given below.

Saunders and Ghil (2001) provided a thorough BDE treatment of the El-Niño/SouthernOscillation (ENSO) mechanism postulated by J. J. Bjerknes (1969). Their Fig. 7 of the
"Devil's bleachers" shows the dependence of the model ENSO's periodicity on two model
parameters that characterize the wave propagation along the equator and the local ocean–
atmosphere heat exchanges, respectively; see also Ghil, Zaliapin, and Coluzzi (2008, Fig. 6).
The projection of the latter 3-D axionometric plot on its 2-D parameter plane is strikingly similar to Fig. 9 herein.

This similarity is the first example of good numerical correspondence between two adjacent vertices of the rhomboid in Fig. 8, since the "Devil's terrace" in Fig. 9 is based on the intermediate model of Jin, Neelin, and Ghil (1994, 1996). The latter model is governed by a system of nonlinear PDEs in one space dimension, namely longitude along the equator, with the parameters μ and δ_s that appear in Fig. 9 here; the two play a roughly similar role in the PDE model to that of the two parameters, local and global, in Ghil, Zaliapin, and Coluzzi (2008, Fig. 6).

The early applications of BDEs to the climate sciences only used small systems of 705 a few variables (e.g., Darby & Mysak, 1993). The first BDE application on a network 706 was to a very simple model of seismic activity. The model consists of a ternary tree with 707 a direct cascade of loading from a top node that represents a major plate, down to smaller 708 and smaller plates. This direct cascade collides with an inverse cascade of failures that 709 starts with the bottom nodes and travels up to larger and larger plates, possibly all the 710 way to the top, depending on the delayed effects of healing (Zaliapin, Keilis-Borok, & 711 Ghil, 2003a, 2003b, and references therein). 712

⁷¹³ Clearly, to analyze extensively and systematically systems of 3^L ODEs would be ⁷¹⁴ fairly prohibitive, even for a tree depth L as small as 6 or 7. Fairly surprisingly, though, ⁷¹⁵ the BDE model could be easily analyzed as a function of the loading and healing param-⁷¹⁶ eters, yielding the three well-known seismic regimes of high (**H**), low (**L**) and intermit-⁷¹⁷ tent (**I**) seismicity, as shown in Fig. 10.



Figure 9. Regimes of subharmonic, frequency-locked and chaotic solutions in the (μ, δ_s) parameter plane; here μ is the local ocean-atmosphere coupling parameter and δ_s is an ocean mixed layer parameter that determines the model's intrinsic periodicity, in the absence of the annual cycle. Black areas represent regions where no interannual signal is present. Color scale represents the frequency ratio of the interannual oscillation to the annual cycle in regimes that are frequency locked; e.g., 0.25 indicates one ENSO cycle every four yeas, 0.222 indicates two ENSO cycles repeating every nine years. Chaotic regimes are plotted in grey. Courtesy of Fei-Fei Jin.

- The three regimes are characterized, respectively, by the following key features: 718 H: A cyclo-stationary behavior, with the maximum earthquake intensity reached on 719 every cycle; 720 I: A highly intermittent behavior, with irregular intervals between major earthquakes 721 and high, but not necessarily maximum intensity of the latter; and 722 L: A fairly low and nearly constant level of white-noise-like seismic activity overall. 723 These features are present in observations (e.g., Press & Allen, 1995; Romanow-724 icz, 1993), as well as in much more detailed and sophisticated models (Ben-Zion, 2008, 725 and references therein). On the whole, it is the intermittent behavior that is most widespread, 726 but a particular region can also change regime over time, as parameter values that af-727 fect the collective behavior of earthquakes and faults change. This is the second numer-728 ical example of at least partial equivalence between a **BDE** model and a **Flow**. 729 Network applications, II: Teleconnections and centrality. A very different network-theoretical 730 setting was applied to climatic variability, and we discuss it now very succintly herein, 731 following Tsonis and Swanson (2008) and Donges, Zou, Marwan, and Kurths (2009a). 732 The idea that meteorological, oceanographic or coupled climatic variability might involve 733 "centers of action" that are widely separated in space goes back to Hildebrandsson and 734 Teisserenc de Bort (1898) and to G. Walker's "teleconnections" between them (Walker 735 & Bliss, 1932). The statistical and dynamical study of such teleconnections engaged many 736 important figures in the history of these disciplines over the last century (J. Bjerknes, 737
- ⁷³⁸ 1969; Hoskins & Karoly, 1981; Wallace & Gutzler, 1981).



Figure 10. Three seismic regimes in the internal dynamics of the BDE model, for a tree depth of L = 6, i.e. for n = 1093 nodes. The panels show the density $\rho = \rho(t)$ of broken elements in the system. See Figs. 7 and 8 in Zaliapin et al. (2003a) for loading and healing parameter values and other details. (a) Regime **H**; (b) Regime **I**; and (c) Regime **L**. Note the difference in vertical scale for the three panels. Reproduced from Zaliapin et al. (2003a) with kind permission of Springer Science and Business Media.

One of the main approaches used by A. A. Tsonis and colleagues (e.g., Tsonis, Swan-739 son, & Kravtsov, 2007), as well as by the groups around J. Kurths (e.g., Donges, Zou, 740 Marwan, & Kurths, 2009b) and around S. Havlin (e.g., Gozolchiani, Havlin, & Yamasaki, 741 2011), was labeled complex networks (CNs) and essentially consists in identifying the 742 strongest correlations among time series at different locations. Boers, Bookhagen, Mar-743 wan, Kurths, and Marengo (2013) review relevant climate network literature and pro-744 vide an application to the South American Monsoon System and to the spatial patterns 745 associated with synchronization of extreme rainfall events; see also Boers et al. (2019) 746 for a global analysis of extreme-rainfall teleconnections. 747

Many of the dynamical studies of the atmosphere's low-frequency variability that 748 involve teleconnections have used the highly simplified geometry of a so-called β -channel 749 with periodicity in longitude and solid walls along parallels to the north and south of 750 the channel, away from both the North Pole and the Equator (Ghil & Childress, 1987; 751 Pedlosky, 1987); see also Sec. 3.2 herein. Colon and Ghil (2017, and references therein) 752 showed that signal propagation in networks with distinct topologies in the plane can have 753 very different properties; these properties are quite likely to be entirely different, in turn, 754 from those of networks on the sphere. It is the latter that are most relevant to dynam-755 ical studies on a spherical domain, whether linear (e.g., Hoskins & Karoly, 1981) or non-756 linear (e.g., Legras & Ghil, 1985). Thus BDE models in such geometrically different set-757 tings as shown in Fig. 7 here, on the plane and on the sphere, might complement or even 758 guide further network-based investigations of teleconnections and climate variability. 759

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5.2 The fluctuation-dissipation lamppost

Fluctuation-dissipation theory (FDT) has its roots in the classical theory of statistical mechanics of many-particle systems in thermodynamic equilibrium. The idea is very simple: the system's return to equilibrium will be the same whether the perturbation that modified its state is due to a small external force or to an internal, random fluctuation (e.g., Kubo, 1966, and references therein). We outline below the simplest cases, and point to the generalization to systems out of equilibrium, such as the climate system or a network of seismic faults.

Figure Fluctuation-dissipation theory (FDT). Like so many other ideas in the physical sciences, FDT goes back to Einstein and his Annus mirabilis, 1905. Einstein (1905) formulated the problem of the Brownian motion of a large particle immersed in a fluid formed of many small ones as follows. The presentation here follows Ghil and Childress (1987, Sec. 10.3), where further details can be found. Consider the large particle as moving on a straight line with velocity u = u(t), subject to a random force $\eta(t)$ and to linear friction $-\lambda u$, with coefficient λ . The equation of motion is

$$du = -\lambda u dt + \eta(t), \qquad (7)$$

The random force $\eta(t)$ is assumed to be a "white noise," i.e., it has mean zero $\mathcal{E}[\eta(t;\omega)] = 0$ and autocorrelation $\mathcal{E}[\eta(t;\omega)\eta(t+s;\omega)] = \sigma^2 \delta(s)$, where $\delta(s)$ is a Dirac function, σ^2 is the variance of the white-noise process, ω labels the realization of the random process, and \mathcal{E} is the expectation operator, which averages over the realizations ω . Alternative notations for the latter are the overbar, in climate sciences, and the angle brackets, in quantum mechanics, $\mathcal{E}[F] := \bar{F} := \langle F \rangle$.

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⁷⁶² Equation (7), with $\eta = \sigma dW$, is a linear stochastic differential equation (SDE) ⁷⁸³ of a form that is now referred to as a Langevin equation, where W(t) is a normalized Brow-⁷⁸⁴ nian motion or Wiener process. The necessary stochastic concepts are explained at a com-⁷⁸⁵ fortable level in Dijkstra (2013, Ch. 3). Einstein's main results are that

$$\mathcal{E}[u^2] = \frac{\tau^*}{2\lambda}, \qquad \mathcal{E}[x^2] = \frac{\tau^*}{\lambda^2}t, \qquad (8)$$

with $x(t) = x_0 + \int_0^t u(s) ds$ the displacement of the particle and $\tau^* = \int_{-\infty}^{+\infty} \sigma^2 \delta(s) ds$. There are two remarkable features in Eqs. (8) above. First, the fact that the variance $\mathcal{E}[x^2]$ of the displacement is proportional to time. This leads to the mathematical theory of SDEs distinguishing between the time differential dt and the stochastic differential dW, since $\int_0^t ds = t$, while $\int_0^t dW(s) = t^2$; in other words, $dW \propto (dt)^{1/2}$.

⁷⁹² Second, the friction coefficient λ characterizes in this simple case a dissipation of ⁷⁹³ the fluctuations, since $\mathcal{E}[u(t)] = \mathcal{E}[u_0] \exp(-\lambda t)$. More generally, as Kubo (1966, Se. 2) ⁷⁹⁴ points out, the dissipation constant is $D = \lim_{t\to\infty} \mathcal{E}[(x(t) - x(0))^2]$, and one gets

$$\mu = \frac{D}{kT} = \frac{1}{kT} \int_0^\infty \mathcal{E}[u(t_0)u(t_0 + t)] dt;$$
(9)

here $\mu = 1/\lambda$ is the mobility of the particles, T is the temperature of the thermal bath, and k is the Boltzmann constant. And *voilà*, you have the original and simplest version of FDT, where the acronym also stands for the fluctuation-dissipation theorem.

FDT in general can thus be used either to infer the statistics of thermal fluctua-799 tions from the drag law (e.g., Nyquist, 1928) with known λ or the reverse (e.g., Onsager, 800 1931). The former is more practical in laboratory or industrial situations, like an elec-801 tric circuit, where it is relatively easy to measure the admittance or impedance of the 802 system and we are not that interested in details of what happens at such-and-such a lo-803 cation in an individual wire. It is the latter, though, that is more useful for natural sys-804 tems, like the climate system, where we have many observations localized in time and 805 space, and wish to estimate future response to as-yet-unknown forcings. 806

All of the above apply, however, to systems in thermodynamic equilibrium, and most natural systems — including, of course, the climate system — are not. As Kubo (1966) notes, it is precisely for this reason that FDT has attracted much greater attention "recently" — i.e., in the middle of the 20th century — as it has been extended to "nonequilibrium states [and to] irreversible processes in general." ⁸¹² *FDT applications.* Cecil E. ("Chuck") Leith (1975) showed that FDT applies to a 2-D ⁸¹³ or QG turbulent flow with two integral invariants, kinetic energy E and enstrophy Z, ⁸¹⁴ under additional assumptions of normal distribution of the realizations and stationar-⁸¹⁵ ity. Such flows were reviewed in Sec. 4.2 herein. Subject to the above assumptions (Leith, ⁸¹⁶ 1975), the unperturbed covariance matrix **U** and the average response matrix **G** are then ⁸¹⁷ related by the FDT relation

$$\mathbf{U}(\tau) = \mathbf{G}(\tau)\mathbf{U}(0), \qquad (10)$$

where τ is the interval over which we wish to estimate the response of the system to an arbitrary external forcing. Noting that the regression matrix **R** for linear prediction of the stationary multivariate time series with lagged covariance matrix **U** equals **G**, one then gets that

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$$\mathbf{R}(\tau) = \mathbf{U}(\tau)\mathbf{U}^{-1}(0).$$
(11)

Since the problem of estimating the response of the climate system to both nat-824 ural and anthropogenic forcing on multidecadal time scales is becoming scientifically, as 825 well as socio-economically, more and more important, Eqs. (10, 11) present a huge ad-826 vantage over conventional methods of attacking this problem. Indeed, successive assess-827 ment reports of the Intergovernmental Panel on Climate Change (IPCC: e.g., Houghton, 828 Jenkins, & Ephraums, 1990; IPCC, 2007) carried out ensembles of high-end global cli-829 mate model simulations with a number of prescribed scenarios of such forcings, but were 830 limited by the enormous computational expense of such simulations. 831

In comparison, the linear response of Eq. (11) can be computed, at least in a reduced subspace of leading eigenvectors of the covariance matrix \mathbf{U} — the so-called empirical orthogonal functions ((EOFs: Jolliffe & Cadima, 2016; Preisendorfer, 1988) — relatively easily. And, once that is done, changes in any prescribed scalar or vector observable, say in the globally averaged surface air temperatures or in the entire sea surface temperature field $\{T_{ij}(t)\}$, can be evaluated in turn for arbitrary small forcings $\delta \mathbf{f}(t)$.

Let $\hat{\mathbf{U}}$ and $\hat{\mathbf{R}}$ be the reduced versions of \mathbf{U} and \mathbf{R} , respectively, with $\{\hat{\mathbf{u}}_{\alpha}\}$ the EOFs of $\hat{\mathbf{U}}$, and $\{T_{\alpha}(t)\}$ the projection of said temperature field onto the corresponding EOFs. Component-wise, we can write, following Leith (1975), that

 $\delta T_{\alpha}(t) = \int_{-\infty}^{t} \sum_{\beta} \hat{R}_{\alpha\beta} \delta f_{\beta}(s) \mathrm{ds} \,. \tag{12}$

Once more, this is all very helpful for systems in thermodynamic equilibrium and normally distributed stochastic processes, which turbulent fluids and other subsystems of the climate system are not. Given a normal distribution of an initial state, nonlinearity will break that happy state of affairs to a greater or lesser degree.

Generalizations to systems out of equilibrium have been developed since the early 846 1950s (e.g., Callen & Welton, 1951) and many references appear in Kubo (1966). But 847 a particularly fruitful change in point of view was provided by D. Ruelle (1998, 2009), 848 who considered the problem in the setting of dynamical systems theory, rather than that 849 of statistical mechanics. The former point of view is justified in this context by the so-850 called chaotic hypothesis (e.g., Gallavotti & Cohen, 1995), which states, in rough terms. 851 that chaotic systems with many degrees of freedom possess a physically relevant invari-852 ant measure ν such that averaging with respect to this measure is equivalent to averag-853 ing in time over the system's attractor. This property suffices for using the measure ν 854 in evaluating changes in any observable of the system with respect to any small pertur-855 bation, and we return to this point in Sec. 5.3 below. 856

In the footsteps of Leith (1975), several applications of FDT to climate (e.g., Abramov & Majda, 2008; Gritsun & Branstator, 2007) and ocean (Wirth, 2018) models have been carried out. It is V. Lucarini and colleagues, though, who have systematically applied Ruelle's linear response theory to generalize both equilibrium and transient climate sensitivity (Lucarini, Ragone, & Lunkeit, 2016; Ragone, Lucarini, & Lunkeit, 2015); they also obtained the resonant response and its spatial patterns in one or more frequency bands for time-dependent forcing (Lucarini et al., 2014, and references therein).

The study of resonant response is made possible by the study of the susceptibility operator $\tilde{\mathbf{S}}$, which is given by the Fourier transform of the linear response operator $\tilde{\mathbf{G}}$. The latter operator requires a generalization of the response matrix \mathbf{G} defined in Eq. (10) to the non-equilibrium setting, for which we refer to the work of Ruelle (1998, 2009) and of Lucarini et al. (2014).

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5.3 The random dynamical systems (RDS) lampost

In Sec. 3, we have considered mainly the deterministically nonlinear approach to 870 apprehend the complexities of geosciences in general and climate variability in partic-871 ular. In the previous subsection, we have also hinted, via the Langevin equation (7), at 872 the complementary approach of stochastically linear dynamics to climate variability and 873 change, due largely to K. Hasselmann (1976). Imkeller and Von Storch (2001, and ref-874 erences therein) give a broader view of this approach. In the present subsection, we briefly 875 outline a promising unification of the two complementary approaches to climate variabil-876 ity and change, via the theory of random dynamical systems (RDS). 877

The theory of nonautonomous (NDS) and random (RDS) dynamical systems. As a result of sensitive dependence on initial data and on parameters, numerical weather forecasts, as well as climate projections, are both expressed these days in probabilistic terms. It is, in fact, more convenient — and becoming more and more necessary — to rely on a model's (or set of models') probability density function (PDF) rather than on its individual, pointwise simulations or predictions.

We summarize here results on the surprisingly complex statistical structure that characterizes stochastic nonlinear systems. This complex structure does provide meaningful physical information that is not described by the PDF alone; it lives on a random attractor, which extends the concepts of a strange attractor and of the invariant measure that is supported by it, from the deterministic to the stochastic framework. It is this extension that we describe, in the simplest possible terms, forthwith.

On the road to including random effects, one needs to realize first that the climate system, as well as any of its subsystems, is not closed: it exchanges energy, mass and momentum with its surroundings, whether other subsystems or the interplanetary space and the solid earth. Typical applications of dynamical systems theory to climate variability so far have only taken into account exchanges that are constant in time, thus keeping the model — whether governed by ODEs, PDEs or other differential equations — autonomous; i.e., the models had coefficients and forcings that were constant in time.

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Succinctly, one can write such a system as

$$\mathbf{X} = \mathbf{f}(\mathbf{X}; \boldsymbol{\mu}), \qquad (13)$$

where \mathbf{X} now may stand for any climate or other geophysical field, while \mathbf{f} is a smooth 800 function of X and of the vector of parameters μ , but does not depend explicitly on time. 900 Being autonomous greatly facilitated the analysis of a model's solutions. For instance, 901 two distinct trajectories, $\mathbf{X}_1(t)$ and $\mathbf{X}_2(t)$, of a well-behaved, smooth autonomous sys-902 tem cannot pass through the same point in phase space, which helps describe the sys-903 tem's phase portrait. So does the fact that we only need to consider the behavior of so-904 lutions $\mathbf{X}(t)$ as we let time t tend to $+\infty$: the resulting sets of points are — possibly mul-905 tiple — stationary solutions, periodic solutions, and chaotic sets. 906

We know only too well, however, that the seasonal cycle plays a key role in climate variability on many time scales, while orbital forcing is crucial on the Quaternary time

scales of many millennia, and now anthropogenic forcing is of utmost importance on interdecadal time scales. How can one take into account such time-dependent forcings, and analyze the nonautonomous systems, written succinctly as

$$\dot{\mathbf{X}} = \mathbf{f}(\mathbf{X}, t; \boldsymbol{\mu}), \tag{14}$$

(15b)

to which they give rise? In Eq. (14), the dependence of \mathbf{f} on t may be periodic, $\mathbf{f}(\mathbf{X}, t + P) = \mathbf{f}(\mathbf{X}, t)$, as in various ENSO models, with P = 12 months, or monotone, $\mathbf{f}(\mathbf{X}, t + \tau) \ge \mathbf{f}(\mathbf{X}, t)$ for $\tau \ge 0$, as in studying scenarios of anthropogenic climate forcing.

To illustrate the fundamental character of the distinction between (13) and (14), consider the simple scalar version of these two equations:

$$\dot{X} = -\beta X \,, \tag{15a}$$

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respectively. We assume that both systems are dissipative, i.e. $\beta > 0$, and that the forcing is monotone increasing, $\gamma \ge 0$, as would be the case for anthropogenic forcing in the industrial era. Lorenz (1963a) pointed out the key role of dissipativity in giving rise to strange, but attracting solution behavior, while Ghil and Childress (1987, Sec. 5.4) emphasized its importance and pervasive character in climate dynamics. Clearly the only attractor for the solutions of Eq. (15a), given any initial point $X(0) = X_0$, is the fixed point X = 0, attained as $t \to +\infty$.

 $\dot{X} = -\beta X + \gamma t \,,$

For the nonautonomous case of Eq. (15b), though, this forward-in-time approach yields blow-up as $t \to +\infty$, for any initial point. To make sense of what happens in the case of time-dependent forcing, one introduces instead the pullback approach, in which solutions are allowed to still depend on the time t at which we observe them, but also on a time s from which the solution is started, $X(s) = X_0$; presumably $s \ll t$. With this little change of approach, one can easily verify that

$$|X(s,t;X_0) - \mathcal{A}(t)| \to 0 \quad \text{as} \quad s \to -\infty,$$
(16)

for all t and X_0 , where the pullback attractor (PBA) $\mathcal{A}(t)$ is given explicitly by

$$\mathcal{A}(t) = \frac{\gamma(t - 1/\beta)}{\beta} \,. \tag{17}$$

We thus obtain, in this pullback sense, the intuitively obvious result that the solutions, if started far enough in the past, all approach the time-dependent attractor set $\mathcal{A}(t)$, which grows linearly in time and thus follows the linear forcing.

For the more complicated case of RDSs, where the random attractor \mathcal{A} depends 934 on the particular realization ω of the driving noise, $\mathcal{A} = \mathcal{A}(t; \omega)$, we refer to Chekroun, 935 Simonnet, and Ghil (2011); Ghil, Chekroun, and Simonnet (2008) and Dijkstra (2013, 936 Ch. 4). The beauty and complexity of the results is illustrated herein by four snapshots 937 at successive times $\{t_1, \ldots, t_4\}$ for the Lorenz (1963a) model perturbed by multiplicative 938 noise; see Fig. 11. Note that the support of the invariant measure $\nu(t;\omega)$ may change 939 quite abruptly, from time t to time $t+\Delta t$; see the related short video given as Supple-940 mentary Information in Chekroun et al. (2011), as well as at https://vimeo.com/240039610. 941 This video shows more clearly than a simple sequence of snapshots the interaction be-942 tween the nonlinearly deterministic dynamics and the stochastic perturbations. 943

NDS and RDS applications. We outline here briefly an application of the theory of nonautonomous dynamical systems (NDSs) to the so-called double-gyre problem of the wind-

⁹⁴⁷ The large-scale, near-surface flow of the mid-latitude oceans is dominated by the pres-

ence of a larger, anticyclonic and a smaller, cyclonic gyre. The two gyres share the east-

⁹⁴⁹ ward extension of western boundary currents, such as the Gulf Stream or Kuroshio, and

driven ocean circulation, following Pierini, Ghil, and Chekroun (2016) and Ghil (2017).



Figure 11. Four snapshots of the stochastically perturbed Lorenz (1963a) model's random attractor $\mathcal{A}(\omega)$ and the invariant measure $\nu(\omega)$ supported on it. The model can be written componentwise as $dX_i = f(\mathbf{X}; \boldsymbol{\mu})dt + \sigma X_i dW$, i = 1, 2, 3, with $\mathbf{X} \equiv (X_1, X_2, X_3) \equiv (X, Y, Z)$ and the parameter values $\boldsymbol{\mu}$ equal to the classical ones — normalized Rayleigh number r = 28, Prandtl number Pr = 10, and normalized wave number b = 8/3 — while the noise intensity is $\sigma = 0.5$ and the time step is $\delta t = 5 \cdot 10^{-3}$. The color bar used is on a log-scale and quantifies the probability to end up in a particular region of phase space; shown is a projection of the 3-D phase space (X, Y, Z) onto the (X, Z)-plane. Notice the complex, interlaced filament structures between highly (yellow) and moderately (red) populated regions. The time interval Δt between two successive snapshots — moving from left to right and from top to bottom — is $\Delta t = 0.0875$. Weakly populated regions cover an important part of the random attractor and are, in turn, entangled with regions that have near-zero probability (black). [After Chekroun et al. (2011) with permission from Elsevier.]

are induced by the shear in the winds that cross the respective ocean basins. Results for this problem in the presence of a surface wind stress that is constant in time were reviewed briefly in Sec. 3.2; see, in particular, Figs. 1 and 2 there.

The model domain used by Pierini et al. (2016) is rectangular, like those in Sec. 3.2, and the model equations are based on the equivalent barotropic QG vorticity equation of Simonnet et al. (2005). This PDE is projected here onto four modes that take into account the presence of a western boundary current by including an exponentially decaying factor for the streamfunction field, as suggested by Jiang et al. (1995). The forcing is deterministic, aperiodic, and dominated by interdecadal variability.

The autonomous system exhibits a global bifurcation associated with a homoclinic orbit, like the one illustrated in Fig. 2 herein; it occurs at the value $\gamma = 1.0$ for the parameter γ that scales the intensity of the forcing. Pierini et al. (2016, Appendix) have rigorously demonstrated the existence of a global PBA for the time-dependent forcing case in the weakly dissipative, nonlinear model under discussion, based on general results for nonautonomous dynamical systems (Carvalho, Langa, & Robinson, 2012; Kloeden & Rasmussen, 2011).

Numerically, though, this unique global attractor seems to possess two separate local PBAs, as apparent from Fig. 12. Panels (a) and (b) in the figure refer to parameter values that correspond to subcritical vs. supercritical values of γ in the autonomous model, respectively. While formula (16) seems to require an infinite pullback time, it turns out that convergence to the PBAs in this model only takes about 15 yr.

⁹⁷¹ The mean normalized distance Δ plotted in the figure is defined as $\Delta = \langle \delta_n \rangle_{\tilde{T}}$. ⁹⁷² Here δ_t is the distance, at time t, between two trajectories of the model that were a dis-⁹⁷³ tance δ_0 apart at time $t = t_0$, and the normalized distance $\delta_n = \delta_t / \delta_0$ is averaged over the whole forward time integration \tilde{T} of the available trajectories, with $\tilde{T} = 400$ yr.



Figure 12. Mean normalized distance Δ for 15 000 trajectories of the double-gyre ocean model: (a) $\gamma = 0.96$, and (b) $\gamma = 1.1$. Reproduced from Pierini et al. (2016), with the permission of the American Meteorological Society.

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The maps of Δ in Fig. 12 reveal large chaotic regions where $\delta_n \gg 1$ on average (warm colors) but also non-chaotic regions, in which $\sigma \leq 1$ (blue) and thus initially close trajectories do remain close on average. The rectangular regions in the two panels that are labeled by letters A and B and by numbers 1–4 correspond to subdomains of the initial set Γ ; see Pierini et al. (2016, Sec. 5). The numerical evidence in Fig. 12 suggests that the boundary between the two types of local attractors has fractal properties.

In the autonomous context, the coexistence of topologically distinct local attractors is well known in the climate sciences (Dijkstra, 2013; Dijkstra & Ghil, 2005; Ghil & Childress, 1987; Simonnet et al., 2005, and references therein). The coexistence of local PBAs with chaotic vs. non-chaotic characteristics, within a unique global PBA, as illustrated by Fig. 12 here, seems to be novel, at least in the geosciences literature.

Climate sensitivity and Wasserstein distance. Tamás Tél and associates (Bódai, Károlyi, 986 & Tél, 2011; Bódai & Tél, 2012; Drótos, Bódai, & Tél, 2015) have applied NDS and RDS 987 concepts and methods to climate modeling, while emphasizing the distinctions and ad-988 vantages of the pullback point of view with respect to the much more common one of 989 ensemble simulations (Houghton et al., 1990; IPCC, 2007, and references therein). The-990 oretically speaking, the latter practice merely approximates the PDF that would be ob-991 tained by the forward-in-time solution of the Fokker-Planck equation associated with a 992 given model, a solution that is impossible to obtain for high-dimensional climate mod-993 els (Leith, 1974). An important point raised by the work of these authors is that, aside 994 from the computational difficulties with ensemble size and the PDF approximation, the 995

finite-time averages obtained by the ensemble method do not reflect correctly the changesin time of the climate system's statistics in a transient world.

Following up on the work of Lucarini and colleagues (e.g., Lucarini et al., 2014) in 998 applying linear response theory to climate change and on that of Tél and associates above, 999 Ghil (2015, 2017) proposed using the Wasserstein or "earth mover's" distance $\Delta_{\rm W}$ to gen-1000 eralize the concept of equilibrium climate sensitivity; $\Delta_W \nu$ is the distance between two 1001 invariant measures of equal mass, ν_1 and ν_2 , on a metric space, like an n-dimensional 1002 Euclidean space (Dobrushin, 1970; Kantorovich, 2006; Monge, 1781; Wasserstein, 1969). 1003 Roughly speaking, and dropping the subscript 'W', $\Delta \nu$ represents the total work needed 1004 to move the "dirt" (i.e., the measure) from a trench you are digging to another one you 1005 are filling, over the distance between the two trenches.



Figure 13. Climate sensitivity (a) for an equilibrium model; (b) for a nonequilibrium, oscillatory model; and (c) for a nonequilibrium, chaotic model, including possibly random perturbations. As a forcing (atmospheric CO_2 concentration, say, dash-dotted line) changes suddenly, global temperature (light solid) undergoes a transition: in panel (a) only the mean temperature changes; in panel (b) the mean adjusts, as it does in panel (a), but the period, amplitude and phase of the oscillation can also decrease, increase or stay the same, while in panel (c) the entire intrinsic variability changes as well. From Ghil (2017), with permission from the American Institute of Mathematical Sciences.

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Equilibrium climate sensitivity $\gamma_{\rm e}$ is usually defined as $\gamma_{\rm e} = \partial \bar{T} / \partial \mu$, where \bar{T} is the globally and seasonally averaged surface air temperature and μ is a parameter, such as the suitably normalized incoming net radiation. It was introduced by Charney et al. (1979) and used extensively by the IPCC's first three assessment reports (e.g., Houghton et al., 1990). The associated evolution of $\bar{T}(t)$ for a jump in CO₂ concentration in a scalar linear model is illustrated in Fig. 13(a).

¹⁰¹³ This picture is clearly oversimplified, given the complex evolution of temperatures ¹⁰¹⁴ in the historical record. Figure 13(b) illustrates $\overline{T}(t)$ in a world in which ENSO would ¹⁰¹⁵ be purely periodic, and Fig. 13(c) illustrates schematically the even more realistic case ¹⁰¹⁶ of temperature evolution in a deterministically chaotic, turbulent and stochastically per-¹⁰¹⁷ turbed system. For such a system, a better definition of climate sensitivity would be

$$\gamma_{\rm cs} = \frac{\Delta\nu}{\Delta\mu};\tag{18}$$

Δ.,

here { $\nu_i = \nu_i(\mu_i)$: i = 1, 2} can be the invariant measures on a system's strange attractor, in the autonomous case, or its PBA, whether deterministically nonautonomous or random, and { $\nu_i = \nu_i(\mu_i)$: i = 1, 2} are the corresponding values of a parameter, such as the forcing parameter γ in the Pierini et al. (2016) model in Fig. 12. In this sense, one can think of Eq. (18) as a generalization of the linear response in Eq. (12). ¹⁰²⁴ The Wasserstein distance $\Delta(\nu_1, \nu_2)$ between two measures ν_1 and ν_1 on a metric ¹⁰²⁵ space X is defined as

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$$\Delta(\nu_1, \nu_2) = \inf \mathcal{E}[m(\xi, \eta)]; \qquad (19)$$

here *m* is a metric, the infimum is taken over all possible pairs of random variables ξ and η that have the distributions ν_1 and ν_2 , respectively, and \mathcal{E} is the corresponding expectation. When $X = \mathbb{R}$ is just the real line and *m* the usual Euclidean metric, let Q_1 and Q_2 be the PDFs of the absolutely continuous measures ν_1 and ν_2 . Then

$$\Delta_{\rm W}(Q_1, Q_2) = \int |G_1(x) - G_2(x)| \mathrm{d}x \,, \tag{20}$$

where G_1 and G_2 are the cumulative distribution functions of the two PDFs Q_1 and Q_2 , respectively (Vallender, 1974).

In general, though, the shape of the two trenches as well as the depth along the trench — i.e., both the support of the measure and its density — can differ. Chekroun, Ghil, and Neelin (2018) have described a so-called critical transition of this type — essentially a generalized tipping point — for a simple ENSO model with a seasonal cycle. In such a case, the actual distance calculations require some model reduction to a smaller phase space (e.g., Kondrashov, Chekroun, & Ghil, 2015, and references therein) and they have to rely on more advanced methodologies in the reduced space (e.g., Villani, 2009).

Robin, Yiou, and Naveau (2017) have argued that the usual quadratic norms used to judge distance in the phase space of climate models do not provide an easy interpretation of the dynamics on the attractor. They calculated the Wasserstein distance between the PBAs of the Lorenz (1984) model subject to summer vs. winter forcings and showed how this metric does provide a more intuitive discrimination between the two.

Vissio and Lucarini (2018) evaluated the performance of a stochastic parametriza-1046 tion by using the Wasserstein distance to measure the difference between the behavior 1047 of a full fast-slow system and that of a reduced system in which the parametrization had 1048 replaced the fast subsystem. In their setting, the Lorenz (1984) model governed the slow 1049 behavior and the Lorenz (1963a) model the fast one. Applying the Wouters and Lucarini 1050 (2016) parametrization to the fast component, they showed that "Wasserstein distance 1051 provides a robust tool for assessing the quality of the parametrization, and that mean-1052 ingful results can be obtained when considering [a very coarse-grained] representation 1053 of the phase space." 1054

¹⁰⁵⁵ 6 The Way Ahead: Prediction and Prediction

There are two important meanings of "prediction" in the physical sciences. First, there is the relatively straightforward meaning of predicting in time. There are many other areas of science in which one needs or, at least, wishes to predict: the evolution of an individual illness or of an epidemic, that of human population numbers, the outcomes of national, ethnic or class conflicts.

In the geosciences, this kind of prediction is clearly of paramount importance: pre-1061 dicting routine weather progress, as well as extreme weather events, like a hurricane land-1062 fall or a flash flood; earthquakes, volcanic erruptions; global and regional temperatures 1063 and precipitations many years from now. In all these cases, the usefulness of detailed, 1064 physics-based models is largely predicated on the understanding of the phenomena and 1065 processes involved. Thus, good predictions validate the knowledge that entered a spe-1066 cific model or class of models, while unsatisfactory ones give a sense of the distance still 1067 ahead in the field of interest. 1068

Second, there is the sense in which a theoretical model predicts a phenomenon that
had not been observed at the time of the prediction. The paradigmatic example of this
kind of prediction is the observational confirmation (Dyson, Eddington, & Davidson, 1920)

of the Einstein (1916) prediction of light rays' bending in the gravity field of the Sun.
 More precisely, the 1919 solar eclipse confirmed that the bending of starlight passing near
 the Sun was about twice as much as predicted by using Newtonian gravity alone. This
 kind of prediction tends to be rare, and rather undervalued in the geosciences.

Real-time forecasting. It is clear that numerical weather prediction (NWP) skill has steadily
 improved over the years, since its post-World War II beginnings in the mid-1950s (Thomp son, 1961). Operational forecasts with good local accuracy in surface air temperatures
 for up to 3–5 days are fairly routine, although precipitation forecasts, with their greater
 dependence on more poorly resolved vertical velocities are typically less accurate.

Global forecasts of atmospheric fields on larger scales are much of the time rather accurate up to ten days, thanks to improvements in the physical parametrizations of subgridscale phenomena and the assimilation of massive amounts of remote-sensing data, along with the substantial increase of spatial resolution due to huge increases in computing power and storage capacity.

It appears that the NWP situation is well in hand (e.g., Kalnay, 2003), although there is still room for improvement with respect to theoretical limits of predictability, and substantial misses still occur. A better understanding of the mechanisms associated with the onset, maintenance and termination of blocking, as discussed in Sec. 3.2 herein could help. And so could a better understanding of the interaction between smaller and larger scales, as reviewed in Palmer and Williams (2009) and in Sec. 4.2 here.

John von Neumann's role in starting these modern developments in NWP is well 1092 known, cf. Charney, Fjørtoft, and von Neumann (1950). What is a little less so is his longer-range outlook on the three levels of difficulty in understanding and predicting at-1094 mospheric and climate phenomena (Von Neumann, 1955): (a) short-term NWP is the 1095 easiest, since it represents a pure initial-value problem, as formulated by V. Bjerknes (1904) 1096 and L. F. Richardson (1922); (b) long-term climate prediction is next easiest, since it cor-1097 responds to studying the system's asymptotic behavior, i.e., the possible attractors and 1098 the statistical properties thereof (Dijkstra, 2013; Dijkstra & Ghil, 2005; Ghil & Childress, 1099 1987); and (c) intermediate-term prediction is hardest, since both the initial data and 1100 the parameter values are important. 1101

In fact, long-term climate prediction is a bit harder than Von Neumann envisaged at the time, because the forcing changes in time, too, as discussed here in Sec. 5.3. Concerning the intermediate term, matters tend to get more and more difficult as the prediction horizon is extended further and further, because additional subsystems, with longer time scales and additional evolution mechanisms have to be accounted for (Ghil, 2001).

Thus, subseasonal-to-seasonal prediction is receiving increased attention and is mak-1107 ing good progress (Robertson & Vitart, 2018, and references therein). Interannual cli-1108 mate variability being dominated by ENSO, its prediction concentrates on the coupled 1109 ocean-atmosphere system in the Tropical Pacific and the teleconnection therefrom to the 1110 extratropics. ENSO prediction has made great strides, with the emphasis shifting from 1111 statistical and stochastic-dynamic models in the 1990s to high-end climate models in the 1112 last decade; compare, for instance, the assessments of real-time ENSO forecast skill in 1113 Barnston, Glantz, and He (1999) vs. Barnston, Tippett, Heureux, Li, and DeWitt (2012). 1114 And interdecadal climate prediction is becoming the hardest problem of the climate sci-1115 ences, and one of humanity's hardest ones as well. 1116

On the other hand, there are areas of the geosciences in which even the possibility of prediction is viewed with suspicion, e.g., earthquake prediction (Geller, Jackson, Kagan, & Mulargia, 1997). In spite of the sustained scepticism, the approach outlined by Zaliapin et al. (2003b) might deserve some attention. A key obstacle to prediction is clearly the relative rarity of large earthquakes and of long and accurate earthquake catalogs. One way to extend the record might be to use a model, albeit a more detailed and complete one than the ternary-tree model mentioned here in Sec. 5.1, to generate additional, synthetic catalogs of arbitrary length, which agree in their statistics with existing catalogs of real sequences, as far as the latter go. And then proceed from there.

The situation with respect to predicting volcanic eruptions is somewhat less con-1126 troversial than for earthquake prediction but still far from being as routine as in NWP. 1127 Some volcanoes, like Mt. Etna in Sicily, seem to behave fairly periodically — like the 1128 synthetic earthquakes in Fig. 10(a) of Sec. 5.1 — and their infrasound rumblings have 1129 been used fairly successfully for automated, real-time forecasts (e.g., Hall, 2018). Oth-1130 1131 ers behave more irregularly, like in Fig. 10(b), but still may exhibit characteristic relaxation oscillations of their magma chambers, which could lead to a certain degree of pre-1132 dictability (Walwer, Ghil, & Calais, 2019). 1133

Predicting new phenomena. The typical way that theory, observation in the field or in 1134 the laboratory, and numerical simulation interact in the geosciences is: (i) observation 1135 in the field, be it the atmosphere, ocean or solid Earth, in situ or remotely; (ii) analy-1136 sis and description of the observations; and (iii) attempts at explanation of the observed 1137 phenomena via competing theories and numerical simulations. Moreover, with increas-1138 ing computer power and storage capacity, Ockham's razor is neglected more and more, 1139 preference being given to high-end models with massive details over the simpler and more 1140 easily understandable models. 1141

In fact, philosophical objections do exist to the parsimony principle and it, too, is not infallible. Still, it is simpler to put the Sun at, or near, the center of the solar system than to keep adding epicycles to the geocentric system (e.g., Kuhn, 1962). The main point of applying the principle is that simpler theories cover more observations and should therefore be easier to falsify, in the terminology of Karl Popper (2005), i.e., as the dictionary antonym of "verify" and synonym of "disprove." Recall that, according to Popper (2005), to be scientific, a statement has to be falsifiable.

A way of using more systematically parsimonious models in the geosciences is that 1149 of model hierarchies. Introduced into the climate sciences by Schneider and Dickinson 1150 (1974), they extend from simple, low-order conceptual models, through intermediate ones 1151 with one or more space dimensions, all the way to high-end ones that encompass many 1152 processes and have high 3-D spatial resolution. Rather than hurling epithets of "toy" 1153 models towards one end of the hierarchy and "overkill" towards the other, it is impor-1154 tant to recognize the role of the entire hierarchy in developing ideas, concepts and tools, 1155 on the one hand, and testing them against observations, on the other. 1156

More specifically, Held (2005) has argued for the need to use simpler models in order to understand many aspects of the simulations produced by the more detailed ones. The author of this paper and his colleagues (e.g., Dijkstra & Ghil, 2005; Ghil, 2001; Ghil & Robertson, 2000) have argued that successive bifurcations can play the role of Ariadne's thread across the rungs of this hierarchy. An illustration of this role in the case of the double-gyre problem for the wind-driven ocean circulation was given in Sec. 3.2.

It is important also to remember that when a simpler model and a more detailed disagree, it is not always the former that is wrong; i.e., adding details does not always add realism. Ghil (2015) reviewed a situation of this type, based on the work of Dijkstra (2007). Inspired by the work of Stommel (1961), a series of papers using THC models from simple to intermediate and beyond, had obtained bistability of the MOC, especially in situations mimicking the Atlantic Ocean; see Dijkstra and Ghil (2005, Sec. 3) and Dijkstra (2005, Ch. 6) for a review.

High-end ocean models used in the third Coupled-Model Intercomparison Program
(CMIP3) — on which the conclusions of the IPCC's Fourth Assessment Report (IPCC,
2007) were based — obtained, however, results that contradicted this bistability. As shown
by Dijkstra (2007), observations of the evaporation-minus-precipitation fluxes over the

Atlantic, between the southern tips of Greenland and Africa, tend to agree better with the simpler models than with the CMIP3 ones; and it is this better agreement that supports the bistability results of the former, simpler models.

One more interesting story of bistability will shed further light on the correct use 1177 of a model hierarchy, as well as on that of nonlinearity in the geosciences in general. En-1178 ergy balance models (EBMs) are fairly simple climate models that emphasize the role 1179 of incoming and outgoing radiative fluxes in determining the atmosphere's temperature 1180 field, while parameterizing the role of the velocity field in the energy fluxes (Budyko, 1969; 1181 1182 Sellers, 1969). Studies of the number and stability of the stationary solutions of these models in the early and mid-1970s showed that — in spite of various differences in their 1183 physical formulation and mathematical details (e.g., Ghil & Childress, 1987, Table 10.1) 1184 — they exhibited two stable stationary solutions separated in phase space by an unsta-1185 ble one (Ghil, 1976; Held & Suarez, 1974; North, Howard, Pollard, & Wielicki, 1979). 1186

The warmer of the two stable fixed points could be identified with something like the present climate or, more generally, an interglacial one. The colder one corresponds to an ice-covered planet and was labeled at the time a "deep freeze." The unstable fixed point (e.g., Bódai, Lucarini, Lunkeit, & Boschi, 2015) has been explored more recently by using an edge tracking algorithm (Lucarini & Bódai, 2017).

The presence of the saddle-node bifurcation between the interglacial climate and 1192 the unstable one was promptly confirmed by the results of a simple general circulation 1193 model (Wetherald & Manabe, 1975, Fig. 5). In fact, the authors of the latter study com-1194 mented that "As stated in the Introduction, it is not, however, reasonable to conclude 1195 that the present results are more reliable than the results from the one-dimensional stud-1196 ies mentioned above simply because our model treats the effect of transport explicitly 1197 rather than by parameterization. [...] Nevertheless, it seems to be significant that both 1198 the one-dimensional and three-dimensional models yields qualitatively similar results in 1199 many respects." 1200

In spite of this encouraging confirmation, the fact that a sharp global temperature drop by tens of degrees Celsius could occur given very small insolation changes was not taken seriously for quite a while by many climate scientists. The thinking went that the Sun is a main sequence star and its radiative flux had thus been larger in the past and not smaller, as required by the models for a deep freeze to set in. More recently, though, considerable evidence has accumulated for Neoproterozoic (1 000–543 Myr ago) glaciations at low latitudes, which suggest a completely glaciated Earth, labeled "snowball Earth" (e.g., Hoffman, Kaufman, Halverson, & Schrag, 1998).

Considerable disagreement persists as to whether the Neoproterozoic glaciation was 1209 total or partial, a slushball rather than a snowball; it seems, moreover, to have consisted 1210 of ups and downs in temperatures and ice cover, somewhat like the Quaternary glacia-1211 tion cycles, only longer and stronger. Even so, the much greater difficulty in getting out 1212 of a glaciated Earth than into it (e.g., Crowley, Hyde, & Peltier, 2001; Pierrehumbert, 1213 2004) is in substantial agreement with early EBM results on the hysteresis cycle of tran-1214 sition between the high- and low-temperature solution branches (e.g., Ghil, 2001, Fig. 1). 1215 Finally, atmospheric composition and life clearly played a role not accounted for in the 1216 early work on EBMs or Quaternary glaciations (Rothman, Hayes, & Summons, 2003; 1217 Tziperman, Halevy, Johnston, Knoll, & Schrag, 2011, and references therein). 1218

To summarize, simple models can offer predictive insights into phenomena only discovered after such a prediction. And nonlinear concepts and methods — applied consistently across a hierarchy of models — can help disentangle the additional complexities to be explained once the phenomena have been identified in observations and described in greater detail.

1224 **7 Coda**

We have visited several lamposts that have shed a little light — over the last cen-1225 tury, and especially its more recent decades — into the darkness of phenomena in the 1226 geosciences in general, and into Earth's fluid envelopes and the climate sciences more 1227 specifically. In each case, we have tried to outline the basic ideas and methods that fuel 1228 and focus this light, and to give a few examples of successful application of the theoret-1229 ical ingredients. It is time to conclude with the hope that more lampposts will spring 1230 up over the coming century, and that the overlaps between pairs and triplets of circles 1231 1232 of light will provide even greater clarity.

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¹²⁴⁸ versity Research Initiative (MURI).

1249 A Acronyms

Table A.1.Acronyms^a

Acronym	Meaning
BDE	Boolean delay equation
CA	Cellular automaton (sing.) or automata (pl.)
CNs	Complex networks
DDE	Delay differential equation
ER	Erdős–Rényi (network)
FDE	Functional differential equation
GFD	Geophysical fluid dynamics
IPCC	International Panel on Climate Change
NAO	North Atlantic Oscillation
NDS	Nonautonomous dynamical system
MHD	Magnetohydrodynamics
$O\Delta E$	Ordinary difference equation
ODE	Ordinary differential equation
P-map	Poincaré map
$P\Delta E$	Partial difference equation
PDE	Partial differential equation
PSA	Pacific South American (pattern)
RA	Random acyclic (network)
RDS	Random dynamical system

 a List of acronyms.

1250 **References**

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