SCIENCE CHINA
Earth Sciences

•CLASSICS LIVE FOREVER•

October 2025 Vol.68 No.10: 3407–3417
https://doi.org/10.1007/s11430-025-1714-8

Disillusionment and rebirth of deterministic weather forecasting and climate prediction: A perspective on the Lorenz's chaos theory

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Received August 20, 2025; revised September 21, 2025; accepted September 22, 2025; published online September 25, 2025

Abstract The deterministic chaos in nonlinear systems was discovered by Edward N. Lorenz in 1963, marking the birth of nonlinear sciences. Since then, the sensitivity of predictions to initial conditions is characterized by the "butterfly effect", triggering a scientific revolution that has lasted more than half a century and spans multiple disciplines. This article presents a perspective on the classic paper of the "butterfly effect", which not only help reveal how pioneers challenged the infinite unknown under limited conditions to establish the foundational work, but also demonstrates how these seminal ideas inspired successors to transcend existing paradigms, unlock creative thinking, and achieve cross-disciplinary innovations. The Lorenz's theory of deterministic chaos reveals that even imperceptibly small errors in the initial state can grow to the extent that makes it impossible to forecast at arbitrary future times with acceptable errors. This recognition shook the classical physics view that "determinism implies complete predictability" and prompted meteorologists to shift from the pursuit of "long-term forecasts" to asking "how far into the future the atmosphere is predictable", and from attempts at "perfect prediction" to scientifically "quantifying forecast uncertainty". This transition has also fundamentally promoted the shift of the paradigms in weather forecast and subsequent climate prediction, exerted profound influence on mathematics, biology and economics, and even permeated literature, art, history and social governance—ultimately shaping the renowned Lorenz's chaos theory.

Keywords Lorenz system, Chaos, Butterfly effect, Predictability, Artificial intelligence

Citation: Mu M, Duan W, Qin X. 2025. Disillusionment and rebirth of deterministic weather forecasting and climate prediction: A perspective on the Lorenz's chaos theory. Science China Earth Sciences, 68(10): 3407–3417, https://doi.org/10.1007/s11430-025-1714-8

1. Introduction

The determinism of classical Newtonian mechanics holds that, given the positions and momenta of all particles in a system at a particular moment, together with the forces acting upon them, the future evolution of the system can be calculated with complete certainty according to Newton's laws of motion. The essence of this determinism lies in three components: complete initial information, known laws of motion, and deterministic evolution. In this framework, the motions of the universe and everything within are fully predetermined by physical laws and initial conditions; the future is an inevitable consequence of the past, leaving no room for genuine randomness or uncertainty. The eminent mathematician and astronomer Pierre-Simon Laplace affirmed this view and articulated it to its extreme in the introduction of his seminal work *Essai philosophique sur les probabilités* (Laplace, 1825): if an intelligence—now widely known as "Laplace's demon"—could know the positions and momenta of all particles at a particular moment, then the

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entire past and future trajectories of the universe could be deduced through Newton's equations. This implies that for a dynamical system governed by differential equations describing material motion, there exists a threshold of initial error such that, if the initial error is smaller than this threshold, the evolution at any future time can be successfully predicted with acceptable forecast error by this dynamical system. Such determinism dominated scientific community throughout the eighteenth and nineteenth centuries.

However, in March 1963, Edward Lorenz radically challenged this view with his classical paper *Deterministic Nonperiodic Flow* (Lorenz, 1963), published in the famous *Journal of the Atmospheric Sciences*. This work is a landmark paper (Motter and Campbell, 2013; Luo and Mu, 2015). Lorenz constructed a simple mathematical model using a set of nonlinear ordinary differential equations—now known as the "Lorenz equations" or "Lorenz system"—to describe atmospheric thermal convection. For the first time, this work demonstrated that even deterministic nonlinear equations could exhibit extreme sensitivity of future states to initial conditions. Specifically, no matter how small the initial errors might be—errors that are in fact unavoidable in any real systems, such as the observation errors in synoptic systems—these errors inevitably amplify with time, making it impossible to provide forecasts with acceptable errors at all future times. In other words, regardless of how small the initial error is, the forecast error will inevitably exceed the acceptable threshold at some future moment, leading to a failed forecast. Lorenz revealed to the world that accurate long-term weather forecast is impossible. This shattered the classical determinism that "certainty implies everything can be predicted", thus began a grand revolution in science spanning decades.

2. The Lorenz's chaos theory

The Lorenz system consists of a set of nonlinear autonomous ordinary differential equations that describes atmospheric thermal convection. Lorenz discovered that the solution trajectory of the system exhibits a double-vortex-shaped attractor in the three-dimensional phase space, when the parameters of the equations take specific values σ=10, γ=28, b=8/3, with σ the Prandtl number, γ the Rayleigh number, and b a constant related to space (Figure 1; Lorenz, 1963). This attractor does not converge to a fixed point, nor does it evolve into a periodic orbit; instead, it folds infinitely without repetition, forming a bounded yet highly complex spatial structure. This structure was later termed the "Lorenz attractor" by the international scientific community. The Lorenz attractor is the first internationally recognized example of the "strange attractor", which is different from traditional dynamical system attractors such as the fixed point, periodic orbit, focus, or saddle point (Peitgen et al., 1992). The properties of the Lorenz strange attractor reveal the system's remarkable sensitivity to initial conditions: even an imperceptible difference between two initial states in phase space (on the order of 10^{-6}) can lead to completely divergent trajectories within a finite time, eventually evolving into vastly different outcomes with time. What is even more striking is that the Lorenz strange attractor is entirely governed by deterministic equations, but, due to its extreme sensitivity to initial conditions, exhibits behaviors that is unpredictable and seemingly random. This phenomenon later became widely known as the "deterministic randomness" or "deterministic chaos" (Hunt et al., 2004). Lorenz's work represented the first time in the history of science that using nonlinear deterministic equations to characterize chaotic phenomena through numerical experiments, thus providing a concrete visualization of chaos within a physical model.

Lorenz's pioneering work stimulated mathematicians to explore how chaos could be rigorously defined. In the paper "*Period Three Implies Chaos*" (Li and Yorke, 1975), the famous mathematician Tien-Yien Li and his advisor James Yorke introduced the first rigorous mathematical definition of "chaos". They clearly characterized the special sensitivity of chaotic phenomenon to initial conditions, along with the mathematical properties of complex, non-periodic orbits, elevating "chaos" from a vague concept to a strictly-defined scientific term. For low-dimensional discrete systems, Li-Yorke chaos demonstrated that chaos can be triggered by the existence of periodic points (e.g., period three), thereby offering a concise criterion for the existence of chaos in low-dimensional discrete deterministic systems. Unlike Li-Yorke chaos, Smale's theory of chaos is also highly representative and centers on continuous high-dimensional dynamical systems. Using the celebrated Horseshoe Map, Smale (1967) revealed the geometric mechanism of chaos as a tangled manifold driven by hyperbolic sets and homoclinic transversal points. In fact, Li-Yorke chaos and Smale chaos characterize chaos in mathematical analysis and geometry, respectively, and together they compose the dual pillars of chaos theory. They can be synthesized by discretizing a continuous system with Poincaré sections, enabling a coherent understanding of complex nonlinear dynamical systems. Taking the Lorenz strange attractor as an example, it exhibits the chaotic characteristics of both Smale's horseshoe and period three through the Poincaré map (Rössler, 1977; Tucker, 2002).

Since then, research in nonlinear sciences has emerged worldwide. The aforementioned chaos theories laid the theoretical foundation for many following classical methods in nonlinear sciences, such as the Lyapunov exponent for characterizing chaotic motions (Wolf et al., 1985; Pecora and Carroll, 1990), phase space reconstruction theory for ana-

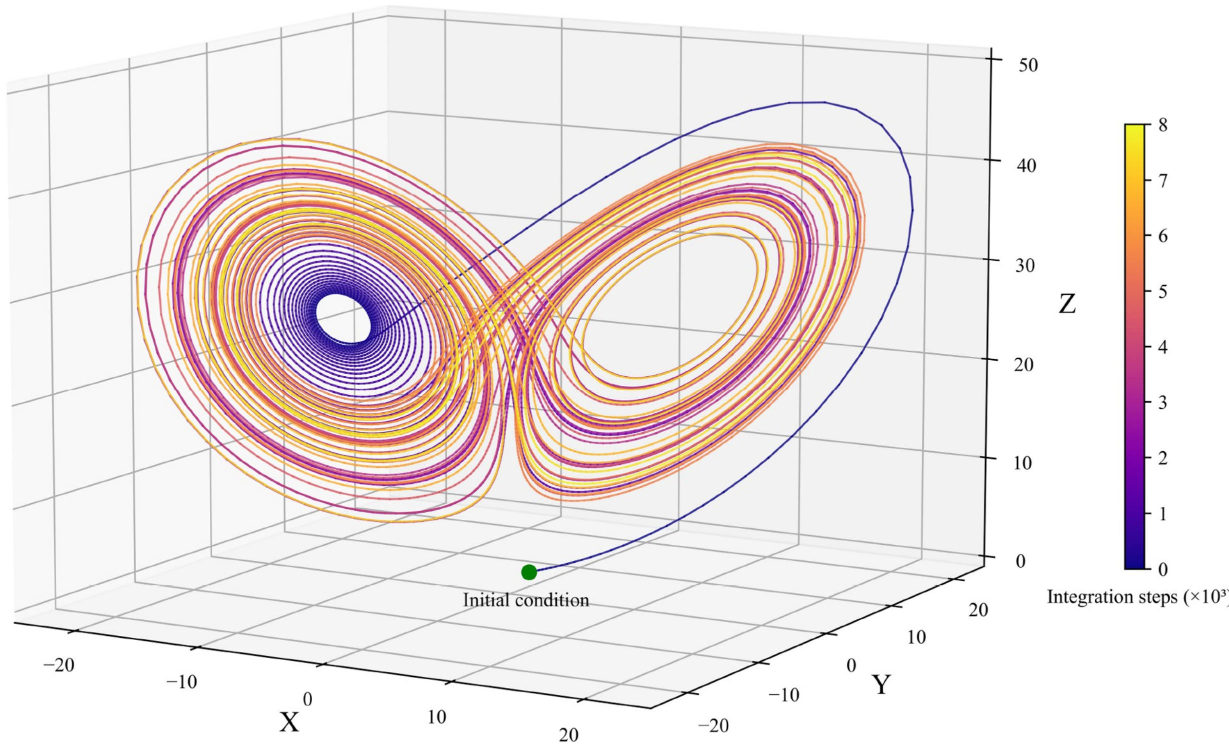

Figure 1 (Color online) Solution trajectory of the Lorenz system.

lyzing nonlinear dynamics and chaotic systems (Takens, 1981; Sauer et al., 1991; Sugihara et al., 2012), and fractal geometry for describing infinite details and self-similar structures (Hentschel and Procaccia, 1983; Falcone, 2003; Viswanath, 2004). Thus, a new paradigm in chaos theory study has been initiated. The proposal of Lorenz's chaos theory marked the birth of nonlinear sciences.

3. The Lorenz' chaos theory in evolution: The intrinsic predictability limit

As revealed by Lorenz's chaos theory, it is impossible to provide forecasts with acceptable errors at all future times. This led meteorologists to recognize the fundamental limitations of forecasting, and to fundamentally shift from pursuing "long-term forecasts" to discussing "how long the atmosphere can be predicted?" On this basis, Lorenz (1969) further proposed the perspective of the Intrinsic Predictability Limit (IPL) for daily weather forecasts.

3.1 Does the real atmosphere have an IPL?

Thompson (1957) first proposed the concept of "predictability", defining it as the range of time over which the weather can be successfully forecasted with initial errors in a perfect model. It should be noted that according to the Lorenz system, for any specified forecast length—a week, a month, or even a year—accurate forecast is theoretically possible as long as the initial error is sufficiently small, with its amplitude depending on the given forecast length. Based on his Lorenz system published in 1963, Lorenz further employed the barotropic quasi-geostrophic vorticity equation to examine the nonlinear interactions among multi-scales of atmospheric motions in his later work published in *Tellus* in 1969. Through numerical experiments, he demonstrated that the smaller the spatial scale of the initial error, the more rapidly it grows over time (Figure 2). After a certain period, the forecast error for synoptic scales exceeds the acceptable threshold. This led Lorenz to conclude that the effective forecast length of a daily weather forecast is inherently limited, and he explicitly quantified this effective forecast length of daily weather forecasts to be about two weeks for the Northern Hemisphere (Table 1). He thus termed this time range as the IPL of daily weather forecasts (Lorenz, 1969). Leith and Kraichnan (1972) later confirmed Lorenz's findings, leading to widespread acceptance within the atmospheric science community that the IPL for daily weather forecasts is approximately two weeks. Two decades later, Tribbia and Baumhefner (2004), using the state-of-the-art NCAR Community Climate Model Version 3 at that time and data from the U.S. National Centers for Environmental Prediction (NCEP), with one of the best supercomputers at that time, reaffirmed that the effective range of daily weather forecasts could not exceed two weeks. Thus, the two-week IPL for daily weather forecasts became deeply entrenched

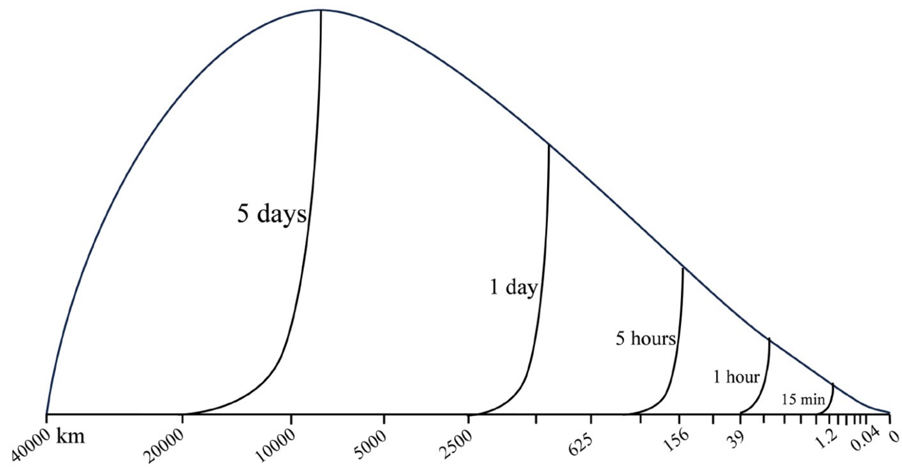

Figure 2 Intrinsic Predictability Limit (IPL) as a function of the spatial scale (wavelength; units: km) of initial errors. The smaller the spatial scale of the initial error, the faster it grows and the shorter the IPL. Adapted from Lorenz (1969).

Table 1 Effective forecast lengths for weather forecast with different spatial scales[a)]

Wavelength (m)	Effective forecast length (minute)	Wavelength (km)	Effective forecast length (hour)
38	2.9 minutes	78	3.6 hours
76	3.1 minutes	156	5.8 hours
153	4.0 minutes	312	9.5 hours
305	5.7 minutes	625	15.7 hours
610	8.4 minutes	1250	1.1 days
1221	13.0 minutes	2500	1.8 days
2441	20.3 minutes	5000	3.2 days
4883	32.1 minutes	10000	5.6 days
9766	51.1 minutes	20000	10.1 days
19531	1.3 hours	40000	16.8 days
39000	2.2 hours		

a) transformed from Lorenz (1969).

and has since been regarded as an intrinsic property of daily synoptic variability.

Unfortunately, unlike Lorenz's chaos theory, the conclusion that the IPL of daily weather forecasts is approximately two weeks has never been strictly proven in mathematics. The internationally renowned climate physicist Tim Palmer and his colleagues offered their own perspective on the conditions under which atmospheric and oceanic fluids may or may not possess an IPL (Palmer et al., 2014). They argued that the system does not exhibit an IPL, if the differential equations governing the dynamical system of fluid motion possesses a globally smooth solution and appropriate estimates can be established. They demonstrated that the Lorenz system possesses globally smooth solutions, implying that the solutions of the Lorenz system continuously depend on the variations of the initial conditions. This means that effective predictions can be made for arbitrarily long timescales as long as the initial error is sufficiently small (with the amplitude again depending on the forecast length), and therefore, the Lorenz system itself does not possess an IPL.

It has been proven mathematically that the two-dimensional Navier-Stokes equations, which describe horizontal fluid motion, possess globally smooth solutions (Ladyzhenskay, 1969; Huang and Li, 2022). According to the perspective of Palmer et al. (2014), this implies that two-dimensional fluid motions do not exhibit an IPL. This naturally raises a question: how is the real atmospheric motion? Clearly, the two-dimensional Navier-Stokes equations cannot capture essential features of real atmospheric vertical motion such as convection. Instead, the three-dimensional Navier-Stokes equations provide a more realistic description of atmospheric motion. Unfortunately, the existence of globally smooth solutions in the time-dimension of the three-dimensional Navier-Stokes equations remains unresolved. It has been one of the famous Millennium Prize Problems posed by the Clay Mathematics Institute, with a reward of one million U.S. dollars for its solution. Consequently, whether the real atmosphere possesses an IPL remains an open and profound scientific challenge on the world stage.

Rotunno and Snyder (2008) found that the three-dimensional turbulent motion possesses an IPL through numerical experiments using a shallow-water quasi-geostrophic model. We therefore hypothesize that the three-dimensional Navier-Stokes equations may possess globally smooth solutions for certain structured initial conditions, implying that the IPL could depend on specific weather events. Palmer et al. (2014), based on ECMWF forecast data, showed that the evolution of large-scale systems (such as atmospheric blocking) can in some cases be influenced by small-scale—even cloud-resolving processes, but not universally so for other cases. This case dependence led them to propose that initial error growth depends on the reference state, and hence the IPL is event-dependent. This conjecture resonates with our own hypothesis above, namely that the existence of an IPL is conditional on specific weather events. Although such studies do not resolve the question of whether globally smooth solutions in the time-dimension exist for the three-dimensional Navier-Stokes equations, they nonetheless offer new perspectives for deepening our understanding of the IPL in real atmospheric motions. Whether these insights can, in turn, inspire mathematicians to make progress on the problem of existence of global smooth solutions in time-dimension for the three-dimensional Navier-Stokes equations, remains an open and intriguing issue.

3.2 The real "butterfly effect": Intermittency

Lorenz's theory of deterministic chaos emphasizes the extreme sensitivity of a system to its initial conditions. To make the concept of chaos accessible to the public, Lorenz illustrated the above extreme sensitivity in a lecture at MIT in 1972 using the poetic notion of the "butterfly effect": the flap of a butterfly's wings in Brazil could trigger a tornado in Texas, USA (Lorenz, 1972). Perhaps because this vivid image resonated so deeply with the public, the IPL of weather forecasts has often been associated with the "butterfly effect", sometimes overshadowing Lorenz's seminal 1969 work, particularly his introduction of the crucial concept of the IPL (Palmer et al., 2014; Mu et al., 2015). Palmer et al. (2014) clarified the discoveries of the "butterfly effect" and the IPL by Lorenz, and termed their own discovery that the IPL depends on specific weather events as the "real butterfly effect", emphasizing that the butterfly effect has intermittency.

In fact, the authors' research team has already discovered this phenomenon in studies addressing the "spring predictability barrier" of El Niño-Southern Oscillation (ENSO) events (Mu and Wang, 2007; Mu et al., 2007; Duan and Wei, 2012). They established a novel nonlinear theory in which significant forecast errors in high-impact ocean-atmosphere events arise from the combined effects of initial errors with specific spatial structures, the background environmental field (i.e., climatological states and particular events), and nonlinear processes. Subsequent studies across different spatial and temporal scales of weather and climate events have validated the scientific robustness of this theory (Mu and Duan, 2025). This new theory demonstrates that the occurrence of significant forecast errors depends on specific weather and climate events. Clearly, the intermittency of the "butterfly effect" discussed above provides support for this theory. Moreover, this theory emphasizes that initial errors with specific spatial structures, rather than random errors in physical space, are responsible for large forecast errors. This finding is consistent with the sensitivity to initial conditions in phase space characterized by deterministic chaos theories, such as Lorenz's, Li-Yorke's, and Smale's chaos theories. Therefore, the nonlinear error growth theory can be seen as an integrated manifestation of Lorenz's chaos theory of sensitivity to initial condition and the intermittency of the "butterfly effect", which in turn demonstrates the scientific rigor of the theory.

The "butterfly effect" of deterministic chaos is a metaphor, not a precise scientific description. This has led to widespread misunderstanding, such as the belief that the flap of a butterfly's wings can directly cause a tornado, which has occasionally been portrayed in popular media as a direct link between minor actions and catastrophic events. In reality, the butterfly's wing flap symbolizes an infinitesimal perturbation in initial conditions, which, in a nonlinear system, can amplify through cascading interactions to produce dramatic changes in long-term behavior—but this relies on the system's intrinsic nonlinear chaotic mechanisms. Additionally, in the context of numerical weather forecast, there is also a common cognitive bias sometimes referred to as the "universal observation-density fallacy," which assumes that adding observations at arbitrary locations can suppress the "butterfly effect" and thus improve forecast accuracy. This notion contradicts a key feature of the Lorenz attractor: initial errors with specific structures, rather than randomly distributed errors, lead to significant forecast deviations. This feature also implies that the sensitivity to initial errors is highly spatially heterogeneous. Studies have shown that initial errors in specific sensitive regions—such as moist convective areas—grow much faster than in stable stratified regions (Hohenegger and Schär, 2007). Blindly increasing observations in non-sensitive regions may have negligible impact on forecast skill (Snyder, 1996; see also Section 4.1 on "Targeted Observations"). Therefore, it is crucial to understand the "butterfly effect" scientifically, so that it can be effectively applied to observational strategies and operational forecasting.

Although Lorenz's conclusion that the IPL for daily weather forecasts is approximately two weeks has been widely accepted within the atmospheric science community, it should not be regarded as a rigid constraint. In fact, as an extension of the "real butterfly effect", increasing evidence from forecasting practice suggests that weather events with larger spatio-temporal scales may exhibit an IPL exceeding two weeks (Ma et al., 2022). For example, certain heavy rainfall events affect only a few thousand square kilometers and last only a few hours, representing small-scale processes whose IPL may be two weeks or shorter. In contrast, extreme cold events in winter can impact millions of square kilometers and persist for a week or longer. In particular, some theoretical studies indicate that such extreme cold events are closely linked to Eurasian blocking, the North Atlantic Oscillation/Arctic Oscillation, and the Arctic sea-ice-atmosphere system, suggesting that their IPL could exceed two weeks (Han et al., 2023). Therefore, as our understanding of atmospheric evolution and its rules deepens, it is essential to progress and advance on Lorenz's IPL. Doing so will provide new insights into intrinsic predictability and further promote the development of numerical weather forecasts.

3.3 IPL: Extension to climate predictability

The discussion above primarily focused on the atmosphere, with a particular emphasis on weather predictability. Since the 1980s, climate prediction issues, represented by ENSO forecasts, have increasingly attracted significant attention from both the international community and the academic field (Zebiak and Cane, 1987; Kirtman et al., 2013). However, the inherent complexity of the climate system dictates the limitations of research confined only to the atmosphere. Taking ENSO as an example, it essentially originates from the coupled interactions between the tropical Pacific Ocean and the atmosphere (Philander, 1983; McPhaden et al., 2006), with oceanic dynamic and thermodynamic processes playing a decisive role in the initiation and evolution of ENSO events. This understanding has led to a broad consensus in the scientific community: accurate climate prediction must be grounded in a thorough understanding of the coupled mechanisms among the atmosphere, ocean, land, and other components of the Earth system. The multi-sphere interactions of the climate system pose significant challenges for climate predictability research. These challenges have propelled the concept of the "climate system IPL" to the forefront of contemporary climate dynamics research, making it a key focus in earth science studies. However, critical questions remain largely unresolved, such as how to investigate the IPL of climate events and whether a specific climate event exhibits an IPL, with very few comprehensive studies available to date.

Although Thompson (1957) defined "predictability" on the basis of weather forecasting and Lorenz (1969) proposed the perspective of the IPL, the literature has offered diverse and sometimes conflicting interpretations of predictability over quite a long time (Mu et al., 2004). It was not until 2013 that the Intergovernmental Panel on Climate Change (IPCC), in its Fifth Assessment Report, clarified several previously ambiguous definitions of predictability based on climate prediction (Kirtman et al., 2013). The report emphasized that "predictability" is the inherent property of the physical system itself, rather than the skill or capability shown in practical forecasts. The former exists objectively and independently of the numerical model or initial conditions used, while the latter depends on the accuracy of the model, initial conditions, and external forcing. Building on this, Mu et al. (2017) further refined the definition of predictability, describing it as a physical property of relevant physical variables (e.g., velocity, temperature, density, salinity, and humidity) within Earth system components including the atmosphere, ocean, and land surface, as well as their associated weather and climate phenomena (e.g., tornadoes, typhoons, heavy rainfall, ocean mesoscale eddies, and ENSO events). This property varies across time and space, depending on the spatio-temporal scales of the evolution of physical variables and associated weather and climate events, and arises from the interactions of nonlinear, multiscale processes. "Predictability" measures the extent to which small errors in the current state of the system can influence its future states: if initial errors grow rapidly over time or the probability density function broadens quickly, the predictability of the system is low; conversely, if errors grow slowly, the system exhibits high predictability.

The modified definition of predictability proposed by Mu et al. (2017) applies to general physical variables and related events, providing a universally applicable framework for both weather forecasting and climate prediction. The clarification of this concept advanced the IPL beyond the traditional two-week limit and provided a theoretical foundation for studying weather and climate predictability, as well as understanding their IPL on longer timescales.

4. Guiding the role of the Lorenz's chaos theory: Numerical weather forecast and climate prediction

The internationally renowned meteorologist Jule Charney is recognized as one of the pioneers of numerical weather forecasts. When he was serving as the editor for the *Journal of the Atmospheric Sciences*, he decisively approved the publication of Lorenz's 1963 paper on "Deterministic Nonperiodic Flow", despite negative reviews from referees. Later, following Lorenz's 1969 *Tellus* paper, which proposed that the IPL for daily weather forecasts is approximately two weeks, Charney promptly redirected the World Meteorological Organization's operational numerical weather forecast efforts to focus on forecasts with lead times of up to two weeks, rather than the originally planned monthly, seasonal, or interannual forecasts. This decision steered the development of modern numerical weather forecast onto a scientifically robust trajectory.

The sensitivity to initial conditions revealed by Lorenz's chaos theory prompted two major transformations within the meteorological community. First, in terms of forecasting philosophy, it led to a paradigm shift from pursuing "perfect forecasts" to scientifically "quantifying forecast uncertainty". Second, in terms of technical approaches, it established two innovative directions: on one hand, the development of targeted observation techniques and data assimilation methods aimed at reducing initial condition errors to improve forecast skill; on the other hand, the pioneering introduction of the ensemble forecasting technique, which represents initial uncertainty through perturbed initial fields, thereby enabling the quantification of forecast uncertainty. These theoretical and technical advances have driven a qualitative leap in numerical weather forecast and climate prediction skills, yielding substantial economic and societal benefits.

4.1 Targeted observations

"Targeted observations", also known as "adaptive observations", focus on the initial errors that are likely to produce significant forecast divergence within a limited time period. Their locations are generally identified as key regions (or "sensitive areas") where implementing additional observations will reduce initial observation errors, thereby improving the forecast skills of high-impact weather and climate events (Figure 3) (Snyder, 1996; Mu, 2013). The Observing System Research and Predictability Experiment, launched in 2005, demonstrated the critical role of targeted observations in improving tropical cyclone forecasts (Majumdar, 2016). In Taiwan province, targeted observations have already been integrated into operational typhoon forecasting. In recent years, Chinese meteorological agencies and related universities have also employed targeted observations to enhance the accuracy of typhoon and marine environment forecasts, and conducted several field campaigns that have significantly improved forecasting skill (Liu et al., 2021; Feng et al., 2022; Chan et al., 2023; Qin et al., 2023).

4.2 Data assimilation

"Data assimilation" refers to the process of integrating observational data from different sources, times, and varying degrees of accuracy, into numerical models to produce dynamically and thermodynamically consistent estimates of the state of the atmosphere, ocean, land, and cryosphere. Through data assimilation, a more accurate "optimal initial condition" can be provided for numerical forecasts, thereby improving forecast skills. It is an indispensable component of modern numerical weather forecast and climate prediction systems (Navon, 2009; Bauer et al., 2015). Classical data assimilation methods include variational assimilation and ensemble Kalman filter (EnKF) techniques. Since the 1990s, four-dimensional variational data assimilation (4D-Var) technology has been increasingly developed and refined, including the assimilation of satellite observations and the use of state-dependent weights to characterize error structures, achieving widespread international application and being regarded as a milestone in the development of numerical weather forecasts. In recent years, building on 4D-Var, international scholars have further developed approaches such as the ensemble four-dimensional variational data assimilation (En4D-Var; Bauer et al., 2015; Bannister, 2017). By using ensemble sampling to construct flow-de-

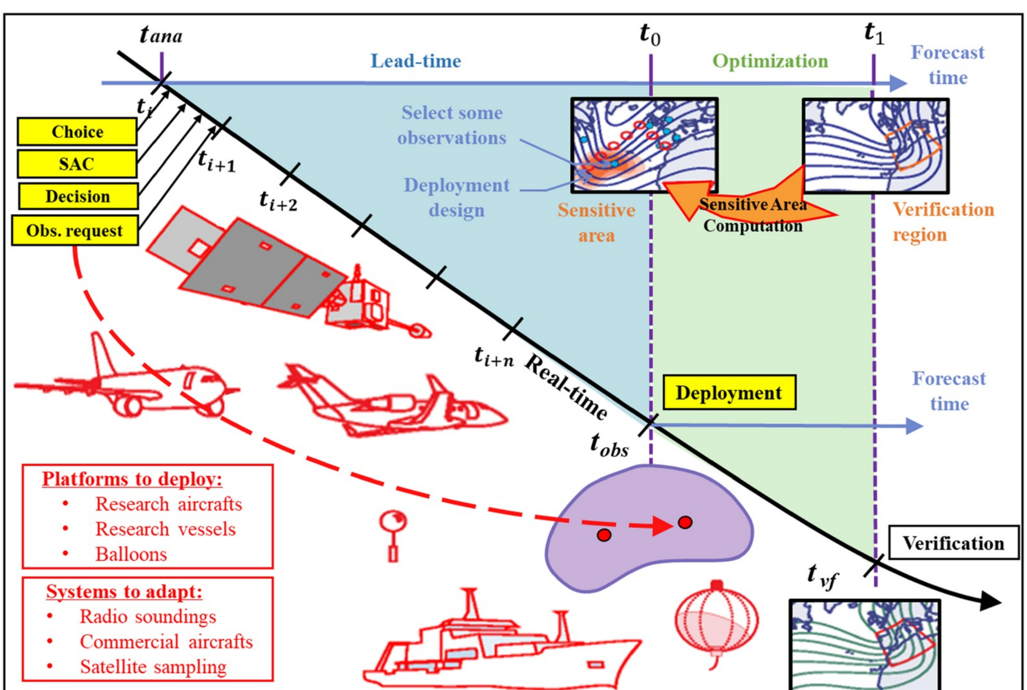

Figure 3 (Color online) Flowchart of the targeted observation field experiment (adapted from https://library.wmo.int/records/item/29004-targeted-observations-for-improving-numerical-weather-prediction).

pendent background error covariances, these methods overcome the limitation of traditional 4D-Var techniques, which cannot account for flow-dependent error characteristics, thereby more accurately capturing the nonlinear evolution of atmospheric motion. Advanced data assimilation techniques are widely considered as one of the main reasons for the significant progress in numerical weather forecasts since the 1990s (Bauer et al., 2015).

4.3 Ensemble forecasting

Although data assimilation can provide an "optimal initial state" and thus a more accurate deterministic forecast, observational errors still introduce uncertainty into this initial state. Due to the butterfly effect, even small initial uncertainties can amplify and cause forecasts to diverge substantially from reality. However, such deterministic forecasts alone cannot inform users about how far the forecast may deviate from the real state, whether alternative forecast results exist, and how reliable the forecast is. To address this limitation, meteorologists developed the "ensemble forecasting" technique, which generates a set of physically consistent perturbations around the "optimal initial state" to actively simulate and represent the range of uncertainties arising from chaotic effects (Palmer et al., 1992; Molteni et al., 1996). Ensemble forecasting is not merely a new forecasting technique; it represents a conceptual shift, from pursuing a single perfect forecast (impossible in chaotic systems) to providing a probabilistic representation of possible future weather states and their likelihoods (Figure 4). Today, ensemble forecasting is recognized by the World Meteorological Organization as one of the three main strategic directions for the future development of numerical weather forecasts.

Evolution and advancements in targeted observations, data assimilation, and ensemble forecasting techniques mark a fundamental shift from pursuing "deterministic forecasts" to systematically understanding and quantifying "forecast uncertainty" in numerical weather forecasts and climate predictions. The core driver of this transformation is Lorenz's chaos theory. Looking back, weather forecasting has undergone a remarkable evolution over the past century. It progressed from the empirical and imprecise judgments of "cloud watching" to deterministic numerical calculations based on atmospheric dynamical equations, and ultimately to modern numerical weather forecast and climate prediction systems that integrate multiple interdisciplinary technologies and can reasonably assess uncertainties. This history not only reflects the development of weather forecasts and climate predictions, but also chronicles humanity's struggle with natural uncertainty—progressing from attempting to understand it, to trying to eliminate it, and ultimately learning to manage it at a higher level. Certainly, improvements in ob-

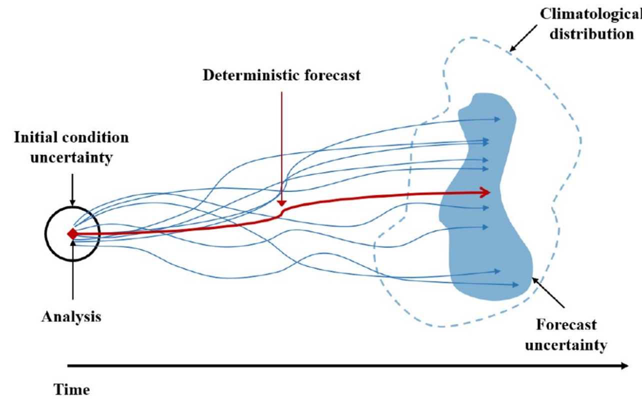

Figure 4 (Color online) Schematic of ensemble forecasting (adapted from https://www.metoffice.gov.uk/research/weather/ensemble-forecasting/what-is-an-ensemble-forecast).

servational data and computational capabilities have gradually enhanced the accuracy and efficiency of numerical weather forecasts and climate predictions. More importantly, Lorenz's chaos theory reshaped people's understanding of nonlinear sciences and, in doing so, fundamentally transformed the paradigms of numerical weather forecasts and climate predictions. Over the past two decades, the authors' team has overcome the limitations of traditional linear methods by adopting the Conditional Nonlinear Optimal Perturbation (CNOP) method (Mu et al., 2003), which fully accounts for nonlinear effects. This method has been applied to identify sensitive areas for targeted observations in the atmosphere and ocean, as well as to conduct associated data assimilation and ensemble forecasting experiments. In particular, these efforts have been progressively extended to high-impact weather and climate events, providing critical scientific and technological support for improving China's numerical weather forecast and climate prediction capabilities (Duan et al., 2023a, 2023b; Mu and Duan, 2025).

5. Discussions on the "butterfly effect" in the era of large AI models

Today, artificial intelligence (AI) is profoundly reshaping the paradigms of weather forecasting and climate prediction, and the discussion of the "butterfly effect" has once again become a research focus.

In AI models driven by meteorological big data, "Pangu-Weather" exhibits characteristics markedly different from those of traditional numerical models. Selz and Craig (2023) found that, when initial errors are small, the system's error growth after 72-hour is five orders of magnitude lower than that of numerical models. Therefore, they concluded that the strong sensitivity to initial conditions, known as the "butterfly effect" in numerical models, does not exist in AI models. Through data assimilation experiments, Zhou et al.

(2025) showed that even assimilating observations in the strongly sensitive regions of a Bay of Bengal storm only improved forecast skill by about 16% over a 24-hour lead time, with no significant initial sensitivity evident at longer lead times. Similarly, based on an AI model for ENSO prediction, Guardamagna et al. (2025) revealed that the fastest-growing initial errors derived from the CNOP method did not increase with forecast lead time. This feature is considered the intrinsic reason that enables the model to overcome the "spring predictability barrier" and achieve successful long-range predictions of El Niño.

In contrast, the "FuXi" model exhibits typical chaotic characteristics consistent with nonlinear dynamical systems. Pu et al. (2025) conducted perturbation dynamics experiments showing that when the initial error of deep-layer wind speed reaches a threshold of 1.5 m s^{-1}, its 72-hour error growth matches that of physical models. Based on this, an ensemble perturbation generation scheme was developed, significantly improving tropical cyclone track forecast skill. The targeted observation studies for tropical cyclone track forecasting by Li et al. (2025) further verified that the fastest-growing CNOP perturbations exhibit substantial growth within the 72-hour forecast period, allowing the assimilation of additional observations in CNOP-based sensitive areas to reduce forecast errors by approximately 55%.

Given the inconsistent conclusions regarding the "butterfly effect" in different AI models, there is an urgent need to investigate the underlying causes of these differences, explore the dynamical stability of AI-based meteorological models, and develop methods for quantifying AI model uncertainty. Ultimately, these will enable the development of high-level AI weather and climate prediction systems, achieve an integrated balance of "interpretable intelligence" and "controllable uncertainty", and promote the evolution of weather and climate predictions in the era of AI.

6. Concluding remarks

When Lorenz discovered "deterministic chaos in nonlinear systems" in 1963, he might have never imagined that the mere flapping of a butterfly's wings could unleash a "storm" spanning over half a century and across multiple disciplines. Lorenz's chaos theory not only prompted numerical weather forecasts to shift from the pursuit of "perfect forecasts" to the "scientific quantification of forecast uncertainty", ensuring the rational and robust development of both weather and climate predictions, but it also profoundly influenced fields such as mathematics, biology, and economics. In mathematics, chaos theory has revolutionized classical branches, including dynamical systems, geometry, and numerical analysis, while also giving rise to emerging fields such as fractal geometry. It has also promoted mathematicians to reconsider the relationship between determinism and randomness, with impacts extending to cutting-edge areas such as quantum chaos and information dynamics, thus serving as a vital bridge between pure mathematics and applied sciences. In biology, chaos theory has reshaped the understanding of "complexity" and "uncertainty", revealing that intrinsic randomness in biological systems is actually a reflection of deterministic chaotic dynamics. This insight has promoted the development of the complex system science, mathematical biology, and computational biology. While in economics, the introduction of chaos theory challenged the traditional view that economic development follows periodic cycles and that stock market fluctuations are purely random. It has inspired a new generation of economic modeling and policy simulation tools. Beyond the sciences, Lorenz's chaos theory has also influenced culture, art, history, and even social governance, creating a unique intellectual influence. The "butterfly effect" has become a central metaphor in literature and films for exploring causality, chance, and fate. For example, the film *The Butterfly Effect* (2004) vividly illustrates the philosophical implications of chaos theory's sensitivity to initial conditions, depicting how minute choices can lead to dramatic shifts in life trajectories.

Predicting the future has been an enduring pursuit of human civilization, yet prediction practices grounded in modern scientific theories and methods, tracing back only about three centuries with the beginning of the precise calculation of planetary orbits based on Newtonian mechanics. Within this "scientific garden of prediction", numerical weather forecast and short-term climate prediction have achieved practical success since the mid-20th century, standing out like a strikingly blossomed flower, and have profoundly transformed humanity's understanding of the atmospheric system. While Lorenz's chaos theory and its studies on predictability serve as a key, unlocking new dimensions of cognition. With the iterative advancement of atmospheric science theories, the revolutionary breakthroughs in observational technologies, and the continuous optimization of predictive models, this theoretical framework remains vibrant and influential. First, it acts as a lighthouse, reminding the scientific community to respect the boundaries set by natural laws—any demand for predictions that violate these principles is no more than constructing castles in the air. Second, it is the responsibility of contemporary academia to systematically and comprehensively understand Lorenz's chaos theory, to further develop and deepen it, and ultimately to apply it in guiding observational and forecasting practices.

From the perspective of contemporary scientific development, Lorenz's pioneering work in weather and climate predictions has long transcended the boundaries of any single discipline. Whether it is the challenge of earthquake prediction within the geosciences or broader predictive problems across natural and social sciences, this theoretical framework, which integrates deterministic laws with the inherent nature of randomness, will continue to offer invaluable paradigmatic guidance and methodological inspiration for scientists.

Acknowledgements *The authors gratefully acknowledge Dr. Lichao YANG and Prof. Lei WANG and Ph.D. candidate Jinai BAI for their editorial expertise, along with the substantial assistance provided by Dr. Rong FENG and Ph.D. candidates Yi ZHUANG, Can YOU, and Yijie ZHU during manuscript preparation. This work was supported by funding from the National Natural Science Foundation of China (Grant No. 42330111).*

Conflict of interest The authors declare no conflict of interest.

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(Editorial handling: Yongfei ZHENG)