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

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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

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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-

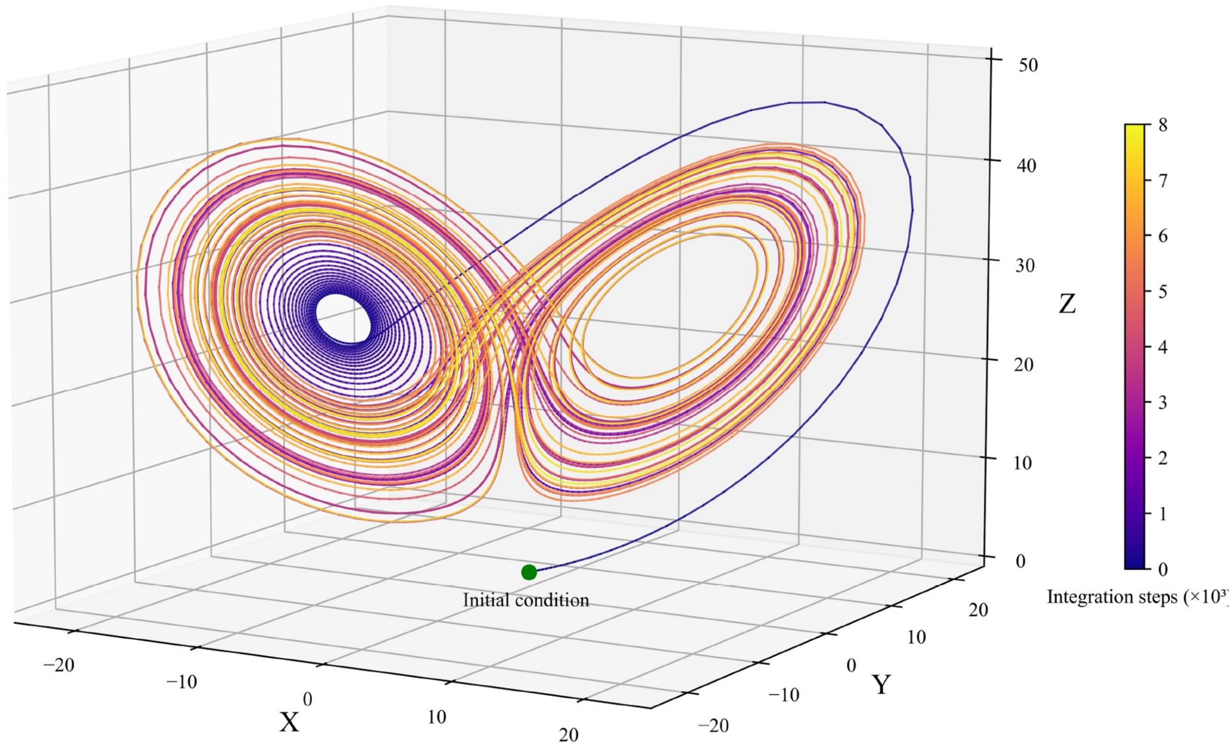

Figure 1 (Color online) Solution trajectory of the Lorenz system.

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

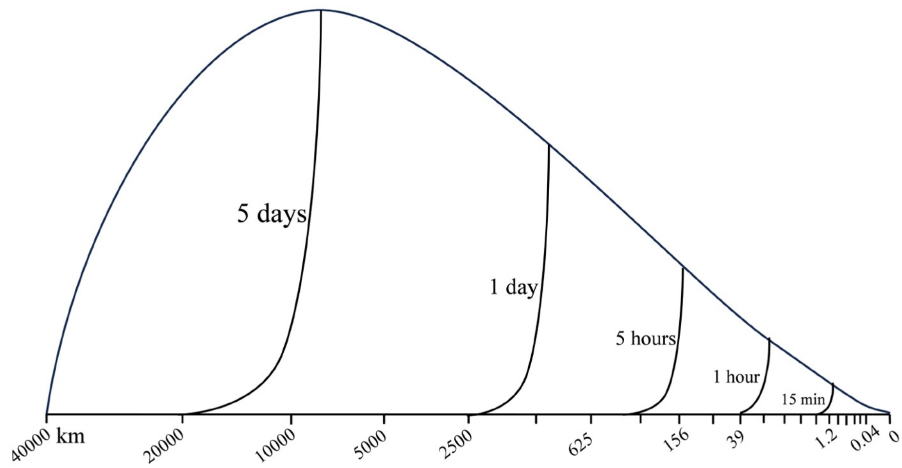

Figure 2 Intrinsic Predictability Limit (IPL) as a function of the spatial scale (wavelength; units: km) of initial errors. The smaller the spatial scale of the initial error, the faster it grows and the shorter the IPL. Adapted from Lorenz (1969).

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-

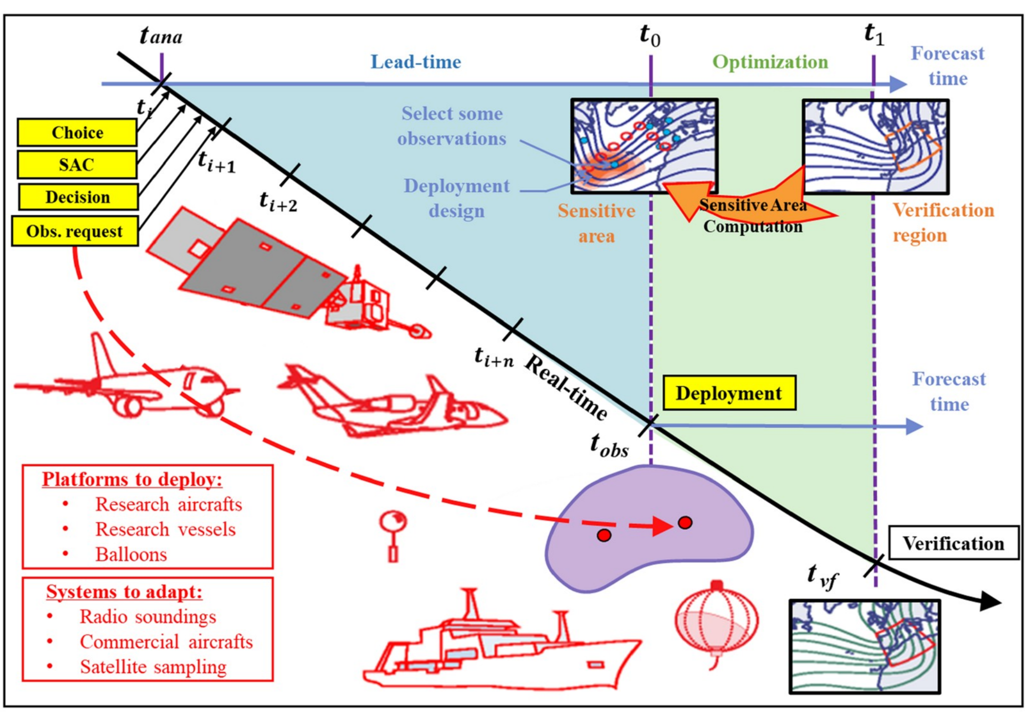

Figure 3 (Color online) Flowchart of the targeted observation field experiment (adapted from https://library.wmo.int/records/item/29004-targeted-observations-for-improving-numerical-weather-prediction).

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-

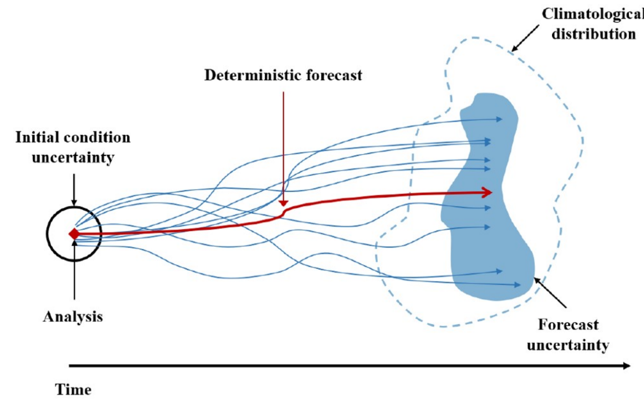

Figure 4 (Color online) Schematic of ensemble forecasting (adapted from https://www.metoffice.gov.uk/research/weather/ensemble-forecasting/what-is-an-ensemble-forecast).

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.

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经典永流传

确定性天气预报和气候预测的幻灭与新生: 洛伦兹经典混沌论文解读

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摘要 洛伦兹1963年发现的“非线性系统的确定性混沌”, 标志着非线性科学的诞生. 自此以“蝴蝶效应”表征的预报对初值的敏感性, 掀起了一场长达半个多世纪, 跨越多学科领域的科学革命. 本文解读“蝴蝶效应”的经典论文, 不仅可以理解先驱们如何在有限条件下挑战无限未知, 诞生经典, 而且可以了解经典思想如何启迪后人跳出既有框架, 破解创新思维密码, 实现跨学科创新. 洛伦兹的确定性混沌理论, 使人们认识到即使初始存在不可觉察的微小误差, 也可导致无法对未来任意时刻状态做出可接受的预测. 正是该认识, 撼动了经典物理的“确定性意味着一切均可预测”观点, 促使气象学家从追求“长期预测”向讨论“究竟可预报多长时间”, 从试图“完美预测”向科学“量化预报不确定性”的转变, 从根本上推动了天气预报, 乃至随后的气候预测范式的改变, 而且深刻影响了数学、生物学和经济学等学科, 甚至渗透到文学、艺术、历史, 以及社会治理领域等, 从而造就了著名的洛伦兹混沌理论.

关键词 洛伦兹系统, 混沌, 蝴蝶效应, 可预报性, 人工智能

1 引言

牛顿经典力学的决定论观点认为, 只要知道一个系统在某一时刻所有粒子的位置和动量, 以及作用于它们的力, 那么根据牛顿运动定律, 就可以完全确定地计算出该系统在未来任何时刻的状态. 牛顿决定论观点的核心要素是完备的初始信息, 已知的运动定律, 和确定性的演化, 认为宇宙及其包含的所有物体的运动是完全由物理定律和初始条件预先决定的, 未来是过去的必然结果, 不存在真正的随机性或不确定性. 著名数学家与天文学家拉普拉斯肯定了这个观点, 并在其名著《概率论之哲学探讨》(“Essai philosophique sur les probabilités”; Laplace, 1825)的导论中将这一观点推向极致, “假设存在全知实体(后称“拉普拉斯妖”)能获取某一时刻所有粒子的位置与动量参数, 即可通过牛顿方程推演宇宙全部历史与未来轨迹”. 该观点意味着, 对于一个描述物质运动的微分方程动力系统, 给定不影响决策的允许预报误差, 可以找到一个值, 只要

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初始误差小于这个值，该系统就可以对未来任意时刻的状态做出成功预报．这种观点在十八、十九世纪科学界占据了主导地位．

然而, 1963年3月, 爱德华·洛伦兹在国际著名期刊《大气科学杂志》(*Journal of the Atmospheric Science*)发表了一篇题为《确定性的非周期流》(Deterministic Nonperiodic Flow; Lorenz, 1963)的文章, 从根本上挑战了这种决定论观点．这是一篇极具里程碑意义的经典论文(Motter和Campbell，2013；罗德海和穆穆，2015)，它通过构建一个简单的刻画大气热对流的非线性常微分方程数学模型(即著名的“洛伦兹方程”或“洛伦兹系统”)，首次用非线性确定性方程展现了未来状态对初始状态的极端敏感性，即无论当前状态存在怎样小的误差(事实上, 这种误差在任何现实系统中是不可避免的, 如天气系统中的观测误差)，该误差都会快速增长, 从而使得对未来所有时刻之状态做出可接受的预测是不可能的. 换言之, 不论初始误差多么小, 预报误差总会在将来的某一时刻, 超出允许的预报误差, 使预报失败. 洛伦兹因此昭告世人: 准确的长期天气预报是不可能的, 从而撼动了经典物理学关于“确定性意味着一切均可预测”的决定论观点, 从此开启了一场长达数十年的轰轰烈烈的科学革命.

2　经典解读: 洛伦兹混沌理论

洛伦兹系统是一个刻画大气热对流的非线性自治常微分方程组．洛伦兹发现，当方程中的系数参数σ=10，γ=28，b=8/3(其中σ为普朗特数，γ为瑞利数，b是与空间相关的常数参数)时，它的解轨迹在三维空间中呈现一个双涡卷形状的吸引子，它既不收敛到固定点，也不形成周期轨道，而是呈现无限折叠、永不重复的有界的复杂结构(图1；Lorenz，1963)．该结构后来被国际学术界称为“洛伦兹吸引子”．洛伦兹吸引子是国际上首次发现的一类不同于动力系统传统吸引子(如不动点、周期轨道、焦点，以及鞍点等)的“奇怪吸引子”(Peitgen等，1992)．洛伦兹奇怪吸引子的性质揭示了系统对初始条件惊人的敏感性：相空间两个初始状态之间即使存在不被察觉的微小差别(如10^{-6}量级)，它们也可能在有限时间内彻底分叉, 并随时间发展, 演化为巨大的不同. 更为奇妙的是, 洛伦兹奇怪吸引子完全

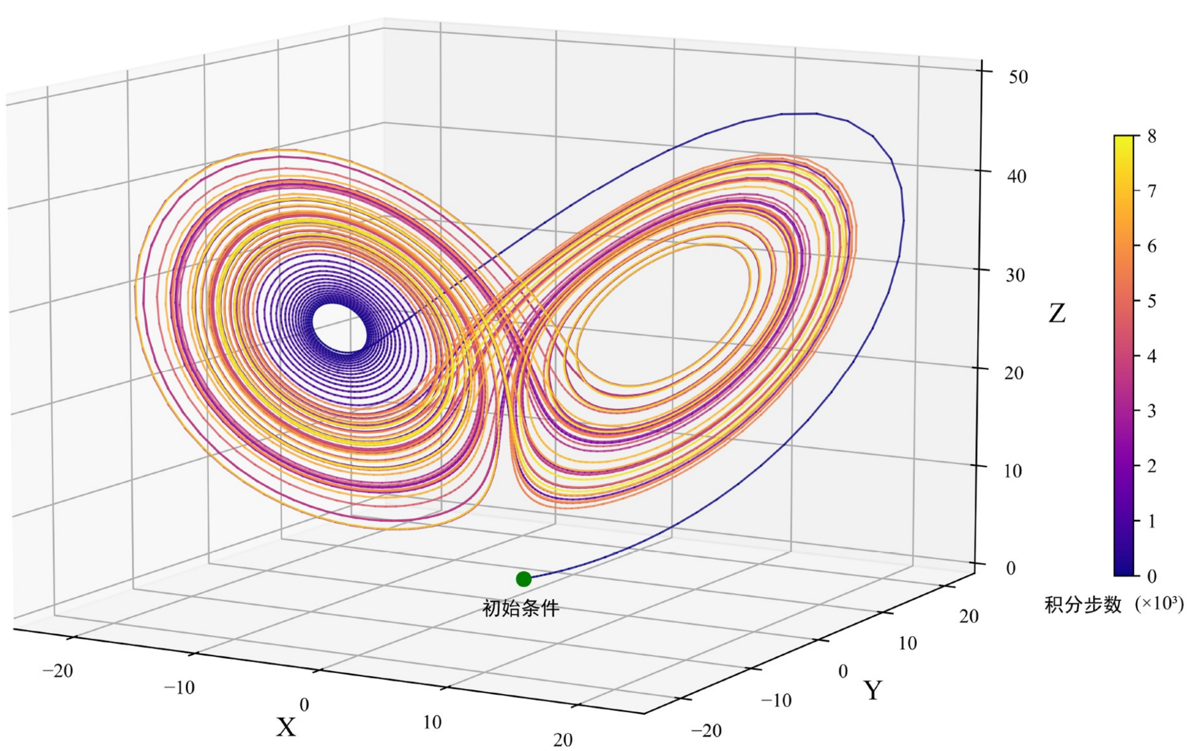

图 1　(网络版彩图)洛伦兹系统的解轨迹

由确定性方程支配，却因为对初始条件的极端敏感性，表现出不可预测、类似随机的运动．后人通常称该现象为“确定性的随机”或“确定性的混沌”(Hunt等, 2004)．这是科学史上首次用非线性确定性方程，通过数值试验来刻画混沌现象的工作，展示了混沌在物理模型中的具体图像.

洛伦兹的工作激发了数学家们关于如何严格定义混沌的研究兴趣．著名数学家李天岩与其导师约克在1975年发表的论文“周期三意味着混沌”(Period Three Implies Chaos, Li和Yorke, 1975)中，首次在数学上严格定义了“混沌”，清晰地刻画了混沌现象特有的初始条件敏感依赖性及其存在的复杂非周期轨道的数学特征，使“混沌”从一个模糊的概念提升为一个有严格定义的科学术语．李-约克混沌针对离散低维系统，证明了该类系统的混沌通过周期点的存在(如周期三)来触发，给出了一个离散低维确定性系统混沌存在的简明判据．与李-约克的低维离散系统的混沌不同；另一极具代表性的Smale混沌理论聚焦于连续高维动力系统，采用著名的马蹄映射模型，给出了双曲集和同宿横截点导致流形缠绕并驱动混沌的几何机制(Smale, 1967). 事实上，李-约克混沌与Smale混沌分别从分析学和几何学角度刻画了混沌，二者共同构成了混沌理论的双翼．它们可通过庞加莱截面将连续系统离散化而融合，实现对复杂非线性动力系统的统一理解，如洛伦兹奇怪吸引子，既符合Smale马蹄的几何混沌特性，又可通过庞加莱映射展示其周期三的混沌特征(Rössler, 1977; Tucker, 2002).

自此，国际上掀起了关于非线性科学研究的热潮. 上述混沌理论为后续关于非线性科学研究的诸多经典方法，如用于识别混沌运动特征的李雅普诺夫指数(Wolf等, 1985; Pecora和Carroll, 1990)，分析非线性动力学和混沌系统的相空间重构理论(Takens, 1981; Sauer等, 1991; Sugihara等, 2012)，以及研究具有无限细节和自相似结构的分形几何学(Hentschel和Procaccia, 1983; Falcone, 2003; Viswanath, 2004)等的提出奠定了理论基础, 从而开创了混沌理论研究的新范式. 洛伦兹混沌理论的提出标志了非线性科学的诞生.

3 经典理论的延伸: 固有可预报性上限

洛伦兹混沌理论揭示的不可长期预测性，使得气象学家们接受了预测的根本局限性, 开始从追求“长期预测”到讨论“究竟能预报多长时间”的根本转变，并提出了逐日天气预报存在“固有可预报性上限”(Intrinsic Predictability Limit, IPL)的观点(Lorenz, 1969).

3.1 真实大气运动是否存在IPL?

Thompson(1957)首次提出了“可预报性”这个概念, 并将其定义为: 在模式准确和初始资料有误差的情形下，能在多长时间范围内成功预报天气．应该指出，按照洛伦兹混沌模型, 对于给定的预报时长, 如一周、一月，甚至一年，只要初始误差足够小(但该初始误差的大小依赖于给定的预报时长)，我们就可以预报一周、一月或一年内的天气．洛伦兹在1963发表的微分方程模型工作的基础上，于1969年在发表于著名期刊*Tellus*上的文章中，采用正压准地转涡度方程，考虑大气运动的多尺度非线性相互作用，从数值试验的角度，揭示了初始误差空间尺度越小，它随时间的增长越快(图2)，在一段时间后，天气尺度信号出现不可接受的预报误差，使得成功预报天气的有效时长存在上限，并明确给出了北半球逐日天气预报的有效预报时长可达两周左右的结论(表1)，他称该预报时长为逐日天气预报的IPL(Lorenz, 1969). Leith和Kraichnan(1972)随后验证了他的工作，使得大气科学界普遍接受了逐日天气预报的IPL为两周左右的结论．二十年后，Tribbia和Baumhefner(2004)利用当时最先进的大气模式NCAR Community Climate Model Version 3与美国国家环境预报中心的资料, 并结合当时的超级计算机, 进一步验证了逐日天气的有效预报时长无法突破两周的结论, 从而使逐日天气预报IPL为两周的观点深入人心, 并被认为是逐日天气变化的固有属性.

但令人遗憾的是, 逐日天气预报IPL为两周左右的结论，并未像洛伦兹混沌理论一样在数学上被严格证明．国际著名气候物理学家Tim Palmer等针对大气海洋流体在何种情形下存在或不存在IPL给出了自己的见解(Palmer等, 2014). 他们认为, 如果刻画流体运动的微分方程动力系统存在整体光滑解，并能够建立恰当的估计，那么该系统就不存在IPL．他们证明了洛伦兹系统存在整体光滑解，表明了洛伦兹系统的解连续依赖初值变化，即无论预报多长时间，只要初始误差足够小(该误差大小依赖于预报时长)，洛伦兹系统均可给出有效预测, 不存在IPL.

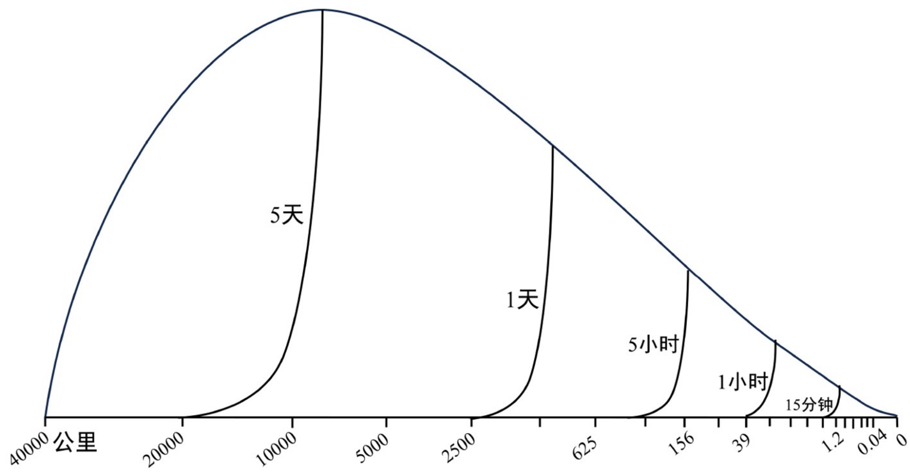

图 2　不同空间尺度(波长; 单位: 千米)初始误差对应的IPL

初始误差空间尺度越小, 其增长越快, 对应的IPL越短. 修改自Lorenz(1969)

表 1　不同波长天气尺度的有效预报时长[a)]

波长(m)	有效预报时长	波长(km)	有效预报时长
38	2.9分钟	78	3.6小时
76	3.1分钟	156	5.8小时
153	4.0分钟	312	9.5小时
305	5.7分钟	625	15.7小时
610	8.4分钟	1250	1.1天
1221	13.0分钟	2500	1.8天
2441	20.3分钟	5000	3.2天
4883	32.1分钟	10000	5.6天
9766	51.1分钟	20000	10.1天
19531	1.3小时	40000	16.8天
39000	2.2小时		

a) 该表改造自Lorenz(1969)

数学上已有证明, 描述流体水平运动的二维纳维-斯托克斯方程存在整体光滑解(Ladyzhenskay, 1969; Huang和Li, 2022). 根据Palmer等(2014)的观点, 二维流体的运动不存在IPL. 这自然令人产生一个疑问, 真实的大气究竟如何运动? 显然, 二维纳维-斯托克斯方程无法刻画真实大气垂直运动(如对流)的特性, 真实大气运动应由三维纳维-斯托克斯方程所刻画. 但是, 令人遗憾的是三维纳维-斯托克斯方程关于时间维的整体光滑解的存在性, 目前仍是未解的国际难题, 曾被美国克莱数学研究所列为七个“千禧年大奖难题”之一, 悬赏一百万美元求解, 所以真实大气究竟是否存在IPL, 仍然是悬而未决的世界难题.

Rotunno和Snyder(2008)采用可描述三维湍流运动的表层准地转模式, 通过数值试验发现该系统存在IPL. 我们猜想, 三维纳维-斯托克斯方程可能对某些特定结构的初始条件存在整体光滑解, 即IPL可能依赖具体的天气事件. Palmer等(2014)采用ECMWF的预报资料分析发现, 大尺度(如阻塞系统)系统的发展会受到如小尺度甚至云分辨尺度的影响, 但并不总是这样, 存在个例依赖性, 因此他们猜测: 初始误差的增长与参考态有关, IPL依赖不同的天气事件. 该猜测与我们上述猜想不谋而合, 即IPL的存在性依赖具体的天气事件. 虽然这些研究未能回答三维纳维-斯托克斯方程关于时间维的整体光滑解的存在性问题, 但为我们深入理解真实大气运动的IPL提供了新思路, 是否这些研究可为数学家研究三维纳维-斯托克斯方程关于时间维的整体光滑解的存在性带来新的思路, 也是值得关注的.

3.2　“蝴蝶效应”的真实体现: 间歇性

洛伦兹的确定性混沌理论强调初始条件的极端敏感性. 为了让大众能够理解混沌特性, 洛伦兹在1972年于麻省理工学院进行的一次演讲中, 采用具有诗意的“蝴蝶效应”来阐释确定性混沌的初值敏感性: 南半球巴西的蝴蝶扇动翅膀, 可能引发北半球美国得克萨斯州的龙卷风(Lorenz, 1972). 可能是因为“蝴蝶效应”对确定性混沌的科普深入人心, 导致人们把天气预报的

IPL与之相联系, 反而忘记了Lorenz(1969)的著名工作, 特别是在该文中提出的最重要的IPL的概念(Palmer等, 2014; Mu等, 2015). Palmer等(2014)厘清了蝴蝶效应与IPL的发现历程, 并将他发现的IPL依赖具体天气事件的现象称为“真实的蝴蝶效应”, 即蝴蝶效应存在间歇性.

事实上, 作者团队在关于厄尔尼诺-南方涛动(ENSO)事件“春季预报障碍”问题的研究中, 已经发现了这一现象(Mu和Wang, 2007; Mu等, 2007; Duan和Wei, 2012), 并建立了特定空间结构初始误差、环境场(气候态和具体事件)和非线性过程共同作用导致高影响海气事件显著预报误差的非线性新理论, 后续关于不同尺度天气气候事件的研究, 证实了该理论的科学性(Mu和Duan, 2025). 非线性误差增长新理论阐明了显著预报误差的产生依赖具体的天气气候事件, 显然, 上述“蝴蝶效应”间歇性支持了该理论. 另外, 该理论强调的特定空间结构初始误差导致显著预报误差的结论, 也应证了确定性混沌理论(如洛伦兹混沌理论、李-约克混沌理论和Smale混沌理论)刻画的相空间初值敏感性, 即意味着特定空间结构初始误差, 而非物理空间的随机初始误差, 导致显著预报误差. 所以, 作者团队建立的非线性误差增长新理论是洛伦兹混沌理论初值敏感性和蝴蝶效应间歇性的综合体现, 反过来也说明了该理论的科学性.

确定性混沌的“蝴蝶效应”是一种隐喻, 不是严谨的科学描述, 这导致了许多人对“蝴蝶效应”的误解, 如认为蝴蝶扇动翅膀可直接导致龙卷风, 从而使得一些影视作品将微小动作与灾难直接关联. 事实上, 蝴蝶扇动翅膀象征初始条件的微小扰动, 其在非线性系统中通过级联放大导致长期行为发生剧变, 但需依赖系统内在的非线性混沌机制. 另外, 对于数值天气预报, 学界存在“观测密度万能论”的认知偏差, 即认为在任意位置增加观测均可通过抑制“蝴蝶效应”来提高预报精度. 这种认知实际违背了洛伦兹吸引子的关键特征——特定结构初始误差导致显著预报误差. 该特征亦意味着初始误差的敏感度具有显著的空间异质性. 研究表明, 特定敏感区域(如湿对流区域)的初始误差, 显著快于平稳层结区(Hohenegger和Schär, 2007), 盲目增加非敏感区的观测, 对改善预报技巧的作用可能微不足道(Snyder, 1996; 亦见第4.1节“目标观测”). 因此, 我们应科学地理解蝴蝶效应, 使其更好地服务于观测和业务预报.

尽管洛伦兹关于逐日天气预报的IPL为两周的结论已被大气科学界认可, 但我们不能将其作为束缚我们的紧箍咒. 事实上, 作为真实蝴蝶效应的延伸, 越来越多的预报实践表明, 具有较大时空尺度的天气事件可能拥有突破两周的IPL(Ma等, 2022). 以暴雨和冬季寒潮事件为例, 某些暴雨影响范围仅几千平方公里, 持续时间至多达几小时, 是时空尺度都比较小的天气过程, 它的IPL时长可能是两周甚至更短, 但后者通常影响范围达数百万平方公里, 维持时间长达一周甚至更长, 尤其是一些理论研究指出, 极端冷事件与欧亚阻塞、北大西洋涛动/北极涛动联系紧密, 进而与北极海-冰-气系统密切相关, 它的IPL应能超过两周(Han等, 2023). 所以, 随着人们对大气演变特征和规律认识的不断深入, 我们应深化和发展洛伦兹的IPL研究, 获得对固有可预报性的新认识, 从而促进数值天气预报的进一步发展.

3.3 IPL: 气候可预报性拓展

上述讨论主要聚焦大气, 关注天气可预报性. 自20世纪80年代以来, 以ENSO预测为代表的气候预测问题逐渐受到国际社会与学术界的高度关注(Zebiak和Cane, 1987; Kirtman等, 2013). 然而, 气候系统的复杂性决定了单一大气圈层研究的局限性. 以ENSO现象为例, 其本质是热带太平洋海气相互作用的产物(Philander, 1983; McPhaden等, 2006), 海洋动力和热力过程在ENSO事件的发生、发展过程中起着决定性作用. 这一认知促使学界达成共识: 准确的气候预测必须建立在理解大气、海洋、陆地等多圈层耦合机制的基础之上. 多圈层相互作用给气候可预报性问题的研究带来挑战, 该挑战将“气候系统IPL”推向了当代气候动力学研究的核心议程, 成为了地球科学研究的热点问题之一, 但如何研究气候事件的IPL, 气候系统中具体气候事件是否存在IPL等诸多问题, 至今仍鲜有力作出现.

尽管Thompson(1957)基于天气预报, 给出了“可预报性”的定义, Lorenz(1969)提出了IPL概念, 但很多文献关于什么是可预报性的描述仍众说纷纭(Mu等, 2004), 直至2013年, 联合国政府间气候变化专门委员会(IPCC)第五次评估报告基于气候预测, 才对可预报性的若干提法进行了厘清(Kirtman等, 2013). 该报告

认为, “可预报性”是物理系统自身的固有属性, 而不是实际预测中做出的有技巧的预报的能力. 前者是不依赖所使用的数值模式和初始场而客观存在的, 后者则取决于数值模式、初始条件, 以及外强迫的精度. 随后, 穆穆等(2017)对该可预报性定义做了进一步修改, 认为“可预报性”是大气、海洋、陆面等地球系统圈层中有关物理变量(如速度、温度、密度、盐度、湿度等)与各种相关的天气、气候事件(如龙卷、台风、暴雨、海洋中尺度涡、ENSO事件等)本身的物理属性, 该属性随时间与空间变化, 依赖物理变量与相关天气气候事件演变的时空尺度, 是非线性多尺度过程相互作用的产物; “可预报性”度量了当前状态或系统的微小误差对未来状态的影响程度: 如果初始误差随时间发展迅速放大或概率密度分布迅速变宽, 那么系统的可预报性较低; 相反, 系统的可预报性较高.

穆穆等(2017)给出的关于可预报性定义的修改, 适用于一般物理变量与事件, 是一个对天气预报和气候预测具有普遍意义的可预报性定义. 这一概念的厘清, 使得IPL跳出了两周上限的框架, 为在更长时间尺度上研究天气、气候可预报性, 认知它们的IPL奠定了理论基础.

4 经典理论的指导作用: 数值天气预报和气候预测

国际著名气象学家Jule Charney是数值天气预报的奠基人之一, 他在担任美国*Journal of the Atmospheric Sciences*杂志的编委时, 面对审稿人负面评价洛伦兹1963年关于“确定性非周期流”的文章, 拍板将其发表; 之后洛伦兹在1969年发表于*Tellus*的文章中提出逐日天气预报IPL为两周左右后, Charney又果断地将世界气象组织数值天气预报业务的主攻方向调整为两周以内, 而不是原先要做的月、季和年际尺度的预报, 从而推动了现代数值天气预报的在正确道路上的良性发展.

洛伦兹混沌理论揭示的初值敏感性现象, 促使气象学界实现了两个重要转变: 首先, 在预报理念上完成了从追求“完美预测”到科学“量化预报不确定性”的范式转换; 其次, 在技术路径上形成了两条创新主线: 一方面发展目标观测技术和资料同化方法, 通过减小初始场误差来提高预报水平; 另一方面开创性地提出集合预报技术, 通过构建初始扰动场来表征初始不确定性, 从而达到量化预报不确定性的目的. 这些理论突破和技术创新推动了数值天气预报能力, 乃至气候预测水平的质的飞跃, 产生了显著的经济和社会效益.

4.1 目标观测

“目标观测”, 又称“适应性观测”, 它瞄准那些在有限时间内产生显著分叉的初始偏差, 将它们的位置标记为关键区域(或敏感区), 通过在敏感区域内实施加密观测, 减小初始观测误差, 进而达到提高未来高影响天气气候事件预报技巧的目的(图3)(Snyder, 1996; 穆穆, 2013). 2005年启动的全球大气十年研究发展(THORPEX)计划, 验证了目标观测在提高台风预报水平中的重要作用(Majumdar, 2016), 我国台湾地区已将目标观测作为台风预报的业务手段. 我国气象部门和有关院校也于近年来将目标观测作为提高台风和海洋环境预报的手段, 开展了多次目标观测外场试验, 有效提高了预报水平(Liu等, 2021; Feng等, 2022; Chan等, 2023; Qin等, 2023).

4.2 资料同化

“资料同化”是指将不同来源、不同时刻, 精度各异的观测数据, 与数值模式相融合, 生成动力和热力上协调一致的大气、海洋、陆面和冰雪等系统状态估计的过程. 通过资料同化, 可为数值预报提供一个更为准确的“最优初始场”, 进而提高预报水平. 资料同化是现代数值天气预报和气候预测系统不可或缺的一环(Navon, 2009; Bauer等, 2015). 经典的资料同化方法包括变分同化和集合卡尔曼滤波同化. 自20世纪90年代起, 四维变分同化技术逐渐发展完善, 包括增加对卫星观测资料的同化, 采用状态依赖权重描述误差特征等方面, 在国际上获得广泛应用, 被称为数值天气预报发展的里程碑. 近年来, 在四维变分同化的基础上, 国际学者们又进一步发展了集合四维变分资料同化等方法(Bauer等, 2015; Bannister, 2017), 这些方法通过集合采样构建流依赖的背景误差协方差, 克服了传统四维变分资料同化方法无法考虑流依赖特性的局限性, 从而能更准确地捕捉大气运动的非线性演化规律. 先进的资料同化技术被认为是90年代后数值天气预报取得显著进展的主要原因之一(Bauer等, 2015).

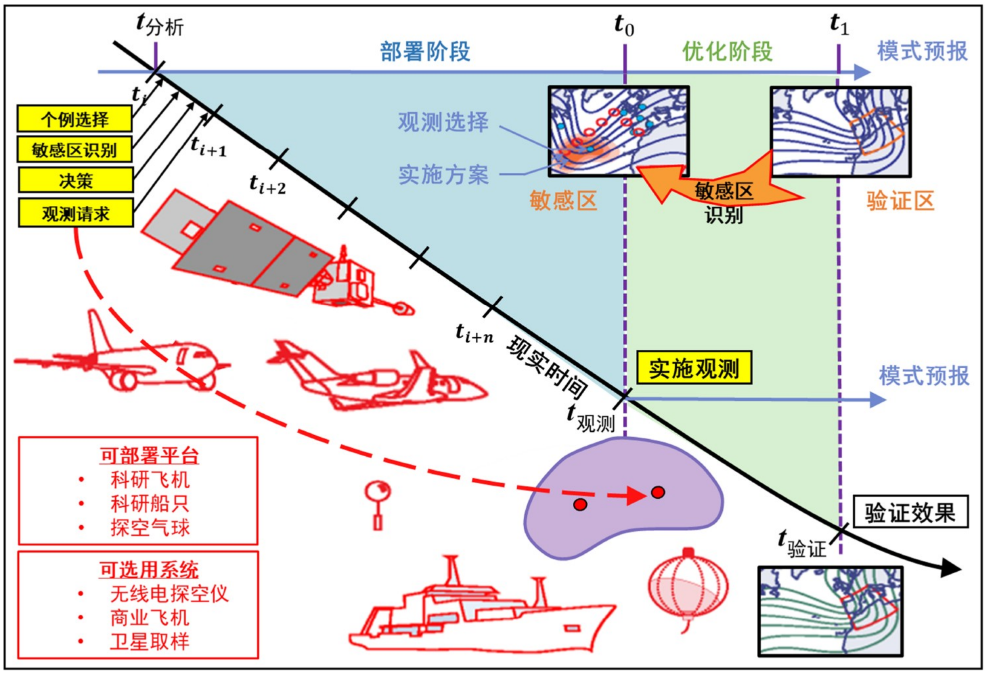

图 3　(网络版彩图)目标观测外场试验流程图

修改自https://library.wmo.int/records/item/29004-targeted-observations-for-improving-numerical-weather-prediction

4.3　集合预报

虽然通过资料同化可以给出一个“最优初始场”，提供一个更为准确的确定性预报结果，但由于观测误差的存在，这样的最优初始场仍存在不确定性，而且由于蝴蝶效应，它可能导致一个与真实情况很不一样的预报结果．然而，这样的确定性预报无法告诉用户这个预报结果离真实情况可能有多远，是否存在其他可能性，预报结果有多可靠等．针对确定性预报的这种困境，气象学家们提出了“集合预报”技术，它通过生成一组围绕“最优初始场”且物理上合理的微小扰动预报，主动模拟和展现混沌效应导致的不确定性范围(Palmer等, 1992; Molteni等, 1996). 集合预报不仅仅是一种新的预报技术, 更带来一种观念上的变化, 即从追求完美的单一答案(这在混沌系统中不可能实现)，转变为提供未来天气可能性的图谱及其发生概率(图4). 集合预报已被世界气象组织列为未来数值预报发展的三大主要战略之一.

目标观测、资料同化和集合预报技术的提出与发展, 标志着数值天气预报和气候预测从追求“确定性预测”到系统认知“预报不确定性”的根本转变，而导致这种根本性转变的核心驱动力即是洛伦兹混沌理论．回顾过往，天气预报在百年间走过了辉煌的发展历程．从“看云识天气”的经验模糊判断，到大气动力学方程的确定性数值计算，再到融合多种跨学科、跨领域技术，能够合理评估不确定性的现代数值天气预报和气候预测系统．这既是天气预报和气候预测的发展史，也是一部人类与自然不确定性的斗争史——从尝试理解, 试图消除, 最终在更高的层次上驾驭. 诚然, 观测资料的增加与计算机技术的发展，逐步提高了数值天气预报和气候预测的精度和计算效率，但更为关键的是洛伦兹混沌理论重塑了人们对非线性科学的认知，由此从根本上推动了数值天气预报和气候预测范式的改变．作者团队近二十年来，克服传统方法的线性局限性，采用全面考虑非线性影响的条件非线性最优扰动方法(CNOP; Mu等, 2003)，努力找寻大气海洋的目标观测敏感区，以及开展相关资料同化和集合预报试验，尤其将其逐步拓展至高影响天气气候事件的目标观测和集合预报业务，为提高我国数值天气预报和气候预测水平提供了重要科技支撑(Duan等, 2023a, 2023b; Mu和Duan, 2025).

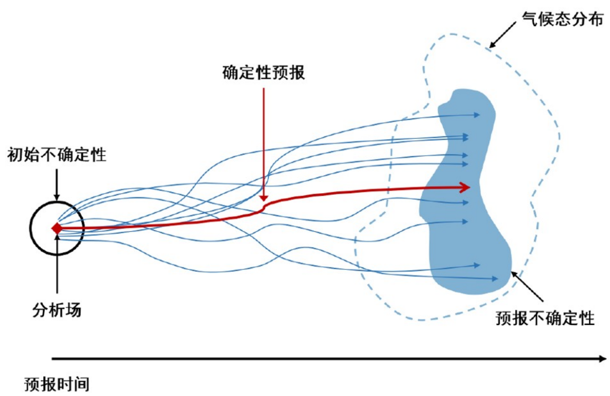

图 4　(网络版彩图)集合预报概念图
修改自https://www.metoffice.gov.uk/research/weather/ensemble-forecasting/what-is-an-ensemble-forecast

5　人工智能大模型时代关于“蝴蝶效应”的讨论

如今, 人工智能(AI)技术正深刻重构天气预报和气候预测范式, 而关于“蝴蝶效应”的讨论又一次成为了研究热点.

在气象大数据驱动的AI模型中, “盘古-天气”(Pangu-Weather)展现出与传统数值模式截然不同的特性. Selz和Craig(2023)发现, 当初始误差较小时, 该系统72小时后误差增长较数值模式低5个量级, 因而他们认为没有出现类似数值模式中解对初值极端敏感性的“蝴蝶效应”现象. Zhou等(2025)通过同化试验发现, 即便在孟加拉湾风暴的强敏感区同化观测, 盘古模型也仅能在24小时预报时长内呈现约16%预报技巧的提升(预报误差的减小), 而无法在更长时间体现初值敏感性. Guardamagna等(2025)针对一个用于预测厄尔尼诺的AI模型的计算揭示出: 随着预报时长的增加, 用CNOP方法求取的该AI模型的最快增长初始误差并不增长, 从而被认为是该模型突破“春季预报障碍”现象, 实现长时效成功预测厄尔尼诺的内在原因.

与之形成对照的是, “伏羲”(FuXi)模型呈现出符合非线性动力系统的典型混沌特征. Pu等(2025)构建的扰动动力学试验表明, 当初始深层风速误差达到1.5m/s阈值时, 其72小时增长幅度与物理模型一致. 基于此发展的集合扰动生成方案, 使热带气旋路径预报技巧显著提高. Li等(2025)的热带气旋路径预报目标观测研究进一步验证: 最快增长CNOP扰动在72小时预报期内呈现显著增长, 从而使得在CNOP确定的敏感区内同化额外资料, 可使台风路径预报误差减少约55%.

面对上述AI模型关于“蝴蝶效应”不一致的结论, 我们迫切需要研究造成这种差异的原因, 探索AI气象预报模型的动力稳定性, 发展AI模型不确定性的量化方法, 最终发展高水平的AI天气气候预报系统, 实现“可解释的智能”与“可控的不确定性”的有机统一, 推动天气预报和气候预测在AI时代的发展更新.

6　结语

当洛伦兹在1963年发现“非线性系统的确定性混沌”时, 他或许未曾料到, 这只偶然扇动翅膀的“蝴蝶”, 竟会掀起一场长达半个世纪, 跨越多学科领域的风暴. 洛伦兹混沌理论不仅促使数值天气预报从“完美预测”转向“科学量化预报不确定性”, 使得数值天气预报与气候预测在科学理性的道路上健康发展, 还深刻影响了数学、生物学和经济学等学科. 如在数学中, 混沌理论不仅革新了动力系统、几何学和数值分析等传统数学分支, 还催生了分形几何等新兴领域, 并促使数学家重新思考确定性与随机性的关系, 其影响持续渗透到现代数学的前沿问题中, 如量子混沌, 信息动力学等, 成为链接纯粹数学和应用科学的重要桥梁; 在生物学中, 混沌理论重塑了生物学对“复杂性”和“不确定性”的认知, 厘清了生物系统的内在随机性实为确定性混沌的结果, 推动了复杂系统科学、生物数学和计算生物学等领域的兴起; 而在经济学领域, 混沌理论的引入改变了传统认为经济发展过程是周期性波动, 而股市价格变动是随机趋势的观点, 并催生了新一代经济建模与政策仿真工具. 此外, 洛伦兹混沌理论也广泛渗透到文化、艺术、历史甚至社会治理领域, 形成了独特的思想辐射. “蝴蝶效应”已成为文学和影视作品中探讨因果链、偶然性与宿命的核心隐喻, 如电影《蝴蝶效应》(2004)通过主角回溯微小选择改变了人生轨迹的情节, 直观展现了混沌理论的“初始条件敏感性”的哲学内涵.

预测未来是人类文明亘古不变的追求, 而建立在现代科学理论和方法基础上的预测实践, 若从牛顿力学精确计算行星轨道开始, 其历史不过三百余年. 在这片科学预测的百花园中, 数值天气预报与短期气候

预测自上世纪中叶陆续获得成功实践，犹如一株傲然绽放的奇葩，彻底革新了人类对大气系统的认知范式，而洛伦兹提出的混沌理论及其可预报性研究，恰似一把开启认知新维度的钥匙．随着大气科学理论的迭代更新、观测技术的革命性突破以及预测模型的持续优化, 这一理论体系始终焕发着蓬勃生机: 其一, 它如同灯塔, 警示科学界必须恪守自然规律的边界, 任何超越科学原理的预测苛求都无异于建造空中楼阁; 其二, 通过基础研究, 全面完整地理解洛伦兹混沌理论, 并发展和深化, 进而用于指导观测与预报实践, 也是当代学界的责任.

站在当代科学发展的维度审视，洛伦兹开创的天气预报与气候预测研究，其价值早已超越单一学科疆域．无论是地球科学领域的地震预测难题，还是更广阔的自然科学与社会科学预测课题，这套融合确定性规律与随机性本质的理论框架，都将持续提供弥足珍贵的范式参考与方法论启迪.

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