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The predictability of atmospheric and oceanic motions: Retrospect and prospects

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Abstract This paper reviews the historic understanding of the predictability of atmospheric and oceanic motions, and interprets it in a general framework. On this basis, the existing challenges and unsolved problems in the study of the intrinsic predictability limit (IPL) of weather and climate events of different spatio-temporal scales are summarized. Emphasis is also placed on the structure of the initial error and model parameter errors as well as the associated targeting observation issue. Finally, the predictability of atmospheric and oceanic motion in the ensemble-probabilistic methods widely used in current operational forecasts are discussed. The necessity of considering IPLs in the framework of stochastic dynamic systems is also addressed.

Keywords Atmosphere-ocean, Predictability, Intrinsic predictability limit, Ensemble forecast

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1. Introduction

The study on the atmospheric and oceanic predictability can be traced back to Thompson (1957), who studied the impact of the initial errors from insufficiently accurate observations on numerical weather forecasting under the hypothesis that the model is perfectly accurate. Later, Lorenz discovered the chaos of the atmospheric motions using the Lorenz model (Lorenz, 1963) and further studied the nonlinear interactions among atmospheric motions of different scales, from which the well-known concept of intrinsic predictability was derived (Lorenz, 1969). These studies basically focused on the predictability of weather scales. Since the early 1980s, high attention have been paid by both social and research communities globally to climate prediction of important climate modes represented by ENSO. The predictability of the climate then rapidly became an intensively researched field. Since the beginning of this century, with the implement of a series of international programs and initiatives, including the World Climate Research Program (WCRP), the Variation and Predictability of the International Climate Research program (CLIVAR) and the Global Observational System Study and Predictability Experiment (THORPEX), the predictability studies have become a main research field in geoscience.

What is predictability? An accurate answer is difficult in a rigorous sense, which could explains why there have been various definitions and descriptions of predictability in the literature (e.g., Mu et al., 2004). The newest IPCC AR5 evaluation report defined it as an inherent characterization of a physical system rather than our ability to make skillful predictions in practice (Kirtman et al., 2013). The former is inherent in the system and independent of the models and initial conditions, whereas the latter is dependent on the accuracy of model, initial conditions and the external forcing. In any case,

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our understanding and description of concerned physical variables, their associated events and evolution law are imperfect. For example, all the observations have errors, and none of the models can perfectly describe the inherent evolution of a climate system in time and in space. Therefore, the definition of climate predictability from the IPCC fifth report can be rectified to become a new definition of predictability in a more general framework that is suitable for all physical variables and events. That is, predictability is an inherent property of physical variables (such as velocity, temperature, density or salinity) and weather or climate events (such as tornados, typhoons, heavy rainfall, ENSO, oceanic mesoscale eddies) in the atmospheric and oceanic systems. This property varies with time and space and is a product of multiscale interactions. The evolution of the property is nonlinear. The predictability measures the impact of tiny errors in current states and model system on the future states. If the initial errors grow rapidly or the probability density distribution becomes wide quickly, the predictability of the concerned target is low, and vice versa.

It has been believed by most people in scientific community that the classic chaos theory proposed by Lorenz (1963) resulted in the concept that atmospheric motions have intrinsic predictability, which is actually a misunderstanding. As addressed by Palmer et al. (2014), it was not the famous chaos model of three variables proposed by Lorenz (1963), but the classic work about nonlinear interactions among different atmospheric scales that suggests the day-by-day weather forecast having an IPL, which then makes us to accept the viewpoint that the atmospheric intrinsic predictability exists objectively.

Currently, many papers confuse the forecasting skill of a model or a kind of forecast method with the "predictability". Theoretically, when we use a norm (such as anomaly correlation coefficients, root-mean-square error, and signal-to-noise ratio) to measure the forecast errors, the forecasting skill of a model or a method should be regarded as an evaluation of predictability. The predictability should be the upper limit of the forecast skill and not dependent on the model or data used. However, as our knowledge and technology improve, forecast skill can be improved. Thus, it is easier to understand why the forecast skills would be different when we use different norms to measure the forecast errors.

Mu et al. (2004) suggested the "study of predictability" as "studying the reason and mechanism of the uncertainty of forecast result (e.g., forecast error) and studying the way or methodology to reduce such kind of uncertainty". Loren (1975) proposed two kinds of predictability, namely, the first kind of predictability and the second kind of predictability, which explores the source of the forecast uncertainty from the view point of the initial errors and the model errors respectively. Both kinds of predictabilities are to meant to reduce the uncertainty of the forecast result and thus to improve the forecast skills, finally making the forecast skill approach the predictability. Just like the predictability should not be confused with prediction skill, Mu et al. (2004) emphasized that the predictability and predictability studies are two different concepts and thus should not be confused with each other.

With the development of atmospheric and oceanic science and the deepening understanding of the weather and climate forecasts (prediction), scientists have a greater insight into the predictability. The connotation of predictability is more reasonable and is more suitable for the demands of not only weather but also climate study. However, there still remain many challenging issues that require further study. The authors will present these issues in the following sections, which could provide a useful reference for readers who wish to examine weather and climate predictability.

2. The issue with the IPL

As discussed above, Lorenz (1969) proposed that the IPL exists in the day-by-day weather forecasts. In his work, the evolution of the initial errors was studied based on the barotropic quasi-geostrophic vorticity equation, concluding that the initial errors grow faster as the spatial scale of the initial errors becomes smaller (Figure 1). The initial errors increase with time, resulting in the prediction errors of weather-scale signals that are beyond the tolerance limit after a period, which was called IPL by Lorenz (1969). Later, Leith and Kraichnan (1972) and many other studies confirmed the findings of Lorenz (1969). Since then, it has been well recognized that day-by-day weather forecasts do have IPLs, which has been established to be approximately two weeks (Figure 1). Tribbia and Baumhefner (2004) further validated this result using the Community Climate Model Version 3 (CCM3) of NCAR in a supercomputer. With time, people gradually interpreted the inherent property of the IPL as the predictability of day-

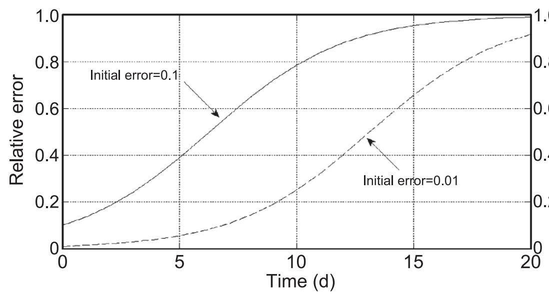

Figure 1 The ratio of the root mean square of the forecast errors from the different initial errors and different magnitudes to the root mean square of the climate variance, i.e., the relative error. The smaller the initial error is, the faster the growth of the initial error will be; All the relative errors exceed 0.5 at around two weeks, no matter what kind of initial errors there are. This is when the weather signal is exceeded by the forecast errors, and the predictability is lost. This suggests that the IPL of the numerical weather forecast is about two weeks (the figure is from Kalnay (2011)).

by-day weather forecast. Later, people related the predictability of the weather forecasts to the famous chaos model of Lorenz, gradually forgetting the classic work of Lorenz (1969) especially the concept of IPL in this work (see detailed in Palmer et al. (2014)).

It should be noted that the predictability of weather or climate events or any physical variables (such as temperature and wind speed) is an inherent property. This was a great finding in atmospheric sciences in the 1960s, although it is not as classic as the concepts of velocity, temperature, or mass, etc. It was the famous work of Lorenz (1969), among numerous papers discussing predictability, that made the predictability been broadly accepted as an inherent property of variables and events. However, these previous studies only focused on the IPL of weather events. With the developments of numerical weather forecasts and climate predictions, it was found that the forecast skills were much different for different scales of weather or climate events (such as heavy rainfall, the blocking high, and ENSO). To further solid predictability basis, it is necessary to discuss the IPL of events with different spatio-temporal scales.

Usually, a numerical model is needed to investigate the IPLs for different spatial and temporal scale events. Additionally, the model errors should be not too large to reflect the dynamical features of the growth of different scale errors. In the following, we will address the IPL problems of several weather and climate events that can be reasonably simulated by numerical models, but it is difficult to determine the magnitude of model errors. In such cases, can we still use the numerical model to study the IPL problems? We would like to argue that when a model has a reasonable ability to simulate these events, the model thus has the ability to describe their primary physical and dynamical process, thus allowing its use to study IPL instead of waiting passively for the improvement of the model. Note that during the 1960s to the 1970s, although the model error was very big, it did not block Lorenz from investigating the IPL. Of course, it is difficult and challenging to well design the numerical experiments to study IPL, and thus, to analyze the result to obtain valuable conclusions, under the circumstance of considering the impact of model error.

2.1 The IPL for meso-/small-scale weather processes

The IPL of the 2-week upper limit originated from the daily forecast of weather-scale events. Usually, the weather-scale events in time can be classified into three categories: the large, meso and small scale processes. The large-scale weather processes ranging up to thousands of kilometers have an IPL of about two weeks. However, it is still an open question as to whether meso-/small-scale events (such as heavy precipitation) have IPLs and how long they would be. Scientists have been trying to seek the answer (Zhang et al., 2003; Zhang F, 2005). Bei and Zhang (2007) investigated the predictability of heavy precipitation along the Mei-Yu front. They decomposed the initial errors (perturbations) derived from difference between ECMWF and T106 into three different scales, with small scale meaning less than 300 km, middle scale being from 300 to 1200 km, and large scale being greater than 1200 km. Further, they added these errors separately to the initial conditions of ECMWF to predict 3-h (with a 24-h lead time) and 24-h (with a 36-h lead time) accumulated precipitation predictions. The results show that smaller-amplitude perturbations have faster error growths, while the larger-scale perturbations contribute the most to the total forecast error. There is a complete loss of predictability of precipitation at scales smaller than ~400 km over 36 h, which is still not convincing enough to be deemed as the IPL for small-scale precipitation.

2.2 The IPL for the stable general circulation mode

As discussed above, the IPL of 2 weeks is based on an average concept for daily forecasts. The atmosphere contains some steady modes that can be maintained for a long time (Dole and Gordon, 1983), such as the block systems. The blocks are large-scale circulation mode that are persistent in the mid- and high-latitudes without deterministic period. They can sometimes last over 10 days (Rex, 1950). The onset and breaking down of the blocks often lead to widespread disastrous weathers. For example, the catastrophic floods in the Yangtze-Huaihe river basin in the summers of 1991 and 1998 had a close relationship with the anomalous atmospheric circulation over the Ural region (Li et al., 2001). In January 2008, a block system sustained in the mid- and high-latitudes over Eurasia (Sun and Zhao, 2010), during which severe blizzard and frozen rain occurred in South China. Recently, considerable progress has been made in simulating the intensities and frequencies of the blocks over the Pacific region, but quite small progress were made in the simulation of the blocks over Atlantic Europe (Davini and D'Andrea, 2016). In addition, great achievement have been obtained globally in the maintenance of blocks. Although apparent progress have been made on the onset and decay of blocks, they still cannot be well predicted by general circulation models. There are still large errors in the predicted locations and intensities of blocks (Palmer et al., 1990; Tibaldi et al., 1994; Matsueda et al., 2011). Thus, whether such long-lasting large-scale circulations as blocks also have an IPL of two weeks is unresolved and quite interesting question.

2.3 The IPL for intraseasonal oscillations

Subseasonal or intraseasonal variability often is referred to as the oscillations with periods between 30 and 60 days, of which the Madden-Julian Oscillation (MJO) is the largest mode in the tropical atmosphere. The MJO originates over the tropical western Indian Ocean and propagates eastward, peaking over the eastern Indian Ocean and western Pacific, and weakening gradually as it crosses over the international date line. Occasionally, it is enhanced over the tropical Atlantic (Madden and Julian, 1971, 1972; Zhang C, 2005). MJO is the strongest intraseasonal oscillation signal. It is associated with severe cumulus convection, and bring heavy rainfall over the Indian and Pacific Ocean. Additionally, strong surface winds associated with MJO may evoke equatorial Kelvin wave in the tropical Indian Ocean and activate the intraseasonal variability there. Moreover, MJO is closely linked with many atmospheric and oceanic activities, such as tropical cyclone, the onset of the Asian monsoon system and the transition between the rainy and dry seasons within the monsoon period, the onset and unusual activities of the South China Sea summer monsoon, ENSO and the North Atlantic Oscillation activities (Liebmann et al., 1994; Higgins and Shi, 2001; Chan et al., 2002; Hendon et al., 2007; Tong et al, 2009; Jiang et al., 2017), etc. Therefore, it is of great importance to well predict MJO for global weather forecasts and climate predictions (Zhang, 2013).

Intraseasonal oscillations are, by definition, between weather and climate in their temporal scale, thus can be regarded as the bridge linking weather and climate phenomena. MJO is a key transition from subseasonal to seasonal climate predictions and is of great significance to the seamless connection between weather and season/climate predictions. Currently, the daily forecast skills for MJO in some major scientific research and operational organizations are up to 11–25 days (Kang and Kim, 2010; Seo and Wang, 2010; Rashid et al., 2011; Hudson et al., 2013; Vitart, 2014). Based upon the observed data, Ding et al. (2010, 2011) note that the predictability limit for MJO can reach 5 weeks or so using the nonlinear local Lyapunov exponent (NLLE) method, which is 2 weeks longer than the average level of the mainstream methods (11–25 days). Thus, is 5 weeks the ILP for MJO? Actually, whether the IPL exists or not for MJO still remains unknown. Can the research framework of predictability for weather events be shared with MJO? Or should a completely new framework of IPL be established for MJO in the future? All of these questions are still under exploration.

2.4 The IPL for ocean activities of different scales and related climate events

Similar to the atmosphere, oceanic motion are also observed at multiple scales in time and space. The ocean is an important component of the earth's climate system that controls and adjusts the climate via its variations and interactions with the atmosphere. Unfortunately, our ability to simulate and predict ocean activities has been limited because of the sparse oceanic observations that were available until recently, when satellite data and ARGO profiles became available. Driven by climate change studies and the demands in climate prediction, encouraging progresses have been made in predicting oceanic motion and related climate events, of which ENSO is a successful example. Since the 1986/1987 event was first successfully predicted in 1980s, valuable prediction of an ENSO event can be issued six months in advance currently. Likewise, an important question is what the IPLs are for these oceanic motions at different temporal and spatial scales and their related climate events. Undoubtedly, research findings in these aspects are fundamental to conducting oceanic and relevant climate event predictions. Here, we will discuss some important issues around this topic.

2.4.1 Mesoscale eddies in the ocean

Like the weather scales in the atmosphere, mesoscale eddies are common in the ocean. They have spatial scale from tens up to a hundred kilometers in horizontal, hundreds of meters in vertical, and can remain for tens of days. Mesoscale eddies are transient and vigorous oceanic signals, in much the same way as a typhoon in the atmosphere. Their rotational speeds can reach several meters per second, which is an order of magnitude larger than the current velocities in the ocean. Mesoscale eddies contribute 90% of the total kinetic energy from the large- and mesoscale currents. Hence, such a strong signal will not only influence the oceanic physics, chemistry, and biotic environment but will also be of great significance to the transport and redistribution of the matter and energy, such as heat, salinity, CO_2, and nutrients. In this way, mesoscale eddies can lead to visible global climate variations (Fuglister, 1972). Currently, mesoscale eddies have become a hot issue in physical oceanography, but the studies are still in their early stage (Chelton et al., 2007, 2011a, 2011b) due to either a shortage of observations or the limited understandings of these eddies. Owning to above reasons as well as coarse resolutions, current numerical models are not able to simulate such eddies and related matter transports reasonably (Zhang et al., 2016). In particular, we have no idea whether the simulated eddies and their characteristics are true or not because of the lack of observations. All these bring up a very challenging question for scientists, namely, how to study mesoscale eddies and their IPLs with low-level numerical models and limited observations?

2.4.2 ENSO

ENSO is an ocean-atmosphere coupled phenomenon that presents an irregular oscillation between a warm phase, El Nino, and a cold phase, La Nina. It is accompanied by a seesaw in the pressure of the lower atmosphere between the western and eastern tropical Pacific Ocean (Philander, 1990). It is the strongest interannual climate variability signal that is only weaker than seasonal cycle. Although ENSO occurs in the tropical Pacific Ocean, it has great effects on global weather and climate through atmospheric teleconnections (Cane, 1983; Trenberth et al., 1998; McPhaden et al., 2006; Ham et al., 2014). As a main source and contributor of anomalies in global general circulation, weather and climate, timely and accurate forecast of the occurrences and evolutions of ENSO is in a high demand by policy makers and the public.

There were already numerous studies on the predictability of ENSO from different perspectives (Moore and Kleeman, 1996; Kleeman and Moore, 1997; Mu et al., 2007a, 2007b; Duan and Zhao, 2015). Currently, ENSO prediction is issued in real-time, with a lead time of six months to a year. However, large uncertainties still exist in ENSO predictions, such that it does not meet the demands of disaster prevention and reduction (Kirtman et al., 2002; Jin et al., 2008; Luo et al., 2008). Especially the frequent occurrence of a new type of El Nino event (i.e., Central Pacific El Nino) since 1990s, which is different from the traditional El Nino (i.e., Eastern Pacific El Nino), makes the ENSO forecast more complicated and challenging. Chen et al. (2004) found, in hindcast experiments, that a valuable forecast can be made for ENSO for up to two years ahead. However, Hendon et al. (2009) rarely succeeded in forecasting the variety of El Nino by one month ahead. Jeong et al. (2012) could only skillfully forecast ENSO with a lead time of at most four-month even using the ensemble forecast. Thus, how far in advance can we successfully forecast ENSO? In other words, what is the IPL in the ENSO predictions? This question is a challenging but is also a very important issue, not only for ENSO prediction itself but also for weather and climate prediction as well as for the prevention and reduction of natural disasters.

2.4.3 Indian ocean dipole

The Indian Ocean Dipole (IOD) is an ocean-atmosphere coupled phenomenon with an interannual time scale in the tropical Indian Ocean. Positive IOD events present positive sea surface temperature anomalies (SSTAs) in the western Indian Ocean and negative SSTAs in the southeastern Indian Ocean. Negative IODs show the generally opposite physical characteristics. Positive IODs often bring large amounts of precipitation to East Africa and severe droughts to Indonesia and Australia (Ansell et al., 2000; Ashok et al., 2001; Behera et al., 2005); negative IODs affect these regions in the opposite manner. In addition, the IOD could affect the weather and climate not only of the nearby areas by modulating the monsoon (Saji and Yamagata, 2003; Annamalai and Murtugudde, 2004; Vecchi and Harrison, 2004) but could also affect remote regions by teleconnection effects (Ansell et al., 2000; Guan and Yamagata, 2003).

The study of IOD prediction is still in an early stage. Previous studies showed that, although IOD events can be predicted one season ahead, large uncertainties exist and their forecasting skills are particularly limited by the winter predictability barrier (WPB) (Wajsowicz, 2004; Luo et al., 2005, 2007; Shi et al., 2012). Spring predictability barriers are also observed in IOD forecast possibly affected by ENSO. Feng et al. (2014a) showed that there are WPBs in both the growing and decaying phases of positive IOD events using the geophysical fluid dynamics laboratory climate model version 2p1 (GFDL CM2p1). The initial errors with a west-east dipole pattern are more inclined to cause significant WPB. Correspondingly, there are persistent winter barriers in the growing and decaying phases of positive IOD events in the observations, which indicates that the IOD events have strong dynamical instabilities in the winter, inducing the fast growth of prediction errors in the winter and finally, the occurrence of a significant WPB. The WPB is an important characteristic in IOD predictions. Feng et al. (2014b) demonstrated that the simulating ability of the WPB in the Coupled Model Intercomparison Project (CMIP5) mainly depends on the simulating ability of the climatological conditions associated with the WPB. In spite of a lot studies of the aforementioned IOD predictability, there has been no study, to our best knowledge, about the IPL problem of IOD, presenting us with a challenging and fascinating topic in the field of predictability of IOD.

2.4.4 Pacific Decadal Oscillation

The Pacific Decadal Oscillation (PDO) is a strong signal of climate variability in the Pacific Ocean on the decadal time scale, which is similar to ENSO (Mantua et al., 1997; Zhang et al., 1997; Minobe, 1999). The PDO can be divided into cold and warm phases (or cold and warm "events"). During the warm phase, the tropical central-east Pacific is anomalously warm, the central North Pacific is anomalously cold, and the west coast of North America is anomalously warm. The cold phase has the opposite features. A typical PDO event can last 20–30 years, with the primary signal in the North Pacific and the secondary signal in the tropical Pacific. The PDO plays an important role in adjusting the climates in the North Pacific and surrounding areas and in modulating the interannual variations (such as ENSO and its effects) as a critical background. Although CMIP5 can reproduce the sea temperature structures of the PDO and capture the influence of the PDO signal on the climate of North America, there is still large room to improve its simulation, especially that of the PDO variability (Sheffield et al., 2013). In the decadal forecast experiments of CMIP5, some models show some ability in conducting PDO hindcasts and forecasts, but the overall skills are still low (Pohlmann et al., 2009; Fyfe et al., 2011; Chikamoto et al., 2012; Kim et al., 2012; Mochizuki et al., 2012). Thus, is the IPL of the PDO low itself? Ding et al. (2015) estimated that the predictability limit of the PDO is 9 years by separating the different time scales and using the observational data and linear statistical methods. Considering the nonlinear interaction effects of the different time scale variabilities on the predictability limits of the PDO, the IPL of the PDO remains unsolved. Is it possible to determine the IPL of the PDO using the same framework as that for the interannual variability and even weather-scale phenomenon? These topics are very interesting and have important guidance for PDO predictions.

2.4.5 Atlantic multidecadal oscillation

The Atlantic Multidecadal Oscillation (AMO) (Schlesinger and Ramankutty, 1994; Kerr, 2000) is a climate phenomenon taking place in the North Atlantic, in which the sea surface temperature pseudo-periodically becomes cold or warm and has a basin-wide spatial scale and a multidecadal temporal scale. The period of AMO is approximately 50–70 years (Kushnir, 1994; Enfield et al., 2001), with an SST amplitude of 0.4°C. AMO is a dominant factor through which the ocean affects the climate (Chylek et al., 2014), which not only modulates climate change by influencing the Arctic sea ice but also plays an important role in the formation of the significant negative correlation between the Antarctic and Arctic temperatures (Polyakov et al., 2003; Chylek et al., 2010; Frankcombe et al., 2010). AMO also has profound climate effects on Asia, and even on China. For example, AMO is often considered to be a key cause of the East Asian climate warming, summer monsoon enhancement, and winter monsoon weakening (Lu et al., 2006; Li and Bates, 2007; Wang et al., 2009; Si and Ding, 2016). In particular, some recent research suggests that the positive phases of AMOs have made significant contributions to global warming over the past 30 years (Chylek et al., 2014), whereas the decay of the associated Atlantic Meridional Overturning Circulation (AMOC) may be the major cause for the subsequent global warming hiatus (Song et al., 2014). The AMO prediction has special significance for global climate prediction. As the predictability source of the AMO may mainly come from the subsurface oceans, the ocean data initialization is helpful for improving the AMO forecast skill (Keenlyside et al., 2008; Chikamoto et al., 2013). For different versions of the Model for Interdisciplinary Research on Climate (MIROC), the multimodel ensemble forecast skill is higher than the single-model skill, indicating that the multimodel ensemble of CMIP5 can also improve the AMO forecast skill (Chikamoto et al., 2013). However, the simulation ability of the SSTA mode of AMO in CMIP5 shows no obvious improvement compared with that in CMIP3 (Ruiz-Barradas et al., 2013), but the AMO in the North Atlantic is better forecasted than the PDO (Meehl et al., 2014). Despite these studies on AMO prediction, the studies on the IPL of AMO are still rare. Recently, Ding et al. (2015) noted that the predictability limit of AMO is 11 years, but the authors did not determine whether the predictability limit represents the IPL of the AMO. Considering the modulating effects of AMO on the global climate and global warming, the IPL of AMO is also an important issue worth discussing.

2.4.6 The variations of ocean circulation (e.g., Kuroshio path variations)

The Kuroshio is the western boundary current of the North Pacific subtropical gyre. The traits of the Kuroshio are that its velocity is fast, its current is large, and the Kuroshio contains both high temperature and salinity waters. In the south of Japan, the Kuroshio has bimodal paths: a large meander (LM) path and a non-large meander (NLM) path. Both paths have effects on the local climate change (Xu et al., 2010), fisheries, and navigation. The Kuroshio paths last for years to decades, but the transitions between the two different paths occur in a matter of several months (Kawabe, 1986, 1995). The Kuroshio path variations may affect local and nearby climate conditions. Xu et al. (2010) noted that a cool water pool form between the Kuroshio and Japanese coasts during a large meander event, and affect the general circulation through air-sea interaction. The colder surface water caused a reduction of the wind speed and thus, decreased the precipitation over it. Shi (2004) indicated that the Kuroshio path variations had significant effects on precipitation in the Yangtze River Basin. In addition, the Kuroshio path variations are closely related to fisheries and national security of China. Consequently, it is important to predict the variations of the Kuroshio path.

Japan Agency for Marine-Earth Science and Technology (JAMSTEC) has been carrying out experiments to predict Kuroshio path variations (Miyazawa et al., 2009). Due to the complexities of Kuroshio path variations, the unclear mechanism of their behaviors, and insufficient observations, large uncertainties are observed in the predictions of Kuroshio path variations. Hence, it is a great challenge, but worth the effort to investigate the IPL problem of the Kuroshio path variations, which will lay a foundation for the mechanism research and target observation.

3. The problems of initial errors and model parameter errors

The predictability problems are usually classified into two types. The first and second type of predictability is related to the initial errors and the model errors respectively (Lorenz, 1975). In the preceding part of the text we mainly discussed the first type of predictability, which is of commonness in point of view initial error. The second type of predictability is to explore the effects of model errors, therefore the uncertainties of specific dynamics and physical processes need be investigated. These uncertainties may be different for different weather and climate events. However, as one of the main sources of model errors, the uncertainties of model parameters have generic characteristics for both weather and climate prediction. The common problems with initial errors and model parameter errors will be discussed in this section.

3.1 The problem of initial errors

As mentioned earlier, the uncertainties of prediction due to the initial errors are classically as the first type of predictability problems. A core issue is to determine the types of initial errors that evolve faster and could cause larger prediction errors. It is generally thought that the less the initial errors are, the better the forecast results will be. However, it is found that things are not that simple in both the theoretical studies and the actual forecasts. In fact, in some cases, a "smaller" initial error may lead to a larger prediction errors, while a "larger" initial error may not cause a larger prediction error. This phenomenon is closely related to the spatial structures of the initial errors (Mu et al., 2003). The differences of prediction errors may be very large due to the initial errors, which are constrained by the same measures (such as the energy norm) and have the same amplitudes, but have different spatial structures (Moore and Kleeman, 1996; Mu et al., 2007b). Hence, the types of initial errors that could have important impacts on the prediction errors should be explored in predictability studies. In addition, the influence of random errors should be also taken into account based on the chaos theory of the butterfly effect by Lorenz.

At the early stages of numerical weather prediction that occurred around the early 1950s, it was found that the prediction skill in an area was impacted by the initial conditions of some of the local regions of the previous steps (Riehl et al., 1956). This finding led to an observational strategy, called the targeted observation approach, in the late 1990s. Targeted observation aims to conduct additional observations (Snyder, 1996) at a targeted time (t_0) for some regions (sensitive regions) whose initial errors can lead to the largest forecast error within the verification region for the variables of interest at the verification time ($t_1>t_0$). The additional observations were expected to produce more accurate initial conditions and forecast through data assimilation (Figure 2). With the development of The Observing-System Research and Predictability Experiment (THORPEX, Rabier et al., 2008) in the 21st century, the targeted observational study was closely incorporated into the predictability studies. The target observation research and practical application are built on a hypothesis

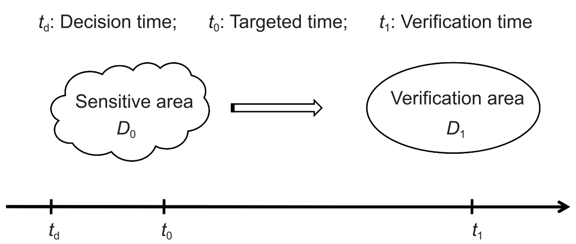

Figure 2 The diagram of the targeted observation apparoach.

that a specific structure of initial errors in a specific region can lead to a prediction error larger than other kind of initial errors, which include the random initial errors spatially distributed.

The authors and their collaborators developed and applied the approach of conditional nonlinear optimal perturbation (CNOP, Mu et al., 2003) to explore the predictability of high-impact ocean-atmospheric environmental events, including typhoons, ENSO, IOD and path variations of the Kuroshio currents in the southern Japanese seas (Wang et al., 2013; Mu et al., 2009; Yu et al., 2012a, 2012b; Feng et al., 2014a; Hu and Duan, 2016). These studies confirm the above hypothesis that the initial error with the special spatial structures does cause more notable prediction errors compared to the random error. This provides firm fundamental theoretical basis for conducting the targeted observations of aforementioned weather and climate events.

For other types of weather and climate events, we intuitively hypothesized that the above conclusion is still true but needs further study. This kind of study will be difficult considering, for examples, that it is not clear whether the initial errors with special spatial structures will cause larger prediction errors for the forecasts of ocean variables in the northern Pacific region that are mainly manifested as wind-driven gyres, compared to the random error (Duan and Wu, 2015; Wu et al., 2016). For meso- and small scale convective systems in the atmosphere, it is either not clear whether the prediction errors can have significant differences while initialized from optimal initial errors and from random errors, which also need further study.

3.2 The problem of model parameter errors

Generally, there are two kinds of parameters in a numerical model. The first type of parameter is related to numeric configurations, such as computational stability, and is unrelated to observations. The second type of parameter can be estimated directly or indirectly using observational data. It is important to reduce the uncertainty of the second type of parameter estimation using observations in the predictability study.

In some numerical models, the number of parameters to be estimated directly or indirectly using observational data is huge. For example, there are approximately 500 parameters to be estimated in the well-known Lund-Potsdam-Jena (LPJ, Sitch et al., 2003) model. There are even more model parameters in the coupled atmosphere-land-ocean models. It is costly in both human power and finance when conducting additional observations to estimate all these parameters. Mu (2013) proposed the concept of parameter-targeted observations, which simply originates from the idea that model parameters can be treated as special 'variables'. Then the strategy and algorithm of the traditional target-observation analysis in a geographical space can be applied to detect the sensitive area in the phase space of model parameters , and sensitive and important (instead of all) parameters are estimated. The parameter-target observations can sufficiently reduce the costly observational expenses comparing to reduce the uncertainty of all model parameters.

Apparently, the key issue in parameter-targeted observation is detecting the sensitive area in the phase space of the model parameters. There are some works in the literature about this issue (e.g., Bastidas et al., 2006; Demaria et al., 2007; Razavi and Gupta, 2015), but they were all conducted without considering the impact of nonlinear combination of model parameters on the uncertainties of prediction. The authors and their collaborators are trying to determine the optimal combination of parameter error that has the largest impact on the forecast (simulation) at the verification time, using the parameter involved CNOP (CNOP-P) proposed by Mu et al. (2010) (Sun and Mu, 2011, 2013, 2016). A further application conducted using the targeted-observation experiment to determine the model parameters is still under the way.

It should be noted that the predictability is dependent on the spatial-temporal scales and controlled by multiple external forcings. Therefore it is challenging and important to explore the influences of the model errors represented by the uncertainties of different external forcings on the predictabilities, although some progresses have been made (Duan and Zhou, 2013; Duan and Zhao, 2015; Li and Ding, 2015).

4. The predictability of ensemble forecasting (probabilistic forecasting)

Ensemble forecasting has become a mainstream approach of numerical weather prediction and numerical climate prediction in the world since the 1990s (Leith, 1974; Leutbecher and Palmer, 2008; Figure 3). Many operational centers, such as ECMWF, NCEP and JMA, have released their ensemble forecasting products. However, there was no such influential benchmark as Lorenz's work in the 1960s, either in the theoretical field or in the applied field, about the ensemble-based predictability study. In fact, ensemble forecasting is a specific form of probabilistic forecasting. As a result, in the study of predictability of ensemble forecasting, it is necessary to extend the concept of deterministic prediction to probabilistic forecasting. For example, the physical variables to be predicted, such as the wind and precipitation, should be treated as random variables. The uncertainties of the predictions should be measured by the difference between the predicted target and their observational counterparts (the observations should also be treated as random variables characterized by their probability density distributions). The methods to assess these kinds of "differences" should be defined under the stochastic dynamic system.

Based on the definition of predictability discussed and interpreted above, the fifth IPCC characterized the rapid evolution of the probability density of ensemble forecasting as a property of the predictability of a physical variable or climate event. Thus, it is easy to understand that ensemble forecasting is a new prediction approach and can improve prediction skills but cannot change the intrinsic predictability of the prediction targets.

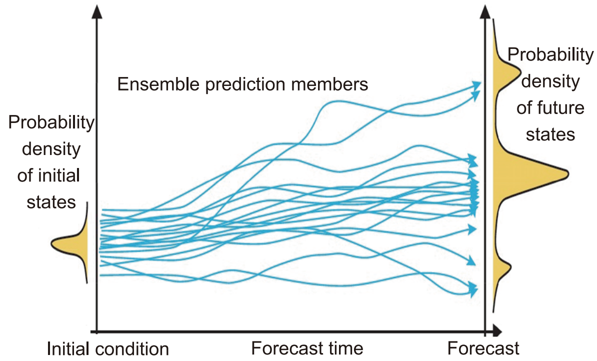

Figure 3 The framework of ensemble prediction (from http://old.ecmwf.int/about/corporate_brochure/leaflets/EPS-2012.pdf).

To the best of our knowledge, there has been no report about the IPL study under the framework of the stochastic dynamical systems. Studying the IPL in a stochastic dynamical system is a complex problem, which first requires an understanding of how to generate perturbation of different spatial scales and how to explore their evolution and nonlinear interactions, under the concept of the probability density distribution. One very attractive question here is whether the concept of optimal growth of perturbation in a deterministic nonlinear system is still held in a nonlinear stochastic system. That is, can a small perturbation with a specific spatial structure result in an increased rate of growth compared to any random perturbation in a nonlinear stochastic system? In other words, does the IPL exist in the atmospheric-ocean nonlinear stochastic dynamical systems? If the answer is no, it would challenge the foundation that the predictability is an inherent property of climate events and physical variables. We guess that the answer should be 'yes'. Therefore, it is of great value to employ a predictability study, both in theory and in practice, in the framework of a nonlinear stochastic system.

5. Summary and discussion

In this paper, we review discussions on the concept of predictability, and extend the concept of the traditional predictability of weather and climate to that of the general physical variables and events of coupled atmosphere and ocean systems. The definition of predictability here can be described in three aspects: (1) The predictability is an inherent physical property of the physical variables, weather and climate events in the atmosphere-ocean system, which have spatial and temporal dependences. Predictability is the product of multiscale interactions, and its evolution shows nonlinear characteristics. (2) The predictability describes the extent to which the tiny errors of the current state or system affect the future state. (3) The predictability can be measured by the ratio of the prediction errors over time to the initial errors or the ratio of the width of the predicted probability density distribution to the initial value. If the initial error increases rapidly or the initial probability density distribution widens rapidly in a system, the system then has a low predictability and vice versa. Based on this definition, this paper summarizes the challenging and urgent to be solved problems of the predictability of weather and climate phenomenon of different spatial and temporal scales, which includes IPL problems, initial errors problems, model error problems and the targeted-observation problems, as well as the predictability problems of the probabilistic forecasting. At the same time, this paper emphasizes the importance of these problems, both in theory and in practice.

Predicting the future is one of the eternal pursuits of human beings; meanwhile, the uncertainties of predictions are also one of the eternal troubles of human beings. For any kind of high-impact weather or climate events related to the national economy and people's livelihoods, it is necessary to study their predictabilities before launching operational or quasi-operational forecasts. Under this circumstance, the questions to be answered include the following: How large is the prediction error and how long is the forecast time limit for our present understanding and knowledge of the system? Is it suitable to carry out the operational forecast, which aims to benefit the economy and society? Even though the operational forecast is realized, it is still necessary to investigate the causes and mechanisms of prediction errors and to find ways to reduce the prediction errors. It is always of great value to improve the prediction models and prediction skills and to provide better prediction products.

Predictability study, as shown by its development process, has run through the whole process of the concerned disciplines, from the observation collection, to the founding of the theory and determination of a mechanism, to the development of the numerical model, to the simulation of the phenomenon and finally, to the operational forecast. The predictability study is closely related to nonlinear science, turbulence and mathematics, as well as the designs of numerical model and observational systems. Therefore, researchers who specialize in either the basic theory or the application of prediction can find interesting and important topics in the field of predictability studies. In addition, due to its complexity, the continued progress of predictability studies need the effective cooperation of experts from the fields of atmospheric sciences, oceanology, physics, mechanics, mathematics and computer science. Only through effective cooperation and joint efforts can we make continuous breakthroughs in predictability studies, thereby ultimately improving the prediction skills in operational forecasting.

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