Advances in Atmospheric Sciences
Impact Factor: 5.8
E-alert
ISSN 0256-1530
CN 11-1925/O4

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Citation: Ren, H.-L., and Coauthors 2023: Seamless Prediction in China: A Review, *Adv. Atmos. Sci.*, 40, 1501–1520. doi: 10.1007/s00376-023-2335-z.

View online: https://doi.org/10.1007/s00376-023-2335-z

ADVANCES IN ATMOSPHERIC SCIENCES, VOL. 40, AUGUST 2023, 1501–1520

• Review •

Seamless Prediction in China: A Review※

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(Received 4 November 2022; revised 27 March 2023; accepted 10 April 2023)

ABSTRACT

Seamless prediction is a weather–climate integrated prediction covering multiple time scales that include days, weeks, months, seasons, years, and decades. Seamless prediction can provide different industries with information such as weather conditions and climate variations from the next few days to years, which have important impacts on economic and social development and important reference value for short-, medium- and long-term decision-making and planning of the country. Therefore, seamless prediction has received widespread attention from the international scientific community recently. As Chinese scientists have also carried out relevant research, this paper reviews the research in China on developments and applications of seamless prediction methods and prediction systems in recent years. Among them, the main progress of seamless prediction methods studies is reviewed from four aspects: short- and medium-range weather forecasting, subseasonal-to-seasonal, seasonal-to-interannual, and decadal climate prediction. In terms of development and application of seamless prediction systems, the main achievements made by meteorological operational departments, scientific institutes, and universities in China in recent years are reviewed. Finally, some of the issues in seamless prediction that need further study are discussed.

Key words: seamless prediction, weather–climate integrated prediction, prediction system

Citation: Ren, H.-L., and Coauthors, 2023: Seamless prediction in China: A review. *Adv. Atmos. Sci.*, **40**(8), 1501−1520, https://doi.org/10.1007/s00376-023-2335-z.

Article Highlights:

- Some representative and the latest prediction methods on multiple time scales from weather to climate in China are summarized.
- Separate weather and climate prediction systems and two weather–climate integrated prediction systems have been developed in China.
- Future directions including model improvements, initialization, and prediction methods of seamless prediction in China are discussed.

※ This paper is a contribution to the special issue on the National Report to the 28th IUGG General Assembly by CNC-IAMAS (2019−2022).

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1. Introduction

There has been a growing desire to obtain weather and climate information on time scales from several days to weeks, months, seasons, years, and decades. The weather and climate prediction business aims to provide society and government with products of different time scales. It is a challenging project to establish seamless prediction of weather and climate, and is one of the main tasks of modern weather and climate prediction. This is also an important part of "weather forecasting, climate prediction and long-term climate prediction" proposed by the World Climate Research Program (WCRP, 2005). The concept of "seamless prediction" was first presented in 2005 and first used by Palmer et al. (2008), referring to predictions across the range of weather and climate time scales. Since then, seamless prediction has attracted wide attention (Brown et al., 2012; Hoskins, 2013; Kumar and Murtugudde, 2013; Delworth et al., 2020; Ruti et al., 2020). The Working Group on Subseasonal to Interdecadal Prediction (WGSIP) contributes to WCRP studies on predictability and prediction on a wide range of time scales from several weeks to seasons, years, and decades. WGSIP promotes scientific research and an international programme of seamless prediction. Traditionally, weather and climate prediction issues are seen as different disciplines. However, integrated modeling and seamless prediction across multiple time scales stem from a recognition that the evolution of weather and climate are linked by the same physical processes in the atmosphere–ocean–land–cryosphere system operating across multiple spatial and temporal scales (Brown et al., 2012). Establishing a weather–climate integrated prediction system is also an important development direction of seamless prediction (Hurrell et al.,2009; Brown et al., 2012).

Seamless prediction covers short- and medium-range, subseasonal-to-seasonal (S2S), seasonal-to-interannual (S2I), and decadal time scales. With the efforts of Chinese scientists and meteorological operational departments in the past three decades, short- and medium-range weather forecasts and S2I climate prediction in China have developed relatively maturely. A representative achievement in short- and medium-range weather forecasts is the four-dimensional variational (4DVar) assimilation system independently developed by the Numerical Weather Prediction Centre (NWPC) of the China Meteorological Administration (CMA), making it one of the few national forecast centers in the world with independent development and operational application of a 4DVar assimilation system (Shen et al., 2021). In terms of S2I climate prediction, meteorological operational departments, scientific institutes, and some Chinese universities have developed several prediction systems (Bao et al., 2013, 2019; Liu et al., 2015, 2021a; Ren et al., 2017; He et al., 2020a; Song et al., 2021). Based on these systems and some international advanced systems (Saha et al., 2014; Takaya et al., 2018; Johnson et al., 2019), the National Climate Center (NCC) of the CMA developed the China Multi-Model Ensemble prediction system (CMME), which performs well in global and regional climate prediction (Ren et al., 2019b). Extended-range forecasting lies between medium-range weather forecasting and short-term climate prediction, and decadal prediction lies between interannual climate prediction and long-term climate change projection, both of which are essential components of seamless prediction. In recent years, the sources of predictability, initialization schemes, and prediction methods of extended-range and decadal prediction have become the focus of international research. Chinese researchers have also participated extensively and made important contributions. For example, several extended-range forecast methods and decadal prediction initialization schemes have been proposed (Ren et al., 2014a; Hsu et al., 2015; Wu et al., 2018a, 2022). Multiple S2S and decadal prediction systems have been developed and used for operational prediction (Liu et al., 2017; Wu et al., 2018a). These systems participated in the international S2S Prediction Project and Decadal Forecast Exchange, separately. Research on different time scales lays a solid foundation for developing a seamless prediction system.

Since the concept of seamless prediction was proposed, several international research and operational centers have used the seamless approach to develop weather–climate integrated prediction systems that provide forecasts with multiple time scales (Vitart et al., 2008; Brown et al., 2012; Ham et al., 2019a; Delworth et al., 2020). For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) developed a combined medium-range and monthly coupled forecasting system (Vitart et al., 2008), and the UK Met Office developed the Met Office Unified Model for weather and climate prediction (MetUM; Brown et al., 2012). These achievements indicate that seamless prediction has transitioned from concept to practice. In recent years, the CMA and the Institute of Atmospheric Physics of the Chinese Academy of Sciences (CAS-IAP) have independently developed weather–climate integrated prediction systems—namely, the CMA Climate Prediction System version 3 (CMA-CPSv3) and CAS Flexible Global Ocean–Atmosphere–Land System model finite-volume 2 (FGOALS-f2). The development of these systems demonstrates that China has taken a significant step towards developing seamless prediction systems providing forecasts from weather to climate scales.

In the past three decades, Chinese researchers have made many achievements in weather and climate prediction, as well as some significant progress in weather–climate integrated prediction. This paper reviews the main research achievements of prediction methods and systems on different time scales in seamless prediction in China over the past 30 years, including the recent achievements in weather–climate integrated prediction. A summary and discussion of future research directions in seamless prediction are provided in the final section.

2. Progress of seamless prediction methods

2.1. *Progress of short- and medium-range weather forecasts*

The short- and medium-range weather forecast is the main component of the traditional weather forecast, which has the characteristics of a long development time, solid foundation, and high level of maturity (Dai et al., 2016; Xiu, 2019). The uncertainty of the initial value is the primary source of forecast error in numerical weather prediction (NWP). A high-quality initial value of a model is formed by a specific data assimilation scheme based on meteorological observation data and background field information at the initial time. Therefore, data assimilation is a key technology for NWP (Gong, 2013). Advanced data assimilation technology is considered one of the important reasons for improving NWP skills (Bannister, 2017). With multi-year research efforts, CMA-NWPC realized the operational implementation of its 4DVar assimilation system in 2018 (Zhang et al., 2019). Its subsequent application has great significance for global medium-range weather forecasts in China and demonstrates that operational NWP assimilation technology in China has reached the forefront of the international NWP field. The 4DVar assimilation system can significantly increase the types of available observation data, improve the quality of global analyses, and further improve NWP skills (Zhang et al., 2019; Shen et al., 2021). Currently, the observation data of the NWP data assimilation system mostly come from satellite data. However, bias correction of satellite data is one of the critical factors affecting the assimilation effect of satellite data. In terms of satellite data bias correction technology, Zhang et al. (2018) developed a dynamic bias correction scheme suitable for satellite radiance data. This scheme is used in actual business and can effectively solve the drift of observation data caused by the aging of satellite detection instruments, degradation of the bias correction equation coefficients, and seasonal changes.

Precipitation forecasting is the key to short- and medium-range weather forecasts. Improving the accuracy of precipitation forecasts has long been the focus of meteorological business and scientific research. In recent years, NWP has changed from a single-value forecast to an ensemble forecast, and from a deterministic forecast to a probabilistic forecast. Chinese researchers have used different parametric schemes to confirm that ensemble forecasting can improve the skills of precipitation forecasts (Chen et al., 2003; Li et al., 2007). However, due to the existence of initial value error, the approximation of numerical calculation, and the imperfection of the physical processes in the NWP model, there are often certain systematic and random errors in precipitation forecast results. Therefore, it is vital to correct model outputs to obtain more accurate precipitation forecast results. Four methods are usually used for post-processing precipitation forecasts, including quantitative precipitation correction and integration methods, probabilistic forecast processing, statistical downscaling, and stepwise correction based on segmented hierarchical clustering (Bi et al., 2016; Gao et al., 2023). They are also important ways to improve precipitation forecasts in practice. In addition to precipitation elements, other continuous variables such as temperature, wind, and visibility adopt the same correction method: on the basis of the model background field and urban stations' guidance forecasts, the grid-point forecast is gradually approximated to the stations' guidance forecasts to form the final refined grid forecast products by considering the stepwise interpolation analysis method of refined geographic information correction (Jin et al., 2019).

2.2. *Progress of S2S prediction*

The extended-range forecast is a crucial component of establishing a seamless prediction system. The error source of weather forecasts is mainly the initial value, and the error source of climate prediction is mainly the boundary value. The extended-range forecast lies between the weather forecast and short-term climate prediction, which constitute both an initial value problem and boundary value problem. In 2013, the World Meteorological Organization (WMO) identified the extended-range forecast as one of the most critical tasks and proposed the international S2S Prediction Project, which focuses on the sources of S2S predictability.

The difficulty of S2S prediction is the lack of predictability sources. Many studies have pointed out that the Madden –Julian Oscillation (MJO) plays a critical role in bridging weather and climate, and its activities (propagation, intensity, and phase evolution) have essential effects on weather and climate (Zhang, 2005; Jia et al., 2011; Hsu et al., 2016). Therefore, the MJO has long been considered the most important predictability source for S2S prediction (Brunet et al., 2010; Robertson et al., 2015). However, MJO signals are weaker in boreal summer than in other seasons (Wheeler and Hendon, 2004; Zhang, 2005). Boreal Summer Intraseasonal Oscillation (BSISO) is the most remarkable large-scale convection and circulation mode in the Asian summer monsoon region (Wu et al., 2016). The East Asia–Pacific (EAP) teleconnection pattern is the dominant mode of circulation variability over East Asia in boreal summer (Lin et al., 2018; Wu et al., 2020b). They are important predictability sources of subseasonal variability in boreal summer (Wang et al., 2009; Lee et al., 2013; Hsu et al., 2020a). Sudden stratospheric warming (SSW) is the most intense circulation evolution phenomenon in the stratospheric polar region in boreal winter. Many studies have noted that the downward propagation of the Northern Annular Mode signal during SSW from the stratosphere to the troposphere can increase the predictability of surface weather on subseasonal time scales (Tripathi et al., 2015; Domeisen et al., 2020a, b). In addition, external forcing factors with "memory" characteristics, such as the ocean, soil moisture, and snow, are also predictability sources for S2S prediction (Koster et al., 2011; Jeong et al., 2013; Yuan et al., 2015).

S2S prediction methods mainly include physical statistical models, dynamical models, and dynamical–statistical approaches. Physical statistical models are generally established by the linear or nonlinear relationship between meteorological elements (prediction variables) and large-scale signals (prediction factors). In recent years, Chinese researchers have established several physical statistical models to carry out S2S prediction research; for example, the Low-Frequency Synoptic Map (Li et al., 2018), Extended Complex Autoregressive model (Yang, 2018), and Spatial-Temporal Projection Model (STPM, Hsu et al., 2015, 2020b). Among them, the STPM method uses the coupling mode of the evolution of prediction factors and variables with time and space to establish a statistical model, which effectively extracts and utilizes the low-frequency components and historical information in the observation data and is widely used in the subseasonal prediction of precipitation (Hsu et al., 2015; Zhu and Li, 2017a), tropical convective activities (Zhu et al., 2015), tropical cyclones (Zhu et al., 2017), winter surface air temperature and extremely cold days (Zhu and Li, 2017b), and summer surface air temperature and heat waves (Zhu and Li, 2018), showing higher forecast skill than traditional statistical models. Pan et al. (2020) confirmed that the STPM method could also be used for S2I prediction, such as ENSO evolution prediction. To date, the STPM method has also been applied to the operational prediction system of the CMA. Hsu et al. (2020b) pointed out that, although the STPM method can provide highly skilled and stable S2S prediction products, its ability to predict the intensity and process of extreme weather needs to be further improved.

In the past decade, dynamic models have become the most powerful tool for S2S prediction. Since 2013, the CMA-NCC has successively developed the Beijing Climate Center Atmospheric General Circulation Model version 2.2 (BCC-AGCM2.2) and the Beijing Climate Center Climate System Model version 1.2 (BCC-CSM1.2), which fills the gap between the medium-range weather forecast and short-term climate prediction. The Beijing Climate Center Sub-seasonal to Seasonal prediction system version 1 (BCC-S2Sv1) was established based on BCC-CSM1.2, which is the first model in China to participate in Phase I of the S2S Prediction Project. The widely used metric to measure the MJO and its prediction is the Real-time Multivariate MJO (RMM) index developed by Wheeler and Hendon (2004). The main characteristics of the MJO, such as intensity, periodicity, spatial structure, and temporal evolution, can be well simulated by BCC-S2Sv1 (Zhao et al., 2015). However, the prediction skill of the MJO (RMM) index is only about 16 days for the submitted dataset (Liu et al., 2017), which is relatively lower than most of the other participants in the S2S Prediction Project (Lim et al., 2018). To improve the prediction skills for the MJO, Chinese researchers have carried out a lot of research work, such as improving the initial conditions of dynamical models and optimizing ensemble prediction strategies. Liu et al. (2017) stated that improving atmospheric and oceanic initial conditions can increase the MJO prediction skill to 21–22 days. Introducing a moderate moisture initialization scheme could also extend the MJO prediction skill by about 2–3 days and enable a more reliable subseasonal prediction of extratropical circulation and precipitation through a more realistic description of MJO-related teleconnections (Wu et al., 2020a). Moreover, by combining the perturbations of multiple parameters that are mainly responsible for cloud and convection parameterization schemes, MJO prediction can be further enhanced during lead times of 2–3 weeks, as well as an improved spectrum, intensity, spatial structure, and propagation of the MJO (Liu et al., 2019). In terms of optimizing ensemble prediction strategies, several studies have shown that the lagged average forecasting (LAF) scheme (Ren et al., 2017), an ensemble of different initialization schemes (Ren et al., 2016; Wu et al., 2020a), and the multi-model ensemble (MME) of several S2S project models (Wang et al., 2020b), are helpful for improving MJO prediction. As the number of models participating in the S2S Prediction Project increases, the MME will be recognized as an important development direction in S2S prediction. In addition to MJO prediction, the submitted dataset shows that the prediction skills for the EAP teleconnection during May–September and BSISO index are about 10 days and 9 days, respectively (Bo et al., 2020; Wu et al., 2020b). Bo et al. (2020) showed that optimizing atmospheric and oceanic initial conditions can also increase the prediction skill for the BSISO index to 12 days.

Dynamical–statistical prediction methods have been widely used for S2S prediction in recent years. The prediction skills of dynamical models can be further improved by effectively combining dynamical models and empirical/statistical methods. Ren et al. (2014a) proposed the Dynamical-Analogue Ensemble Method to effectively reduce prediction errors and increase prediction skills for the monthly mean and daily atmospheric circulation forecasts. Wu et al. (2018b) established a seasonal rolling MJO dynamical–statistical downscaling precipitation prediction model based on the forecasted MJO information by a dynamical model and achieved higher prediction skills than in the original dynamical model's forecast. In addition, Wu et al. (2022) recently developed a dynamical–statistical prediction model that improves the prediction skills for the MJO (RMM) and BSISO indices to 22–23 days and 10–13 days, respectively, both of which are largely improved compared with the original dynamical model forecasts (Jie et al., 2017; Liu et al., 2017).

Since 2019, the CMA and CAS-IAP have successively developed the latest generation of climate prediction systems. The third-generation climate prediction system was developed by the CMA (CMA-CPSv3). The S2S prediction sub-system of CMA-CPSv3 (BCC-S2Sv2) has participated in Phase II of the S2S Prediction Project. Compared with BCC-S2Sv1, BCC-S2Sv2 has significantly improved the prediction skill for the MJO (RMM) index, which is about 23 days for the submitted dataset. Version 1.3 of the FGOALS-f2 (FGOALS-f2-V1.3) subseasonal-to-decadal (S2D) prediction system was developed by the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG) at CAS-IAP. The S2S prediction subsystem of the FGOALS-f2-V1.3 S2D system also participated in Phase II of the S2S Prediction Project, which was launched in January 2019. Based on the MJO (RMM) index calculated by ECMWF, the prediction skill for the MJO for the submitted dataset is about 23 days, as determined by the maximum lead time with an anomaly correlation coefficient (ACC) exceeding 0.5. They have reached the advanced international level for MJO prediction.

2.3. *Progress of S2I prediction*

Primary sources of S2I predictability consist of slowly evolving boundary conditions, such as sea surface temperature (SST), land surface conditions (moisture and snow cover), and sea-ice variations (Zuo et al., 2016; Acosta Navarro et al., 2020). Quasi-Biennial Oscillation (QBO; Marshall and Scaife, 2009; Portal et al., 2022) and stratospheric states (Butler et al., 2016; Nie et al., 2019) are considered the upper boundary conditions to affect S2I prediction. It has been well recognized that El Niño–Southern Oscillation (ENSO) is considered the most important source of S2I predictability, which is the primary mode of interannual variability and affects temperature and precipitation anomalies in various regions through global teleconnection.

S2I prediction methods also mainly include physical statistical models, dynamical models, and dynamical–statistical approaches. In recent years, supported by high-performance computing, big data, and advanced algorithms, machine learning has provided new ideas for S2I prediction. In terms of physical statistical models, Liu and Chan (2003) developed a statistical prediction model based on ENSO-related indices and predicted reasonably the annual number of landfalling tropical cyclones. Ren et al. (2019c) and Wang et al. (2019) developed different statistical prediction models based on the comprehensive use of external precursors and effectively improved the prediction skill of ENSO. Fan et al. (2008) proposed an interannual incremental prediction method, which chooses the year-to-year increment for a quantity as the object that is to be predicted. This unique statistical model is considered an efficient prediction approach and is widely used in S2I prediction of summer rainfall in eastern China, temperature in northeastern China, activity of western North Pacific typhoons, Atlantic hurricanes, and the winter North Atlantic Oscillation (NAO) (Fan et al., 2008; Fan, 2009, 2010; Fan and Wang, 2009; Huang et al., 2014; Tian and Fan, 2015), showing increased prediction skills and application prospects.

With the continuous improvement of physical processes in dynamical models and the rapid development of high-performance computing, some Chinese universities, meteorological operational departments, and scientific institutes have developed several relatively complex dynamical models in recent years, such as a global atmosphere–ocean coupled model (He et al., 2020a), atmosphere–ocean–land–ice coupled climate system models (Li et al., 2013a; Ren et al., 2017; Bao et al., 2019; Wu et al., 2021), and atmosphere–ocean–land–ice–wave coupled climate system models (Bao et al., 2020b; Song et al., 2020). Several studies have demonstrated that these dynamical models have good prediction skills for climate phenomenon, such as precipitation (Wu et al. 2017; He et al., 2020a; Liu et al., 2021c; Wang et al., 2022a), SST (Zhao et al., 2019; Song et al., 2020, 2022; Ying et al., 2022), sea surface height (Wang et al., 2023), and tropical cyclones (Lang and Wang, 2008; Li et al., 2021b), as well as major climate variability modes, such as ENSO (Luo et al., 2008b; Ren et al., 2017, 2019a; Cheng et al., 2022), the Indian Ocean Dipole (IOD; Luo et al., 2007, 2008a; Ren et al., 2017), and the primary East Asian summer circulation patterns (Ren et al., 2017; Zhou et al., 2020a). However, the existence of model errors in a single dynamical model, which leads to limited prediction ability, means the MME has been found to be an effective approach to improve S2I prediction (Palmer et al., 2000; Wang et al., 2009, 2020a, 2022a). In recent years, several major international research and operational centers, such as the ECMWF, the Asia-Pacific Economic Cooperation Climate Center (APCC), and the National Centers for Environmental Prediction (NCEP), have developed their own MME prediction systems for dynamical seasonal climate prediction. To fill the gap in the field of operational MME prediction in China, the NCC/CMA developed a Chinese operational MME prediction system, the aforementioned CMME, based on a combination of several Chinese operational climate prediction systems and imported prediction data of international advanced climate models (Ren et al., 2019b). The CMME system is presently applied to real-time climate prediction at the NCC/CMA, which provides monthly and seasonal predictions of several climate variability modes, such as ENSO and the IOD, as well as climate anomalies of temperature, precipitation, and so on. On the other hand, many studies have shown that improving the initial conditions of dynamical models can achieve higher prediction skills. Nie et al. (2019) stated that the upper-stratospheric zonal wind anomaly on the initial date plays a significant role in the winter prediction of the NAO and Arctic Oscillation (AO). Ren and Nie (2021) further significantly improved the prediction skill for the winter AO relative to current multi-model dynamical predictions through constructing a linear empirical model based on the previous-summer tropical oceanic temperature and Arctic sea-ice signals. Song et al. (2020) and Yang et al. (2020) developed different data assimilation frameworks to predict SST and Arctic sea ice, respectively, and pointed out that realistic initial conditions can significantly increase the seasonal prediction skill. Liu et al. (2021b) highlighted the role of sea-ice assimilation for global analysis and developed the first atmosphere–ocean–ice coupled data assimilation scheme in China. This scheme is currently applied in CMA-CPSv3 and can generate stable and reliable initial conditions of the atmosphere, ocean, and sea ice, which are used for weather and climate prediction.

Based on dynamical model prediction, empirically correcting model outputs by using historical information can also improve the prediction skills of dynamical models (Ren and Chou, 2005). Chinese researchers have used several dynamical–statistical prediction methods, such as empirical orthogonal function analysis, singular value decomposition, the Pattern Project Method (Kug et al., 2007), and the Stepwise Pattern Project Method (Kug et al., 2008), to improve the S2I prediction skills for precipitation in China and ENSO (Qin et al., 2011; Kang et al., 2012; Su et al., 2013; Shi et al., 2016; Wang et al., 2017, 2020a). In recent years, based on dynamical models and historical data, a dynamical

–statistical prediction method of analogue correction of errors (ACE) was developed and applied (Ren and Chou, 2005, 2006, 2007a, b; Ren et al., 2009; Li et al., 2013b). Ren et al. (2014b) and Liu and Ren (2017) applied the ACE method to predict ENSO and achieved better prediction results. The ACE method is considered to be a pioneering prediction method in recent years (Xiao et al., 2012), and has been recognized by international scholars (Plenković et al., 2018, 2020; Yang et al., 2018). In addition, Chinese researchers have established a variety of dynamical–statistical downscaling models based on the close relationship between prediction variables and factors from the atmosphere, ocean, or sea ice in different seasons, which have effectively improved the S2I prediction skills for regional climate, such as precipitation (Chen et al., 2012; Liu and Fan, 2012, 2013; Liu and Ren, 2015; Liu et al., 2018, 2021c; Wang et al., 2022b), temperature (Dai et al., 2018; Liu et al., 2022a), and tropical cyclones (Sun and Chen, 2011).

Recently, the rapid progress in machine learning has shown strong potential in S2I prediction. For example, Ham et al. (2019b) established a statistical model based on a deep learning approach and reported good prediction skill for ENSO at lead times of up to 1.5 years. Chinese researchers have conducted a lot of research mainly on two aspects: machine learning prediction models, and improving dynamical prediction by using machine learning methods. Due to the low cost of statistical models and the high capability of machine learning in processing data, many researchers have established statistical models based on machine learning methods to predict climate state variables and climate variability modes, such as summer rainfall, winter temperature, drought conditions, SST, and the IOD (Wu et al., 2006; Feng et al., 2020; Zheng et al., 2020; He et al., 2021a; Jiang et al., 2021; Liu et al., 2022b). On the other hand, many researchers have tried to correct the error of dynamical prediction by using machine learning methods. For example, Wang et al. (2021) developed a machine learning and dynamical hybrid seasonal prediction method that significantly improves the dynamical prediction skill for summer rainfall in China. Jin et al. (2022) proposed a hybrid model that combines a convolutional neural network and ridge regression to predict the seasonal precipitation anomaly over China. These studies show that machine learning methods can not only mine nonlinear relationships, but correct the error of dynamical models and achieve higher S2I prediction skills. Machine learning will be a promising method for improving climate prediction. It is worth noting, however, that the lack of training data is a factor that limits the performance of machine learning prediction models (He et al., 2021b). Nevertheless, this does not mean that having enough "big data" can develop a high-performance prediction model. Establishing a machine learning prediction model based on climate dynamics is essential to realize its potential in climate prediction (He et al., 2021b; Yang et al., 2022).

2.4. *Progress of decadal prediction*

In recent years, decadal climate prediction for the next year to the next 10–30 years has been a hot topic of research in the international climate science community because of its potential value in dealing with the economic and social problems associated with climate change. The focus of decadal climate prediction is the average climate state for many years in the future, especially the next 2–5 years' average prediction for the near-term climate. Phase 5 of the Coupled Model Intercomparison Project (CMIP5) listed decadal prediction as one of the core experiments (Taylor et al., 2012), and prediction results were used in the fifth Assessment Report of the Intergovernmental Panel on Climate Change (Kirtman et al., 2013). CMIP6 established the Decadal Climate Prediction Project (Boer et al., 2016) around the problem of decadal climate prediction.

Decadal climate prediction is considered to be a combination of an initial value problem and an external forcing condition problem, and its predictability depends on internal variabilities in the climate system and changes of external forcing (Palmer et al., 2008; Meehl et al., 2009, 2014; Zhou and Wu, 2017). External forcing, including changes in atmospheric compositions associated with human activity or volcanic eruptions, solar variations, and others, can be done by historical simulations or Representative Concentration Pathway projections in dynamical models (Taylor et al., 2012). The prediction of internal variabilities, such as the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO), depends on the accurate estimation of initial climate states, which is crucial and challenging in decadal climate prediction (Wu et al., 2015; Zhou and Wu, 2017).

Initialization enables the dynamical model to obtain the internal variability signals of the climate systems from observation data. Several studies have shown that initialized decadal prediction has higher prediction skills than uninitialized prediction (Meehl et al., 2009; Xin et al., 2018, 2019). The initialization scheme is key to determining the level of decadal climate prediction skills. In recent years, Chinese researchers have used several assimilation methods, such as nudging (Gao et al., 2012; Wei et al., 2016; Han et al., 2017; Wu et al., 2018c; Xin et al., 2018), Incremental Analysis Updates (IAUs; Wu and Zhou, 2012; Wu et al., 2015), 3DVar (Wang et al., 2013), Dimension-Reduced Projection 4DVar (He et al., 2017, 2020b), Ensemble Optimum Interpolation (EnOI, Wei et al., 2017; Xin et al., 2019), and EnOI-IAU (Wu et al., 2018a; Zhou et al., 2020b), to carry out research on decadal climate prediction. Among them, the EnOI and EnOI-IAU methods are considered to be relatively efficient assimilation methods and have been successfully applied in the decadal climate prediction business.

In previous studies, the initialization of most models just assimilated the temperature and salinity of the oceanic surface and subsurface due to the heat flux and memory of the ocean (Meehl et al., 2021). As noted in Bellucci et al. (2015), the initialization of other components, such as sea ice, the land surface, stratosphere, and aerosols in the climate system, may have a potential impact on decadal climate prediction. However, these components cannot be adequately initialized due to the lack of reliable data, and their effects on decadal climate prediction have yet to be further explored.

3. Development and application of seamless prediction systems

3.1. *Prediction systems of the CMA*

In the past three decades, the operational departments of the CMA have been committed to developing operational prediction systems for weather and climate prediction to meet the needs of national and social development. In terms of weather forecasting, the CMA has developed multiple numerical forecasting systems for weather forecasting at different time scales and in different regions. In terms of climate prediction, the CMA developed several climate prediction systems based on models with different spatiotemporal resolutions in the early stage, which were used for S2S, S2I, and decadal prediction. In recent years, the CMA has successfully developed a weather–climate integrated prediction system based on a common model, which is an important component of the seamless prediction system. This section reviews the development and application of the CMA models in the past three decades from two aspects: separate NWP and climate prediction systems, and weather–climate integrated prediction systems.

3.1.1. *Separate NWP and climate prediction systems*

With the support of the "Tenth Five-Year Plan" and a national key scientific and technology project entitled "Innovative Research on China's Meteorological Numerical Forecasting System", the CMA has cooperated with many other institutes to develop and establish a multi-scale general data assimilation and NWP system, named the Global/Regional Assimilation Prediction System (GRAPES; Xue and Chen, 2008). Since then, with continued support from the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan", scientific and technology project, and the GRAPES-specific project of the CMA, the CMA has made continuous improvements to the GRAPES models (Shen et al., 2020, 2021). In terms of short-range and nowcasting weather forecasts, the CMA established a mesoscale NWP system (GRAPES-Meso; Xu et al., 2017) and further developed a regional typhoon forecasting system (GRAPES-TYM; Qu et al., 2022). These systems play an important role in the daily weather forecast business. In terms of medium-range weather forecasts, the Global Medium-Range Numerical Weather Prediction System (GRAPES-GFS; Zhang and Shen, 2008; Shen et al., 2017) was established, which is the first global weather forecast system with independent development, stable operation, and good forecast results in China. In addition, ensemble prediction is considered an important component of the NWP system. The CMA established a regional mesoscale ensemble prediction system (GRAPES-REPS; Chen and Li, 2020) and a global medium-range ensemble prediction system (GRAPES-GEPS; Chen and Li, 2020; Gao et al., 2020), which both provide probabilistic forecast products and play an important role in weather probabilistic forecasting. To date, the CMA has gradually established a complete operational NWP system with deterministic and ensemble prediction from the regional to the global scale, and cultivated a research and development team for the entire NWP business chain, including observation data preprocessing, quality control, data assimilation, dynamic model framework and physical processes improvement, model parallel computing, model system integration, and prediction product post-processing (Shen et al., 2021).

In terms of climate prediction system development and application, three generations of climate prediction systems have been established by the CMA for operational use since 1995. The first generation of the CMA Climate Prediction System (CMA-CPSv1) was developed from 1995 to 2004, which consists of two sub-systems with different time scales: monthly dynamical extended-range forecasting and seasonal prediction. Among them, the seasonal prediction sub-system was developed based on the Beijing Climate Center ocean–atmosphere Coupled Model version 1.0 (BCC-CM1.0), which participated in CMIP3. CMA-CPSv1 played an important role in China's short-term climate prediction business and climate change research after operational application (Ding et al., 2002, 2004; Zhang et al., 2004; Li et al., 2005). The second generation of the CMA Climate Prediction System (CMA-CPSv2) was developed from 2005 to 2015, which added a new S2S prediction sub-system compared with CMA-CPSv1. In 2005, the CMA began to develop an ocean–atmosphere–land–ice coupled climate system model to improve the ability in climate change simulation and short-term climate prediction. With the efforts of decades-long research, several versions of fully coupled climate models were developed, including the Beijing Climate Center Climate Prediction Model version 1.1 (BCC-CSM1.1), BCC-CSM1.1m, and BCC-CSM1.2. BCC-CSM1.1 and BCC-CSM1.1m both participated in CMIP5. However, the horizontal and vertical resolution of BCC-CSM1.2 is the highest (T106L40, approximately 110 km) among them. It was used in the S2S prediction sub-system and participated in Phase I of the S2S Prediction Project. BCC-CSM1.1m, with a medium horizontal resolution and lower vertical resolution (T106L26), was used in the seasonal prediction sub-system and CMME prediction. CMA-CPSv2 has been able to provide real-time monthly, seasonal and interannual climate prediction products since its operational application in 2015, which can meet the public and society's demands for climate prediction products in the next month to a year. CMA-CPSv2 has a good prediction ability for ENSO, with a lead time of over eight months, as well as for the East Asian, South Asian, Southeast Asian, North Pacific, and Indian summer monsoon indices (Liu et al., 2014, 2015; Ren et al., 2017). Wu et al. (2017) compared the prediction ability of CMA-CPSv2 and CMA-CPSv1 for seasonal temperature, precipitation and circulation, and pointed out that CMA-CPSv2 has higher prediction skills. In terms of decadal climate prediction, BCC-CSM1.1, with a coarse horizontal and vertical resolution (T42L26, approximately 280 km), participated in the Decadal Prediction Experiment in CMIP5 (Xin et al., 2012). Historical hindcasts showed that BCC-CSM1.1 has reasonable decadal prediction skills for SST in the tropical Atlantic, western Pacific, and Indian oceans (Han et al., 2017), the AO (Wu et al., 2018c), AMO (Wei et al., 2017), and near-surface air temperature in East Asia (Xin et al., 2019). However, the decadal climate prediction system needs to be further developed in future research to meet the requirements of operational use.

3.1.2. *Weather–climate integrated prediction system*

Since 2010, the CMA has been developing the second version of its climate system model (BCC-CSM2). BCC-CSM2-HR is the high-resolution version of BCC-CSM2, with a T266 horizontal resolution (approximately 45 km) in the atmosphere, and participated in the High-Resolution Model Intercomparison Project (HighResMIP) in CMIP6 (Wu et al., 2021). Based on this model, the CMA developed its third-generation climate prediction system (CMA-CPSv3) from 2010 to 2020, which consists of three sub-systems: a high-resolution climate model sub-system, a multi-layer coupling assimilation sus-system, and an ensemble prediction sub-system. Compared with the previous generation, the current high-resolution climate model sub-system of CMA-CPSv3 combines many significant scientific and technical improvements for the model resolutions and physical process parameterizations in the atmosphere, land, ocean, and sea ice. The simulation performance for temperature, precipitation, ENSO, the MJO, and QBO has been significantly improved (Wu et al., 2021). The multi-layer coupling assimilation sub-system of CMA-CPSv3 realizes the coordinated assimilation of multi-source data from the ocean, sea ice, and atmosphere. Based on the combination of EnOI and Local Ensemble Transform Kalman Filter algorithms, an ocean ensemble assimilation method was built to assimilate ocean temperature/salinity profiles, SST, and sea level anomaly (SLA) observation data at a daily frequency. Also, OI-based sea-ice assimilation and atmospheric nudging were implemented to incorporate daily sea-ice concentration observation data and 6-hourly atmospheric multi-variable reanalysis data (Liu et al., 2021b). The ensemble prediction sub-system of CMA-CPSv3 consists of 21 ensemble members, which can draw on the best of others and eliminate the forecast uncertainties caused by observation, analysis errors, and the inherent chaos of the atmospheric system. CMA-CPSv3 is a weather–climate integrated prediction system, which can provide prediction products with several time scales. Regarding its weather forecasts, CMA-CPSv3 operates every day and releases daily temperature and precipitation for the next 7 days and weekly average temperature and precipitation for the next 30 days. In terms of S2S prediction, CMA-CPSv3 operates every day and hindcasts twice every week, which integrates for up to 60 days. In addition, CMA-CPSv3 operates once every month to release S2I prediction products and integrates for up to 7 months. Liang et al. (2022) evaluated the seasonal prediction performance of CMA-CPSv3 for the Asian summer monsoon and stated that CMA-CPSv3 has higher prediction skills for summer rainfall, summer monsoon indices, the western North Pacific subtropical high, ENSO, and the IOD than CMA-CPSv2. Overall, CMA-CPSv3 has reached an advanced international level for MJO prediction and is significantly superior to previous seasonal prediction systems in predicting climate phenomena and anomalies of precipitation and surface temperature in China on seasonal scales.

3.2. *Prediction systems of CAS-IAP*

In recent years, CAS-IAP has also paid more attention to the operational use of scientific research models. With multi-year research efforts, CAS-IAP has developed a weather–climate integrated prediction system, named the FGOALS-f2 ensemble forecast display platform, which can provide short- and medium-range weather forecasts and S2S, S2I and decadal climate prediction products. In addition, CAS-IAP also developed a decadal climate prediction system in 2018, and its prediction results are published on the "Decadal Forecast Exchange" platform. This section reviews the progress of CAS-IAP in operational prediction in recent years from two aspects: its weather–climate integrated prediction system and decadal prediction system.

3.2.1. *Weather–climate integrated prediction system*

Jointly funded by the Alliance of International Science Organizations in the Belt and Road Region and a National Natural Science Foundation of China major research project entitled "the Earth–Atmosphere Coupling System on the Qinghai-Tibet Plateau and its Global Climate Effect", CAS-IAP developed the FGOALS-f2 ensemble forecast display platform based on the FGOALS-f2-V1.3 S2D prediction system (Bao et al., 2019; He et al, 2019; Li et al., 2021b). The prediction model used is FGOALS-f2, which is a climate system model representing the interaction between the atmosphere, oceans, land, and sea ice. The atmospheric component of FGOALS-f2 is FAMIL2, which is characterized by a scale-aware convection scheme (Bao and Li, 2020) and FV3 dynamic core (Zhou et al., 2015). The resolution of the prediction system is approximately 100 km for both atmospheric and ocean grids. The nudging technique is adopted as the initialization method for both the atmospheric and oceanic components (Bao et al., 2019; Li et al., 2021b). The S2S prediction sub-system provides real-time S2S prediction products of temperature, precipitation and circulation to CMME-S2S. Regarding the seasonal climate prediction sub-system, the prediction sub-system uses the LAF method to generate two members on each day, which are integrated for up to 12 months, and the forecast frequency is once per day. The seasonal prediction products have participated in CMME-S2D, which includes monthly and seasonal-average prediction data. Historical hindcasts show that the FGOALS-f2-V1.3 prediction system has reasonable prediction skills for ENSO (~0.83 at a 6-month lead time), the IOD (~0.56 at a 5-month lead time) (the initial time for predicting ENSO and the IOD is 20 July during 1981–2017), and tropical cyclone frequency

(~0.6 and ~0.61 in the western Pacific and North Atlantic, respectively) (Bao et al., 2019; Li et al., 2021b).

The FGOALS-f2 ensemble forecast display platform covers the S2D timescales from weather to climate. The prediction products include tropical cyclones, the MJO, ENSO, Arctic sea ice, and global potential vorticity, as well as temperature and precipitation from daily to decadal scales. The prediction products cover global and regional areas, such as the Tibetan Plateau, the Arctic, and "the Belt and Road" countries and regions. The platform provides forecasting services for disaster risk reduction in countries and regions along the Belt and Road. Compared with the traditional prediction system, the FGOALS-f2 system not only provides effective prediction services for disaster prevention and mitigation in China, but is actively oriented to major national needs and strategies such as national sustainable development, the Belt and Road, and Arctic resource development.

3.2.2. *Decadal prediction system*

In 2012, CAS-IAP built the initial version of its decadal prediction system based on FGOALS-gl (Wen et al., 2007) and the IAU initialization scheme (Wu and Zhou, 2012; Wu et al., 2015), which is one of the earliest decadal prediction systems in China. In recent years, based on the IAU initialization scheme, CAS-IAP has developed the EnOI-IAU initialization scheme (Wu et al., 2018a; Zhou et al., 2020b) and established its Decadal Prediction System (IAP-DecPreS; Wu et al., 2018a) based on FGOALS-s2 (Bao et al., 2013). The crucial part of IAP-DecPreS is an initialization scheme for the oceanic component of a coupled general circulation model. EnOI-IAU can initialize the coupled model via assimilating raw observational oceanic temperature profiles, which is of great help in improving the timeliness of prediction. IAP-DecPreS is currently the only system in China to share prediction results with the Decadal Forecast Exchange platform, which is organized by the Met Office with the participation of multiple countries. Historical hindcasts show that IAP-DecPreS has good prediction skills for SST anomalies related to the PDO and AMO (Wu et al., 2018a; Zhou et al., 2020b).

Recently, the decadal prediction sub-system of the FGOALS-f2-V1.3 S2D system was developed and run at LASG, CAS-IAP. The decadal hindcast experiments with eight ensemble members were conducted starting every year over the period 1981–2015. The model was integrated from 1976 with an initial condition taken from the 40-year Global Reanalysis (Li et al., 2021a) datasets, which assimilated the air temperature at each pressure layer, the zonal and meridional winds, specific humidity, and surface pressure, and SST was assimilated as well. The external boundary conditions were consistent with the CMIP6 historical simulations. Given the need to serve the forecasting demands during China's rainy season, every decadal experiment was initialized from 20 March and integrated for 129 months. The hindcast dataset not only provides the climate state of the model, but supports real-time forecasts based on relevant skill evaluation. In 2022, the decadal prediction sub-system carried out real-time forecasts for the next 10 years, and the forecast results were adopted by the NCC to serve the operational work of the disaster risk reduction of the near-term climate prediction. The model outputs contain multiple and sufficient monthly mean atmospheric and oceanic variables.

3.3. *Prediction systems of other institutes in China*

In recent years, several Chinese universities and scientific institutes have also developed their own climate prediction systems, such as the First Institute of Oceanography-Climate Prediction System (FIO-CPS; Song et al., 2021), the Chinese Academy of Meteorological Sciences Climate System Model (CAMS-CSM, Rong et al., 2018; Liu et al., 2021a) climate prediction system, and the Climate Forecast System of Nanjing University of Information Science and Technology (NUIST-CFS; He et al., 2020a; Ying et al., 2022). These prediction systems participated in CMME-S2D and CMME-ENSO, as well as a national climate trend prediction conference for summer and winter–spring.

Two versions of climate prediction systems have been established by the First Institute of Oceanography (FIO) for operational use. The first version (FIO-CPS v1.0) was developed based on the First Institute of Oceanography-Earth System Model version 1.0 (FIO-ESM v1.0, Qiao et al., 2013), which is an Earth System model characterized by a coupled wave model. FIO-ESM v1.0 participated in CMIP5 and showed good simulation performance for the basic patterns and variability of the atmosphere and ocean, including ENSO (Qiao et al., 2013, Song et al., 2014). FIO-CPS v1.0 uses the ensemble adjustment Kalman filter initialization method to assimilate the daily SST and SLA and uses the three-dimensional ocean temperature perturbation method to generate 10 members, which are integrated for up to 6 months (Chen et al., 2016). The hindcast results of FIO-CPS v1.0 show that it has high SST prediction skill over the North Pacific for two seasons in advance, which transfers fairly well to precipitation prediction (Zhao et al., 2019; Song et al., 2020). The new version (FIO-CPS v2.0) was developed based on the First Institute of Oceanography-Earth System Model version 2.0 (FIO-ESM v2.0; Bao et al., 2020b), which participated in CMIP6. There are some significant scientific and technical improvements in the physical process parameterizations and model resolutions of every component in FIO-ESM v2.0. This latest version can simulate the climatological states of the atmosphere and ocean fairly well. The patterns of temperature, precipitation, and SST are greatly improved compared to those of FIO-ESM v1.0 (Bao et al., 2020b). FIO-CPS v2.0 adopts the nudging initialization method to assimilate the upper-ocean temperature in the mixed layer. Similar to FIO-CPS v1.0, FIO-CPS v2.0 uses the three-dimensional ocean temperature perturbation method mentioned above to generate 10 members, but their prediction time extends to 13 months (Song et al., 2021). Compared with FIO-CPS v1.0, FIO-CPS v2.0 has higher prediction skill for SST anomalies, especially over the equatorial Pacific (Song et al., 2022). The ACC score for ENSO is around 0.78 at a 6-month lead time in FIO-CPS v2.0 (Song et al., 2021).

CAMS-CSM was developed by the Chinese Academy of Meteorological Sciences (CAMS), which is an ocean–atmosphere–land–ice fully coupled climate system model (Rong et al., 2018). CAMS-CSM participated in CMIP6 (Rong et al., 2019, 2021) and showed good simulation performance for climatological mean states and seasonal cycles including temperature, precipitation, SST, and sea ice (Rong et al., 2018, 2021; Wei et al., 2018). The major climate variability modes are also reasonably captured by CAMS-CSM, such as the MJO, BSISO, ENSO, AO, PDO, East Asian summer monsoon, and Northern and Southern Hemisphere annular modes (Rong et al., 2018, 2021; Wei et al., 2018; Hua et al., 2019; Lu and Ren, 2019; Nan et al., 2019; Qi et al., 2019; Ren et al., 2019d). The climate prediction system based on CAMS-CSM adopts a nudging initialization scheme to assimilate reanalysis data of the atmosphere and ocean, which include the 55-year Japanese Reanalysis Project reanalysis data (Kobayashi et al., 2015) and NCEP Global Ocean Data Assimilation System reanalysis data (Behringer and Xue, 2004). The prediction system uses the LAF method to generate eight members, which are integrated for up to six months. Liu et al. (2021a) evaluated the seasonal prediction skills of the CAMS-CSM climate prediction system and stated that the system has good prediction skills for ENSO, IOD, temperature, and precipitation anomalies. The ACC score for ENSO is around 0.75 at a 6-month lead time, and for the IOD it is around 0.51 at a 2-month lead time.

NUIST-CFS1.0 was developed based on the SINTEX-F model, which is an ocean–atmosphere fully coupled climate model (Luo et al., 2005a). It has been confirmed that the SINTEX-F model has good simulation and prediction performance for both ENSO and the IOD (Luo et al., 2005b, 2007, 2008a, b). NUIST-CFS1.0 adopts a nudging initialization scheme to assimilate the observed weekly average OISST (Optimum Interpolation Sea Surface Temperature) values to generate realistic and atmosphere–ocean well-balanced initial conditions. NUIST-CFS1.0 is separately perturbed by three different coupled physics schemes and initialization schemes to constitute an ensemble of nine members (He et al., 2020a; Asfaw and Luo, 2022). They are integrated for up to 24 months and their forecast frequency is once per month (on the first day of each month). The hindcast results of NUIST-CFS1.0 show that it has high prediction skills for tropical SST anomalies. In particular, ENSO is skillfully predicted up to 1.5–2 years in advance, and the IOD can be predicted one to two seasons in advance (He et al., 2020a; Ying et al., 2022). In addition, NUIST-CFS1.0 has reasonable prediction performance for the climatological mean states of summer temperature and precipitation in China (He et al., 2020a).

4. Summary and future prospects

Over the past three decades, Chinese researchers have conducted a lot of research on weather and climate prediction. Figure 1 summarizes the main progress of seamless prediction methods and systems in China in the past 30 years and shows potential development directions in future research. Among them, there are many landmark or unique methods and systems for weather forecasting or climate prediction. For example, the operational application of the 4DVar assimilation system demonstrates that the operational NWP assimilation technology in China has reached the forefront of the international NWP field. GRAPES-GFS is the first global weather forecast system with independent development, stable operation, and good forecast results in China. CMME filled the gap in the field of operational MME prediction in China. The ACE method has been recognized and had a profound impact on the subsequent analogue-based prediction method. BCC-S2Sv1 was the first model in China to participate in the S2S Prediction Project, and IAP-DecPreS is currently the only model in China to share prediction results with the Decadal Forecast Exchange platform. Since the concept of seamless prediction was proposed in 2005, Chinese meteorological operational departments and scientific institutes have developed two weather–climate integrated prediction systems—namely, CMA-CPSv3 (developed by the CMA) and FGOALS-f2-V1.3 (developed by CAS-IAP). The operational implementation of these two systems signifies that China has taken a significant step towards seamless prediction.

However, as our understanding of seamless prediction has deepened, more new issues and challenges have gradually been exposed. There are still some systematic biases in prediction models (Zhang et al., 2020b; Wu et al., 2021). The improvement of prediction models depends heavily on our understanding of physical processes and mechanisms and how they work in the climate system. Therefore, more reasonable physics-based parameterization schemes need to be developed and improved in future work. Traditional NWP primarily uses a high-resolution atmospheric model and does not consider the coupling with the ocean and sea ice. In contrast, traditional climate prediction uses an atmosphere–ocean–land–ice coupled climate model, but the resolution is lower than that of NWP models. Improving the resolution of the prediction model will be of great significance to the application of a seamless prediction system. The resolutions of CMA-CPSv3 and FGOALS-f2-V1.3 are 45 km and 100 km, respectively, which cannot meet the requirements of a refined weather forecast. The next-generation high-resolution Earth System model of the CMA is currently being developed. CAS FGOALS-f3-H (Bao et al., 2020a) participated in CMIP6 HighResMIP, and the resolution reached C384 (approximately 25 km), which provided a solid model basis for the future development of high-resolution refined seamless prediction.

Traditionally, separated data assimilation schemes are applied to the uncoupled models, and their products are used to initialize the corresponding components in the coupled model (Saha et al., 2006; MacLachlan et al., 2015; Takaya et al., 2018). There are also some models that used

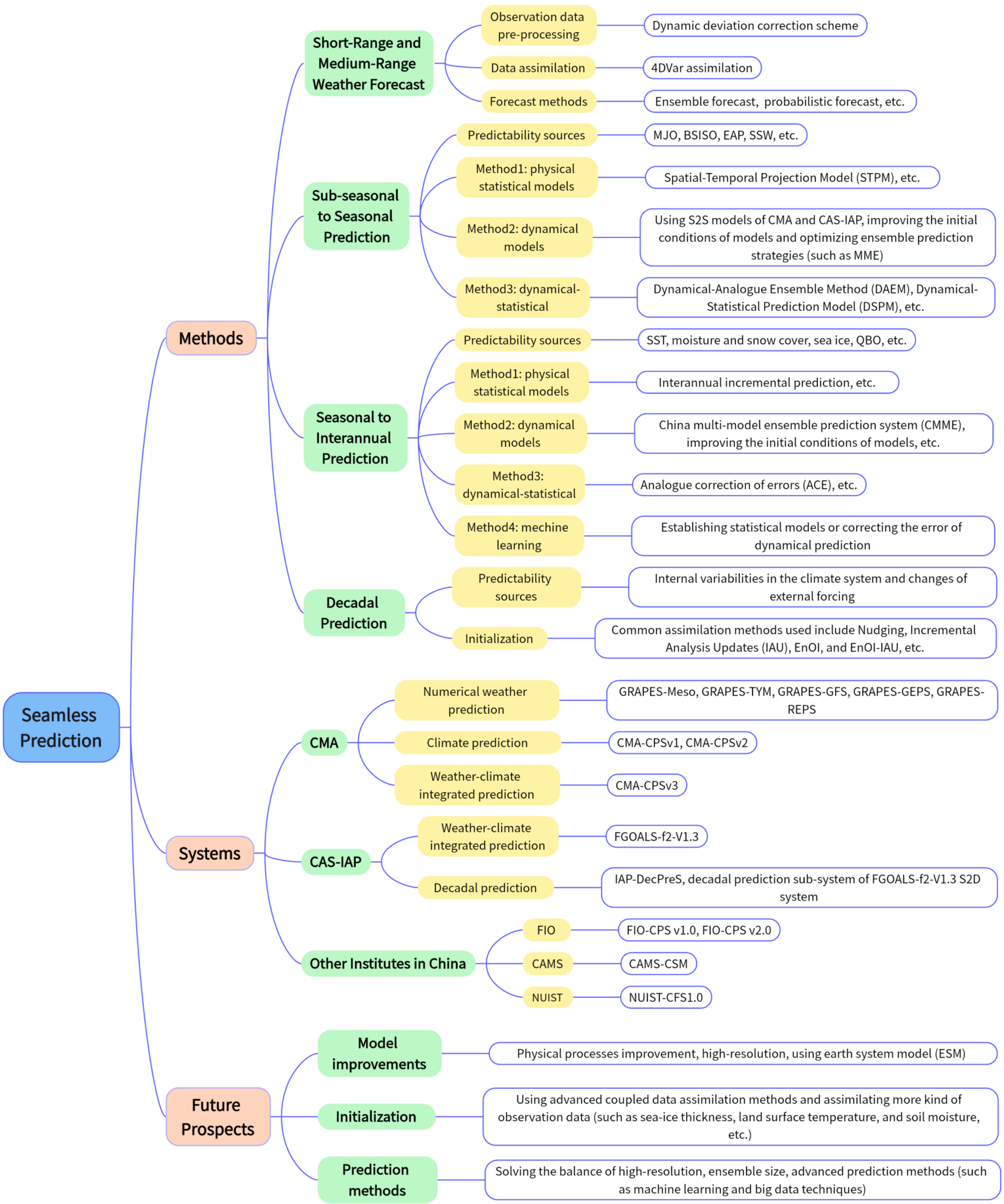

Fig. 1. Schematic of the main progress in seamless prediction methods and systems in China in the past 30 years, as well as development directions in future research.

reanalysis products from external sources to initialize individual model components (Liu et al., 2015; Xin et al., 2018). In recent years, coupled data assimilation schemes were developed to reduce the possible inconsistency caused by uncoupled data assimilation. The coupled data assimilation sub-system of CMA-CPSv3 assimilates multisource observations of ocean, sea ice, and atmosphere. Some other important observation data, such as sea-ice thickness, land surface temperature, and soil moisture, need to be considered in future studies (Liu et al., 2021b).

Ensemble size is an important aspect that determines prediction skills and reliability. In general, the more ensemble members, the higher the prediction skill. The consequences of computing costs need to be considered when using more ensemble members (Meehl et al., 2021). Machine learning and big data techniques provide new possibilities to complement and improve seamless prediction systems (Ruti et al., 2020). The prediction skills of seamless prediction systems will largely depend on the balance between a high resolution, large ensemble size, advanced prediction methods, and advanced data assimilation schemes.

The original use of the term "seamless" (Palmer et al., 2008) referred to predictions across the range of weather and climate time scales. Since then, the definition has evolved toward the idea of predicting "the spatiotemporal continuum of the interactions among weather, climate, and the Earth system" (Brunet et al., 2010). That means that the development of seamless prediction will extend from the physical climate system towards a comprehensive view of the Earth system by including interactions with the biogeophysical components (Hazeleger et al., 2012). The "Science Summit on Seamless Research for Weather, Climate, Water, and Environment" was organized by the WMO in 2017 and emphasized the importance of seamless earth system prediction (Ruti et al., 2020). In recent years, the CMA and CAS-IAP have successively developed earth system models—namely, BCC-ESM1 (Wu et al., 2020c) and CAS-ESM (Zhang et al., 2020a)—which both participated in CMIP6. However, there is still much research to be done in the transition from "weather and climate" to "weather, climate and Earth system" for seamless prediction, both in theory and practice. For example, considering land use and anthropogenic effects in seamless earth system prediction will effectively improve the prediction ability of extreme weather events (Ruti et al., 2020), which is one of the focuses of S2S prediction in recent years. In summary, Chinese researchers should persist with their efforts to develop and improve seamless prediction.

Acknowledgements. This work was jointly supported by the National Natural Science Foundation of China (Grant Nos. U2242206, 42175015, and 41975094) and the Basic Research and Operational Special Project of CAMS (Grant No. 2021Z007).

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