The Flexible Global Ocean-Atmosphere-Land System Model Grid-Point Version 3 (FGOALS-g3): Description and Evaluation

Lijuan Li1, Yongqiang Yu1-2, Yanli Tang1, Pengfei Lin1-2, Jinbo Xie1, Mirong Song1, Li Dong1-2, Tianjun Zhou1-2, Li Liu1, Lu Wang1-5, Ye Pu1, Xiaolong Chen1, Lin Chen1-5, Zhenghui Xie1-2, Hongbo Liu1, Lixia Zhang1, Xin Huang1, Tao Feng1,6, Weipeng Zheng1-2, Kun Xia1, Haolong Liu1-2, Jiping Liu1, Yan Wang2, Longhuan Wang1, Binghao Jia1, Lijuan Li1, Bin Wang1-2, Shuwen Zhao1-2, Zipeng Yu1, Bowen Zhao1, and Jilin Wei1

1State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China, 2College of Earth and Planetary Sciences, University of Chinese Academy of Sciences, Beijing, China, 3Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao, China, 4Department of Earth System Science, Tsinghua University, Beijing, China, 5Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environmental Change (ILCEC)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing University of Information Science and Technology, Nanjing, China, 6Department of Atmospheric Sciences, Yunnan University, Kunming, China, 7Anhui Meteorological Observatory, Hefei, China

Correspondence to:
B. Wang, wab@lasg.iap.ac.cn

Abstract This paper introduces the Flexible Global Ocean-Atmosphere-Land System Model: Grid-Point Version 3 (FGOALS-g3) and evaluates its basic performance based on some of its participation in the sixth phase of the Coupled Model Intercomparison Project (CMIP6) experiments. Our results show that many significant improvements have been achieved by FGOALS-g3 in terms of climatological mean states, variabilities, and long-term trends. For example, FGOALS-g3 has a small (−0.015°C/100 yr) climate drift in 700-yr preindustrial control (piControl) runs and smaller biases in climatological mean variables, such as the land/sea surface temperatures (SSTs) and seasonal soil moisture cycle, compared with its previous version FGOALS-g2 during the historical period. The characteristics of climate variabilities, for example, Madden-Julian oscillation (MJO) eastward/westward propagation ratios, spatial patterns of interannual variability of tropical SST anomalies, and relationship between the East Asian Summer Monsoon and El Niño–Southern Oscillation (ENSO), are well captured by FGOALS-g3. In particular, the cooling trend of globally averaged surface temperature during 1940–1970, which is a challenge for most CMIP3 and CMIP5 models, is well reproduced by FGOALS-g3 in historical runs. In addition to the external forcing factors recommended by CMIP6, anthropogenic groundwater forcing from 1965 to 2014 was incorporated into the FGOALS-g3 historical runs.

Plain Language Summary The sixth phase of the Coupled Model Intercomparison Project (CMIP6) is a crucial support for the sixth Assessment Report of Intergovernmental Panel on Climate Change (IPCC AR6) and will also provide important foundation for research in climate change in the next few years. This paper gives the description of FGOALS-g3 model, its experiment configurations, and the experiments conducted according to the experimental design of CMIP6 and evaluates the preliminary performance of model simulation. This work offers references to CMIP6 data users and provides enormous output data sets for assessing and understanding climate change.

1. Introduction

State-of-the-art climate system models have been widely applied in the climate sciences across multiple scales in time and space; for example, they are the tool available to predict or project future climate change (Intergovernmental Panel on Climate Change, IPCC, 2013). They are established on the mathematical formulations of the natural laws that govern the evolution and interaction of the five components of the climate system (i.e., the atmosphere, ocean, cryosphere, land, and biosphere). Associated with rapid progress in observations, dynamic theories, and computer performance, continuous advances have been made in developing component and fully coupled models during the past few decades.
Since the late 1980s, considerable efforts have been made in developing, assessing, and improving atmospheric, oceanic, land, and sea ice models and coupled climate models, at the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics (IAP), Chinese Academy of Sciences (CAS). To date, there have been six generations of coupled climate models (Bao et al., 2013; Chen et al., 1997; Li, Lin, et al., 2013; Wu et al., 1997; Yu & Zhang, 1998; Yu et al., 2002, 2004; Zhang et al., 1992) developed at LASG-IAP. These coupled models have also contributed to each phase of the Coupled Model Intercomparison Project (CMIP) (Covey et al., 2003; Meehl et al., 2005) and assessment reports of Working Group I of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 1992, 1995, 2001, 2007, 2013).

The latest generation of climate system models developed at LASG-IAP is Version 3 of the Flexible Global Ocean-Atmosphere-Land System model (FGOALS3), which includes three parallel subversions (FGOALS-g3, FGOALS-f3-L, and FGOALS-f3-H). All three subversions were established based on a similar coupling framework, in which atmospheric, oceanic, sea ice, and land component models are connected via a common flux coupler. The same oceanic and sea ice models are shared by these three subversions, but different atmospheric and land component models are used. The present study describes the basic configuration of the coupled model FGOALS-g3 and evaluates its performance in terms of climatological means, climatic variability, and long-term climate trend. The four component models of FGOALS-g3 include Version 3 of the Grid-Point Atmospheric Model of LASG-IAP (GAMIL3) for the atmosphere, Version 3 of the LASG-IAP Climate System Ocean Model (LICOM3) for the ocean, Version 4 of the Los Alamos sea ice model for sea ice (http://climate.lanl.gov/Models/CICE), and the CAS-Land Surface Model (CAS-LSM) for the land (Xie et al., 2018). According to the numerical experiment design for CMIP6 (Eyring et al., 2016), we have conducted lots of CMIP6 experiments, including the Diagnostic, Evaluation, and Characterization of Klima (DECK), historical simulations, Scenario Model Intercomparison Project (ScenarioMIP), Global Monsoons Model Intercomparison Project (GMMIP), and Ocean Model Intercomparison Project (OMIP), which are also published online in the Earth System Grid Federation (ESGF). And we are also conducting other MIPs, such as the Paleoclimate Modeling Intercomparison Project (PMIP) and Decadal Climate Prediction Project (DCPP). In the present study, DECK, historical, and ScenarioMIP simulations are analyzed and evaluated with emphasis on the mean state, and climate variability and change.

The remainder of this paper is organized as follows. Section 2 documents the major developments in FGOALS-g3 components and experiment design and describes the stability of the coupled system after the spin-up processes. Section 3 shows results from climate mean states to major climate variability modes. The model performance for twentieth century climate and Asian Monsoon simulations is also assessed in section 3. Finally, section 4 provides a summary and discussion.

2. Model Description and Experimental Design

2.1. Model Description

GAMIL3 is updated from GAMIL2 (Li, Wang, et al., 2013). Both versions use the same finite difference dynamical core, which conserves many properties, such as total mass and effective energy under the standard stratification approximation (Wang et al., 2004) and employ a 26 vertical \( \sigma \) layers (pressure normalized by surface pressure) coordinate with the model top at 2.194 hPa. Compared with GAMIL2, GAMIL3 has many modifications with respect to parallel computing, horizontal resolution, water vapor advection scheme, physical processes, and external forcings. GAMIL3 utilizes a two-dimensional hybrid parallel decomposition (Liu et al., 2014) replacing the one-dimensional parallel decomposition in the meridional direction, increases the horizontal resolution from \( \sim 2.8^\circ \) (128x60) to \( \sim 2^\circ \) (180x80), and improves water vapor conservation through modification of the two-step shape-preserving advection scheme (TSPAS, Yu, 1994). With regard to physical processes, GAMIL3 incorporates a convective momentum transport scheme (Wu et al., 2007), adopts a simple stability-based stratocumulus cloud fraction scheme based on estimated inversion strength (EIS; Guo & Zhou, 2014), and involves a simple parameterization of the second version of the Max Planck Institute Aerosol Climatology model (MACv2-SP) for anthropogenic aerosol effects (Shi et al., 2019; Stevens et al., 2017) and an improved boundary layer scheme that includes entrainment at the top of the boundary layer, longwave radiative cooling at the top of stratocumulus clouds, and turbulent kinetic energy (TKE) (Sun et al., 2016). In addition, the external forcings recommended by CMIP6 were updated and their
impacts on model stability, twentieth century global warming, and ENSO were evaluated by FGOALS-g2 (Nie et al., 2019).

CAS-LSM is the land component of FGOALS-g3 with the same horizontal resolution as the atmospheric component and is based on the Community Land Model Version 4.5 (CLM4.5). However, it includes unique improvements and additions to the land processes with respect to CLM4.5, such as groundwater lateral flow (Xie et al., 2012; Zeng, Xie, Yu, Liu, Wang, Jia, et al., 2016; Zeng, Xie, Yu, Liu, Wang, Zou, et al., 2016; Zeng et al., 2018), anthropogenic groundwater exploitation (Zeng, Xie, Yu, Liu, Wang, Zou, et al., 2016; Zeng et al., 2017; Zou et al., 2014, 2015), implementation of a new frozen soil parameterization including frost and thaw fronts (Gao et al., 2016, 2019), anthropogenic nitrogen discharge in rivers (S. Liu et al., 2019), and urban processes.

LICOM3 is updated from LICOM2 (Lin et al., 2016; Liu et al., 2012). Its dynamical core with a latitude-longitude grid structure is replaced by arbitrary orthogonal curvilinear coordinates (Madec & Imbard, 1996; Murray, 1996; Yu et al., 2018). Preserved shape advection (Xiao, 2006) and the implicit vertical viscosity (Yu et al., 2018) are used. The Laurent et al. (2002) tidal mixing model (Yu et al., 2017) is introduced into LICOM3. In addition, the eddy-induced mixing of Redi (1982) and Gent and McWilliams (1990), and the buoyancy frequency ($N^2$) related thickness diffusivity of Ferreira et al. (2005), were added to the model. The chlorophyll-a-dependent solar penetration of the Ohlmann (2003) scheme (Lin et al., 2007) and vertical mixing of Canuto et al. (2001, 2002) are used in LICOM3. A tri-polar grid was chosen, with the North Pole split into two poles on-land, which can enlarge the time steps in the Arctic polar region and remove the spatial filter for momentum velocities and tracers. A B-grid was used for the horizontal distribution. The North Pole in the low-resolution LICOM3 is divided into two North Poles on-land at 65°N/65°E and 65°N/115°W. The low-resolution LICOM3 has 360×218 horizontal grids. The vertical direction uses eta coordinates with 30 and 80 layers, but only the 30 layers were used for OMIP and CMIP6.

The sea ice model is the Los Alamos sea ice model Version 4.0, using the same grid as the oceanic model. This is an energy conserving thermodynamic model, which solves the dynamic and thermodynamic equations for five ice thickness categories, with one snow and four ice layers. For the dynamic component, the elastic-viscous-plastic rheology (Hunke & Dukowicz, 1997), mechanical redistribution scheme (Lipscomb et al., 2007), and incremental remapping advection scheme (Lipscomb & Hunke, 2004) are used. For the thermodynamic component, the Delta-Eddington radiative transfer scheme using inherent optical properties based on physical measurements (Briegleb & Light, 2007) is utilized.

There are two couplers: CPL7 developed at the National Center for Atmospheric Research (NCAR) and C-Coupler2 (Community Coupler Version 2) developed at Tsinghua University (Craig et al., 2012; Liu et al., 2018). Compared with CPL6 (Craig et al., 2005), CPL7 possesses improved memory and performance scaling that can support much higher-resolution configurations. The computing performance of the coupled model using CPL7 was improved linearly by use of tens of thousands of CPUs. In addition, CPL7 has a more sophisticated computing resource control and a single executable, which allow the models to run flexibly and simplifies the machine requirements for the dispatcher. In addition to the Model Coupling Toolkit (MCT; Larson et al., 2005) that handles data transfer and interpolation for CPL7, C-Coupler2 was employed as a new option for these two functionalities, which provides exactly the same (bitwise identical) simulation results as MCT. Moreover, the coupling capability of FGOALS-g3 would be upgraded for future development with the new features of C-Coupler2 (i.e., dynamic 3-D coupling, flexible and automatic coupling generations, nonblocking data transfer, facilitation of increment coupling, and automatic remapping weight generation; Liu et al., 2018).

### 2.2. Experimental Design

Prior to analyzing and evaluating the model performance, some basic experiments, including preindustrial control (piControl), historical, and scenario runs were conducted according to the experimental design of CMIP6 (Eyring et al., 2016). In these experiments, the coupling intervals of the atmospheric, land, and sea ice components are the same as the time step (600 s) of GAMIL3, and the coupling frequency of LICOM3 is 8 times/day. Using this configuration, the piControl run spans 2,000 yr and acts as the baseline for other CMIP6-type simulations, where the first 700-yr (200–899) data set after removing the first 200-yr spin-up was
The model tuning includes two steps: component model tuning with observed boundary condition and fully coupled model tuning. In the FGOALS-g3 tuning, the key targets include model stability (numerical stability and small drift), climate variability (mainly refers to ENSO), and mean state (small bias) of piControl runs through tuning the parameters (e.g., mixing parameter in LICOM3 and cloud-related parameters in GAMIL3) and the coupling intervals of LICOM3. In order to control the numerical instability possibly resulted from coupled processes, the LICOM3 time step is reduced from 3,600 s in uncoupled model to 2,160 s in the coupled model. Climate drift in the deep ocean is strongly associated with vertical mixing; thus, the background vertical mixing coefficients dependent on the latitude as suggested by Jochum (2009) are tuned, with the maximum $3.1 \times 10^{-5} \text{m}^2 \text{s}^{-2}$ around $30^\circ\text{S}/30^\circ\text{N}$ and minimum $0.3 \times 10^{-5} \text{m}^2 \text{s}^{-2}$ around the equator, to reduce the long-term trend in the piControl run. The cloud-related parameters, such as the relative humidity thresholds for cloud formation and convection, are tuned to reduce the surface temperature drift through changing the energy balance and to simulate better ENSO amplitude through affecting the atmospheric thermodynamic feedback and the oceanic thermocline feedback (Tang et al., 2016; Tang, Li, Wang, Lin, Chen, et al., 2019). Before the frozen FGOALS-g3, some experiments were performed with different coupling intervals for LICOM3, for example, 1 day, 6 hr, and 3 hr. It has been found that 3-hr coupling frequency (i.e., eight times/day) leads to better ENSO amplitude and smaller climate drift than 1-day coupling. In addition, it should be noted that the tuning was only focused on the piControl run and there is no tuning for other type runs. The 700-yr mean global average surface temperature (GAST) is 13.7°C with a standard deviation of 0.1°C, and the GAST linear trend is $-0.015^\circ\text{C}$ per 100 yr (Figure 1), which is a smaller climate drift than the CMIP5 piControl run ($-0.039^\circ\text{C}$ per 100 yr; Nie et al., 2019). The sea ice extent trend is 397 km$^2$/yr (0.026%/yr) in the Arctic and 83 km$^2$/yr (0.005%/yr) in the Antarctic (Figure not shown).

2.3. Data

For FGOALS-g3, the climatological mean of the six-member ensemble mean from 1980 to 2014 in the historical runs is used to represent the mean states. The daily output of the first historical member from 1980 to 2014 is used to analyze the variability of 10- to 20- and 30- to 80-day (Madden-Julian oscillation, MJO) periods. The monthly output of the first historical member from 1950 to 2014 is used to calculate the interannual variability. For comparison, the climatological mean of the five-member ensemble mean from 1980 to 2005 in the historical runs by FGOALS-g2 is used to represent the mean states. For interdecadal variability, both the first member historical run from 1920 to 2005 by FGOALS-g3 and FGOALS-g2 and 700-yr piControl run by FGOALS-g3 and 900-yr piControl run by FGOALS-g2 are used.

For validation, the observational/reanalysis data sets listed in Table 1 are used: Global Precipitation Climatology Project (GPCP; Version 2.3) data (Adler et al., 2003) and Climate Prediction Center Merged Analysis of Precipitation observations (CMAP) (Xie & Arkin, 1997); ERA-Interim reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Dee et al., 2011); monthly sea surface temperature (SST) data from the National Oceanic and Atmospheric Administration (NOAA)/
Table 1
The Observational/Reanalysis Data Sets Used for Comparison

| Data sets                                         | Periods   | Reference                |
|--------------------------------------------------|-----------|--------------------------|
| Global Precipitation Climatology Project (GPCP; Version 2.3) data | 1980–2014 | Adler et al. (2003)      |
| Climate Prediction Center Merged Analysis of Precipitation observations (CMAP) | 1980–2014 | P. P. Xie and Arkin (1997) |
| ERA-Interim re-analysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) | 1980–2014 | Dee et al. (2011)        |
| monthly sea surface temperature (SST) data from the National Oceanic and Atmospheric Administration (NOAA)/National Climatic Data Center (NCDC) Extended Reconstructed SST Version 5 (ERSST v5) | 1920–2014 | Huang et al. (2017)      |
| Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST1.1) data set produced by the Met Office | 1870–2014 | Rayner et al. (2003)     |
| monthly mean sea level pressure produced by the Hadley Center (HadSLP2) | 1870–2014 | Allan and Ansell (2006)   |
| surface temperature data set HadCRUT4 | 1870–2014 | Morice et al. (2012)     |
| monthly sea ice data retrieved with a Bootstrap algorithm from the Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), and Special Sensor Microwave Imager/Sounder (SSMIS) | 1980–2014 | Comiso (2017)            |
| land temperature data collated by the University of Delaware from a large number of stations | 1980–2014 | Willmott and Matsuura (2001) and Legates and Willmott (1990) |
| Global Land Data Assimilation System Version 2 (GLDAS 2) | 1980–2014 | Rodell et al. (2004)     |

Figure 2. Horizontal distributions of annual mean SST bias (units: °C) (a) from the FGOALS-g3 ensemble mean based on six historical runs and (b) from the FGOALS-g2 ensemble mean based on four historical runs. The ERSSTv5 is referenced as the observed.
National Climatic Data Center (NCDC) Extended Reconstructed SST Version 5 (ERSST v5) (Huang et al., 2017) and Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST1.1) data set produced by the Met Office (Rayner et al., 2003); monthly mean sea level pressure produced by the Hadley Center (HadSLP2) (Allan & Ansell, 2006); surface temperature data set HadCRUT4 (Morice et al., 2012); monthly sea ice data retrieved with a Bootstrap algorithm from the Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), and Special Sensor Microwave Imager/Sounder (SSMIS) (Comiso, 2017); land temperature data collated by the University of Delaware from a large

![Figure 3](image3.png)

**Figure 3.** Annual zonal mean (contours) of (a) temperature and (b) salinity and their biases (colored shading) during 1980–2014 from the ensemble mean based on six historical runs. WOA13 is referenced as the observed. The 0°C and 35-psu contours are shown as thick lines.

![Figure 4](image4.png)

**Figure 4.** The annual mean states of (a) global and (b) Atlantic meridional overturning circulation (i.e., GMOC and AMOC) and (c) global and (d) Atlantic poleward heat transport (PW; 1 PW = 10^{15} W) during 1980–2014 from the ensemble mean based on six historical runs. The red line shows the ensemble mean, and the black dots are the estimates from Ganachaud and Wunsch (2003). The AMOC is only plot north of 32°S due to the unclosed eastern and western boundary of Atlantic Ocean.
number of stations (Willmott & Matsuura, 2001), Global Historical Climate Network and the archive of Legates and Willmott (1990); and Global Land Data Assimilation System Version 2 (GLDAS 2) (Rodell et al., 2004).

3. Analyses and Evaluations

In this section, the climatological mean state of different components, climate variability over periods from days to decades, long-term evolution of surface temperature from 1850–2100, and the monsoon is evaluated.

![Annual mean Precipitation](image-url)

**Figure 5.** Spatial distribution of annual mean precipitation rate (mm/day) from (a) FGOALS-g3 and the biases of (b) FGOALS-g2 and (c) FGOALS-g2 compared to CMAP.
3.1. Climatological Mean State

3.1.1. Ocean

Figure 2 shows the SST bias of both FGOALS-g2 and FGOALS-g3. In terms of global statistics, the SST mean bias is slightly reduced by FGOALS-g3, including its horizontal root-mean-square errors (RMSEs) for the globe, global mean, and maximal and minimal bias (1.15°C, −0.15°C, 5.23°C, and −7.85°C) as compared with those (1.54°C, −0.65°C, 6.16°C, and −7.64°C) from FGOALS-g2 (also in Lin et al., 2013). The warm pool at ≥28°C simulated by FGOALS-g3 is more accurate than that from FGOALS-g2 (Lin et al., 2013). However, obvious cold biases are located in the northwestern Pacific (NWP) between 20°N and 45°N and the Barents Sea, and warm biases are still present in the eastern boundary due to the too small amounts of low-level cloud in FGOALS-g3 (Figure 2a).

The zonal mean temperature biases in FGOALS-g3 (Figure 3) are similar to those in FGOALS-g2. However, the salinity biases are different. A fresh bias is found in FGOALS-g2 (Li, Lin, et al., 2013), while a salt bias is in FGOALS-g3 for the global zonal mean salinity. There is the strong positive salinity bias at around 40°N. The positive salinity anomaly is due to the positive salinity bias in the Mediterranean Sea. This is because the river routing or the representation of the Strait of Gibraltar has deficiencies in the ocean model (figure not shown). The structure of Antarctic Intermediate Water (AAIW), defined as the salinity tongue enclosed by the 34.8-psu contour, is improved. However, the simulated salinity is saltier than the observed.

The global and Atlantic meridional overturning circulation (GMOC and AMOC) are presented in Figure 4, and the spatial pattern simulations are similar to the referenced observations (Lumpkin & Speer, 2007). The wind-driven upper layer (~500 m) cells are well captured by the model. North Atlantic Deep Water (NADW) can reach at the depth of 3,500-m depths and even at the ocean bottom north of 30°N. The maximal NADW is located at ~1,200-m depth between 35°N and 40°N, with a value of 34 Sv. Compared with the observed value at 26.5°N from RAPID (~18.5 Sv; Cunningham et al., 2007), the modeled value is overestimated and is also higher than that from FGOALS-g2. In the Atlantic Ocean, Antarctic Bottom Water (AABW) is mainly limited to south of 30°N, while in the Pacific and Indian oceans, AABW is strong with a value of 20 Sv. Although the AMOC and GMOC are strong in the Atlantic, the meridional heat transport is still smaller than that estimated using observations in the Northern Hemisphere south of 30°N (Ganachaud & Wunsch, 2003). This may be related to the slightly colder water that is transported northward in the upper 200 m and warmer water that is transported southward between 200 and 1,500 m. The simulated heat transport is larger than observed at ~50°N. In the Southern Hemisphere, the heat transport is well captured at ~30°S.

Figure 6. Multivariable Taylor diagram displaying normalized statistical comparisons of FGOALS-g3 (red) and FGOALS-g2 (blue) historical experiment simulated (a) climatology and (b) interannual variability of different meteorological variables with ERA-Interim and GPCP as observations, respectively. The numbers represent different variables, which include precipitation (pr), sea level pressure (psl), 500-hPa geopotential height (z500), 850-hPa air temperature (t850), 200- and 850-hPa zonal wind (u200 and u850), 200- and 850-hPa meridional wind (v200 and v850), and 200- and 850-hPa specific humidity (q200 and q850).
3.1.2. Atmosphere

Figure 5 shows the spatial distribution of annual mean precipitation rate from FGOALS-g3 and the biases of FGOALS-g2 and FGOALS-g3 relative to the CMAP. Generally, the two versions can basically capture the large-scale precipitation features, especially the spatial pattern of precipitation over the tropical region. The globally averaged mean precipitation rate modeled by FGOALS-g3 is 2.74 mm/day, much closer to CMAP (2.66 mm/day) than that (2.82 mm/day) by FGOALS-g2. The biases of FGOALS-g3 are smaller than those of FGOALS-g2 in the tropical region south of the equator, for example, the eastern Indian and Pacific Ocean, which may be related to the improved SSTs by FGOALS-g3. However, there is an obvious wet bias in the western Indian Ocean and too much modeled precipitation in the central Pacific near the equator in FGOALS-g3.

The spatial pattern correlation, root-mean-square difference, and amplitude of variation of different meteorological variables by FGOALS-g2 and FGOALS-g3 are summarized in Taylor diagram (Figure 6), in which the normalization is through the division of the spatial spread of model simulation by the spatial spread of observation for each single variable on the model grids. Generally, the skills of both FGOALS-g2 and
FGOALS-g3 in simulating low-level (850 hPa) circulation variables are higher than for high-level (200 hPa) variables, and the skills in simulating eastward u-wind are better than for northward v-wind (Figure 6a). Among the different variables, the variables best correlated with the ERA-interim for both versions are the geopotential height at 500 hPa (z500) and temperature at 850 hPa (t850) (Figure 6a). When considering the interannual variability, the sea level pressure (psl) is the best simulated variable (Figure 6b). Overall, FGOALS-g3 has a better ability in both annual mean and interannual variability than FGOALS-g2.

3.1.3. Land

Compared with the observational data sets (Willmott & Matsuura, 2001), the overall spatial distribution of the annual mean land surface temperature is basically simulated by FGOALS-g3 (Figures 7a and 7b), although there are still cold biases that cover the regions mostly in the high mountain regions (e.g., the Tibetan Plateau) and the near-Arctic region in the Russia and northern Europe. The magnitude of cold bias in FGOALS-g3 is smaller than that in FGOALS-g2 (Figure 7c), especially in the Northern Hemisphere and the Andes in the Southern Hemisphere. The improvement in the high mountain and near Arctic region may be associated with the improvement of the snow parametrization.

Figure 8 shows the difference in mean soil water content between March–May (MAM) and September–November (SON) between the model simulation and GLDAS2 (Rodell et al., 2009). In general, the simulation agrees with the observations in spatial distribution (Figures 8a and 8b). However, in the regions of the Amazon, southern central Africa, North America, southern eastern Asia, and Australia, the magnitude of the simulation is smaller than that of GLDAS2, which indicates weaker seasonal variations in the simulated soil water content. The hydrology and snow parameterization schemes in the land surface model may be largely responsible for these biases.

3.1.4. Sea Ice

The spatial distributions of annual mean sea ice concentration of FGOALS-g3 compared to the observations of SMMR and SSM/I-SSMIS are shown in Figure 9. In detail, the simulated sea ice is in reasonable agreement with the observations in the Arctic Basin and Antarctic coastal areas. However, in the Arctic, the model produces excess ice along the Eurasian continent and Greenland, including in the Barents Sea, Siberia Sea, Greenland Sea, and Baffin Bay. In the Antarctic, the ice edge in the West Antarctic is more
equatorward but has a lower sea ice concentration, while in the Indian Ocean sector the simulated sea ice is less than the observations.

3.2. Climate Variability
3.2.1. The 10- to 20-Day Variability
The quasi-biweekly (QBW) oscillation (usually referred to as the 10- to 20-day oscillation) is a high-frequency component of the intraseasonal oscillation, which can affect both tropical and subtropical weather and short-term mean climate, or even lead to extreme flooding and heat wave events. QBW events are highly concentrated over the East Asia and western North Pacific (WNP) regions during the boreal summer (Jia & Yang, 2013; Kikuchi & Wang, 2009).

Figure 10 shows the spatial distribution of the 10- to 20-day outgoing longwave radiation (OLR) variance in early (April–June) and late (July–September) summer during 1980–2014. The Bay of Bengal (BOB), South China Sea (SCS), and WNP are the three large-variance areas, according to NOAA OLR observations (Figures 10a and 110d). QBW oscillations over the SCS and WNP show a 7° northward shift (13°N to 20°N) from early to late summer with the variance intensity increasing from 250 to 450 W² m⁻⁴, which is consistent with the analysis by Wang and Zhang (2019). The FGOALS-g3 model can simulate the three active QBW oscillation regions in early summer, but with different amplitude variations (Figures 10a and 10b). In late summer, the strong QBW oscillation center shows a northward shift in the simulation with the center located east of Taiwan Island, which exhibits a position deviation compared with the observation (Figures 10d and 10e). In addition, compared with early summer, the amplitudes of QBW variations in late
summer are further underestimated in the three active regions with biases of greater than \(-200 \text{ W}^2 \text{ m}^{-4}\) (Figure 10c and 10f). Therefore, it remains a challenge for FGOALS-g3 to reasonably simulate such high-frequency components of intraseasonal oscillations in subtropical regions.

### 3.2.2. MJO

Figure 11 shows the wavenumber-frequency power spectra averaged from 10°S to 10°N for OLR and U850 during the boreal winter (November–March). The observed spectral power of OLR and U850 are concentrated over the domain of eastward Wavenumbers 1–3 and periods of 30–80 days, which are referred to as the “MJO band” hereafter. The simulated spectral power also shows prominent signals over the MJO band, but the magnitudes are much weaker than the observations. For a quantitative evaluation of the model simulation, the E/W and E/O ratios were calculated. The E/W ratio is defined by dividing the sum of spectral power over the MJO band by that of its westward propagating counterpart. The E/O ratio is obtained by dividing the sum of spectral power of the simulation over the MJO band by the observed value. These two metrics reflect the robustness of the eastward propagating feature of the simulated MJO, and have been frequently used in model evaluation studies (e.g., Ahn et al., 2017; Lin et al., 2006). The observed (simulated) E/W ratio is \(~3.7\) and \(~3.8\) (1.9 and 3.4) for OLR and U850, respectively. Furthermore, the E/O ratio is 0.4 for OLR and 0.8 for U850. This suggests that the model mainly underestimates the eastward propagation of convection but captures well the eastward propagation of circulation. This is consistent with the CMIP5 model results (Ahn et al., 2017).

Although some deficiencies are detectable in the power spectra diagram of FGOALS-g3, it shows a significant improvement as compared with its previous version (i.e., FGOALS-g2), in which the E/W ratios are \(~2\) for OLR and U850, and the E/O ratio is \(~0.2\) for OLR and 0.5 for U850 (Table 2). Compared with the CMIP5 model results, the performance of FGOALS-g3 is above the average level of the CMIP5 models. The improvement of MJO in FGOALS-g3 could be mainly attributed to the inclusion of convective momentum transport and the modification of boundary layer scheme in GAMIL3 and further enhanced by the atmosphere-ocean coupling process.

Figures 12a and 12b show the winter lag-longitude diagram of correlation coefficients between 20- and 100-day filtered OLR and U850 along the equator (10°S to 10°N) versus the 20- to 100-day filtered OLR.
over a reference region (10°S to 5°N/75–100°E). In order for negative OLR anomalies to indicate enhanced convection anomalies, the sign of the OLR reference time series was reversed before calculating the correlation. The observed MJO convection propagated eastward from the Indian Ocean to the dateline, showing a quadrature phase relationship with U850 (Figure 12a). The eastward propagation of convection can be detected in the simulation, but the signals over the western Pacific are weaker than the observations. The quadrature phase relationship between the convection and zonal wind is well simulated (Figure 12b).

Figures 12c and 12d show the summer lag-latitude diagram of correlation coefficients between 20- and 100-day filtered OLR and U850 along the BOB (80–100°E) versus the OLR reference time series. Continuous northward propagation of convection is evident from the equator to 20°N in the observations, with an easterly anomaly to the north of the convection and a westerly anomaly to the south (Figure 12c). In the simulation, the continuous northward propagation of convection only reaches 10°N, and the asymmetric zonal wind anomalies relative to the convective center are not as clear as the observations (Figure 12d).

Table 2
Statistics for MJO Eastward Propagation Calculated From the Historical Experimental Results Based on FGOALS-g3, FGOALS-g2, and CMIP5 Multimodel Mean (MME)

|            | FGOALS-g3 | FGOALS-g2 | CMIPS MME |
|------------|-----------|-----------|-----------|
| E/W ratio  | 1.9       | 3.4       | 2         |
| E/O ratio  | 0.4       | 0.8       | 0.2       |

Note. The results for FGOALS-g2 and CMIP5 MME were derived from Figure 2a and 2b in Ahn et al. (2017).
### 3.2.3. Interannual Variability

This section focuses mainly on the simulation of the El Niño–Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Atlantic Niño, which are the prominent interannual variabilities in the three tropical basins.

Figures 13a and 13b show the spatial pattern of the standard deviation of the interannual SST anomaly over the tropical Pacific. The simulated SST anomaly shows large interannual variability in the central and eastern equatorial Pacific, indicating FGOALS-g3 captures the observed spatial distribution of ENSO. From a spatial perspective, the simulated ENSO variability is comparable to that which is observed. Specifically, the standard deviation of the Niño3 index is 0.88 K for the observations and 0.99 K for the FGOALS-g3 simulation (Table 3), indicating a reasonable simulation of the ENSO amplitude. The power spectrum of the observed Niño3 index is characterized by a broad peak ranging from 2–7 yr, while the simulated spectrum is characterized by a single peak at ~3 yr (Table 3). These differences in ENSO periodicity simulation may have been inherited from its predecessors (FGOALS-g1 and FGOALS-g2) in which the power of the dominant ENSO frequency is too strong and the bandwidth of the dominant frequency is too narrow (Chen et al., 2016). FGOALS-g3 also exhibits bias in reproducing the observed positive skewness (Table 3), indicating that the simulated ENSO asymmetry is underestimated. This underestimation of ENSO asymmetry remains prevalent in current coupled models (Tang, Li, Wang, Lin, Dong, & Xia, 2019; Zhang & Sun, 2014). The phase-locking characteristic of the ENSO cycle (i.e., ENSO-related SST anomalies usually peak during the boreal winter) is reproduced well by FGOALS-g3 (Figures 13c and 13d).
Figures 14a and 14b show the standard deviation of the interannual anomaly of SST, derived from the observation (left) and the FGOALS-g3 historical simulation (right). (c, d) Standard deviations of SST anomalies for each calendar month. Orange and blue bars indicate the averaged results over the Niño3 and Niño3.4 regions, respectively. Unit is K.

Table 3

|      | Niño3 Std (K) | Niño3 Skewness (K) | Niño period (yr) | IODW Std (K) | IODE Std (K) | Atl3 Std (K) |
|------|---------------|--------------------|------------------|--------------|--------------|--------------|
| OBS  | 0.88          | 0.64               | 2–7              | 0.31         | 0.35         | 0.48         |
| FGOALS-g3 | 0.99         | −0.20              | 3.0              | 0.40         | 0.56         | 0.41         |

Figures 14a and 14b show the standard deviation of the interannual SST anomaly over the tropical Atlantic and Indian Ocean basins. In general, the spatial pattern of the interannual variability of SST anomalies over the tropical Atlantic and Indian oceans is reproduced by FGOALS-g3. In the tropical Indian Ocean, the IOD simulated by FGOALS-g3 has a slightly stronger amplitude than the observations. Specifically, the standard deviation of SST anomalies averaged over the IODW and IODE is 0.31 and 0.35 K for the observations but 0.40 and 0.56 K for the simulation. The overestimated IOD amplitude is clearly evident from the time series of the dipole mode index (DMI; Figures 14c and 14d). The IOD amplitude simulation bias is small compared with the majority of CMIP3 and CMIP5 coupled models, which yield an overly larger IOD amplitude (Cai & Cowan, 2013; Liu et al., 2014). The DMI time series also show that the IOD simulated by FGOALS-g3 exhibits irregular oscillations as observed. Moreover, the phase-locking feature of IOD (i.e., IOD-related SST anomalies usually peak during the boreal autumn) is captured well by FGOALS-g3 (Figure 14g). In the tropical Atlantic Ocean, the observed and simulated amplitude of the Atlantic Niño are 0.48 and 0.41 K (Table 3), respectively, which shows it is well simulated by FGOALS-g3. As indicated by the Atlantic Niño3 index (Figures 14e and 14f), the Atlantic Niño reproduced by FGOALS-g3 exhibits reasonably irregular oscillations as is observed. However, FGOALS-g3 has a bias in duplicating the phase-locking behavior of Atlantic Niño (i.e., Atlantic Niño-related SST anomalies usually peak during June–July; Figure 14h).
3.2.4. Interdecadal Variability

The Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO) are two important modes of interdecadal climate variability, which have significant impacts on regional and global climate. In this section, the performance of FGOALS-g3 in simulating the spatial and temporal characteristics of the PDO and AMO is evaluated against the observational data sets. The PDO index was calculated here as the leading principal component (PC1) of the 9-yr low-pass-filtered annual SST anomalies over the North Pacific (20°W to 0°, 3°N to 3°S), and the two boxes in Indian Ocean denote the western pole of IOD (IODW; 50°–70°E, 10°N to 10°S) and eastern pole of IOD (IODE; 90°–110°E, 0° to 10°S). Time series of DMI (c, d) and Atlantic Niño3 index (e, f) for the observation and FGOALS-g3. Standard deviations of (g) DMI and (h) Atlantic Niño3 index for each calendar month. Unit is K for each panel.

3.2.4. Interdecadal Variability

The Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO) are two important modes of interdecadal climate variability, which have significant impacts on regional and global climate. In this section, the performance of FGOALS-g3 in simulating the spatial and temporal characteristics of the PDO and AMO is evaluated against the observational data sets.

The PDO index was calculated here as the leading principal component (PC1) of the 9-yr low-pass-filtered annual SST anomalies over the North Pacific (20°-70°N). The global warming signal was removed by subtracting the linear trend before the empirical orthogonal function (EOF) analysis. The regression shows a characteristic horseshoe-shaped pattern in the North Pacific, with negative anomalies from the Kuroshio-Oyashio extension (KOE) to the central North Pacific and positive anomalies along the west coast of North and South America and tropical central eastern Pacific during a positive PDO phase (Figures 15a and 15b). The spatial pattern is reversed during a negative PDO phase. The explained variance for the PDO pattern is 42% and 45% in the ERSST and HadISST, respectively. FGOALS-g2 is one of the CMIP5 models, which show reasonable performance in simulating the observed PDO pattern (Wang & Miao, 2018;
The leading EOF (EOF1) patterns, that is, the PDO, derived from the historical and piControl runs of the FGOALS-g2 explain 56% and 30% of the total variance, respectively (Figures 15g and 15h). Compared with the observations, the EOF1 derived from the historical and piControl runs of FGOALS-g3 shows the horseshoe-shaped positive SST anomalies over the North Pacific (Figures 15c and 15d). However, the positive SST anomalies over the Bering Sea are notably overestimated. Meanwhile, the negative SST anomalies from KOE to the central North Pacific are nearly absent in the EOF1 but instead show in the EOF2 patterns (Figures 15e and 15f). The explained variance of the first two EOF modes is 53% and 17% in the historical run and 37% and 16% in the piControl run. Furthermore, the EOF2 patterns derived from the FGOALS-g3 are similar to the EOF1 patterns derived from the FGOALS-g2 (Figures 15e and 15h).

Zhou et al., 2014). The leading EOF (EOF1) patterns, that is, the PDO, derived from the historical and piControl runs of the FGOALS-g2 explain 56% and 30% of the total variance, respectively (Figures 15g and 15h). Compared with the observations, the EOF1 derived from the historical and piControl runs of FGOALS-g3 shows the horseshoe-shaped positive SST anomalies over the North Pacific (Figures 15c and 15d). However, the positive SST anomalies over the Bering Sea are notably overestimated. Meanwhile, the negative SST anomalies from KOE to the central North Pacific are nearly absent in the EOF1 but instead show in the EOF2 patterns (Figures 15e and 15f). The explained variance of the first two EOF modes is 53% and 17% in the historical run and 37% and 16% in the piControl run. Furthermore, the EOF2 patterns derived from the FGOALS-g3 are similar to the EOF1 patterns derived from the FGOALS-g2 (Figures 15e and 15h).
Further analysis of the power spectra of the PDO index derived from ERSST indicates two significant spectral peaks of 10–15 and ~25 yr, while only the longer peak is significant in the HadISST (Figures 16a and 16b). The PC1 time series derived from the historical and piControl runs of the FGOALS-g2 well reproduce the observed spectral peaks (Figures 16g and 16h). Due to the longer time coverage of the piControl runs, the power spectra derived from the historical runs look more similar to the observations. In the FGOALS-g3, both the PC1 and PC2 derived from the historical run and piControl run, respectively, reasonably simulate the two spectral peaks of the observed PDO (Figures 16c–16f). However, the PC1 of the FGOALS-g3 piControl run also shows a significant spectral peak at a longer time period (~50 yr).

The AMO index is defined as the area average of detrended annual SST anomalies over the North Atlantic (80°W to 0°/0° to 60°N). The detrending is performed by subtracting the global mean SST anomaly time series as suggested in a previous study (Trenberth & Shea, 2006). Considering the multidecadal timescale of the

![Figure 16. Power spectra (black lines) of (a) the PDO index from the ERSST, (b) the PDO index from the HadISST, (c) the PC1 of FGOALS-g3 historical runs, (d) the PC1 of FGOALS-g3 piControl runs, (e) the PC2 of FGOALS-g3 historical runs, (f) the PC2 of FGOALS-g3 piControl runs, (g) the PC1 of FGOALS-g2 historical runs, and (h) the PC1 of FGOALS-g2 piControl runs. The red, blue, and light blue lines represent the power spectra of red noise, the 10%, and 90% confidence levels, respectively.](image-url)
Figure 17. SST anomalies regressed onto the standardized AMO index: (a) HadISST, (b) FGOALS-g3 historical runs, and (c) FGOALS-g3 700-yr piControl run, (d) FGOALS-g2 historical runs, (e) FGOALS-g2 900-yr piControl run. Power spectra of the AMO indices (black lines) from: (f) the HadISST, (g) historical runs and (h) 700-yr piControl run of FGOALS-g3, (i) historical run, and (j) 900-yr piControl run of FGOALS-g2. The red, blue, and light blue lines represent the power spectra of red noise, the 10%, and 90% confidence level, respectively.
AMO, the HadISST data set that covers a longer time period was used as the observations. The regression pattern derived from the HadISST data set has a characteristic "comma" shape, with large amplitude SST anomalies over the subpolar regions, along the west coast of north Africa, and over the subtropical North Atlantic (Figure 17a). The historical run of the FGOALS-g2 reasonably simulates the spatial pattern of the AMO (Figure 17d), as also indicated in previous study (Lin et al., 2019). However, the positive SST anomalies over the west of Greenland and the Labrador Sea in the piControl run of FGOALS-g2 are overestimated as compared with the observations (Figure 17e). In the FGOALS-g3, both the historical and piControl simulations reproduce the overall warming over the North Atlantic with relatively large anomalies over the subpolar regions (Figures 17b and 17c). However, the positive SST signals over the Labrador Sea are also overestimated. Moreover, a significant negative SST bias is evident in the Gulf Stream. The AMO pattern by FGOALS-g3 is comparable to but slightly worse than that simulated by FGOALS-g2 (Figures 17d and 17e). The power spectra of the observed AMO index peak at 70–80 yr (Figure 17f). Power spectral analyses of the AMO index derived from the historical run of FGOALS-g3 broadly reproduce the dominant time period (Figure 17g), which shows a better performance than the FGOALS-g2 (Figure 17i). The power spectra of the 700-yr piControl run of FGOALS-g3 peak at a period of 20–40 yr (Figure 17h).

3.3. Evolution of SAT in Historical and Scenario Runs

The time series of the global surface temperature anomalies from the historical and four future scenario runs are shown in Figure 18 and compared with observations during the historical period. During the historical period, the ensemble mean of the FGOALS-g3 simulations reproduces the general features of the increase in
the globally averaged annual mean surface temperature. The warming trends during the periods 1910–1940 and 1970–2005, as well as the cooling trend during the period 1940–1970, are simulated better by FGOALS-g3 than FGOALS-g2 (Table 4). In the FGOALS-g3, the improvement of the warming trends may be associated with the use of the external forcings of CMIP6 that are quite different from those of CMIP5 (Nie et al., 2019). The cooling trend in observation is mainly due to the natural external forcing (e.g., solar irradiation and natural aerosols) and/or internal variability associated with atmosphere-ocean interactions (Thompson et al., 2008; Wang & Dickinson, 2013). Based on the Detection and Attribution Model Intercomparison Project (DAMIP) by FGOALS-g3, the cooling trends are found mainly from the natural forcing experiments (hist-nat) and partly from the aerosol forcing experiments (hist-aer). Taking into account that the cooling trend could not be correctly reproduced by FGOALS-g2 with CMIP5 and CMIP6 forcings (Nie et al., 2019), the obvious cooling trend in FGOALS-g3 could be related to its internal variability. However, the relationship between the model improvement and internal variability is needed for further analysis. The future projections of FGOALS-g3 adopted a new set of scenarios produced with six integrated assessment models (IAMs), based on different SSPs according to CMIP6. The global mean surface temperature anomalies projected by FGOALS-g3 under SSP1-2.6 (the updated RCP2.6 pathway; the low end of the range of future forcing pathways in the IAM literature), SSP2-4.5 (the updated RCP4.5 pathway; the medium scenario of the range of future forcing pathways), SSP3-7.0 (a new Representative Concentration Pathway, RCP; a combination of moderate social vulnerability and radiative forcing), and SSP5-8.5 (the updated RCP8.5 pathway; the high end of the range of future pathways in the IAM literature) from FGOALS-g3 are also shown in Figure 18b. Under the SSP1-2.6 scenario, the global mean surface temperature increases very slowly during 2016–2085 and exhibits a slight decrease during 2085–2100. By 2100, the temperature is comparable to the present day. Under the other scenarios, all the projections show continuous warming trends, and increases in surface temperature by 2100 relative to 1960–1990 of 1.8°C, 3.2°C, and 3.5°C, respectively. Compared with other three Chinese CMIP6 projections, the warming in FGOALS-g3 is middle among them, positively correlated with their model equilibrium climate sensitivity (ECS) (Zhou et al., 2020). The ECS of FGOALS-g3 is 2.8°C, within the range of 2.27–4.65°C for four Chinese CMIP6 models (Figure 9 in Zhou et al., 2020).

### 3.4. Monsoon Evaluation

The global monsoon domain and precipitation annual range simulated by FGOALS-g3 were firstly evaluated using GPCP as the observations
Three submonsoon systems are clearly present in the observations, including the African, Asian-Australian, and American monsoons where there are large annual ranges in precipitation (Figure 19). The observed global monsoon domain and the distribution of annual range are generally well captured by FGOALS-g3, but with some biases (Figure 19b). The pattern correlation and RMSE of FGOALS-g3 against the observations are 0.73 and 2.3 mm/day, respectively. The simulation is close to those (0.76 and 1.51 mm/day) of FGOALS-g2 (Zhou et al., 2014). From the difference between FGOALS-g3 and GPCP in simulating the annual range of precipitation (Figure 19c), a systematic weaker monsoon intensity is simulated over the Northern Hemisphere with a negative bias over the northern African, Indian, Southeast Asian, and North American monsoon regions. The main bias is seen over the Asian-Australian monsoon region, with a smaller area in the Indian monsoon region and larger area in the NWP monsoon region. The former bias is caused by the dry bias for the Indian monsoon, which is a common bias in CMIP5 models (Sperber et al., 2013; Zhang et al., 2018). This bias also existed for FGOALS-g2. The latter bias is different from that of FGOALS-g2, which showed a smaller monsoon area in the NWP (Zhou et al., 2014), suggesting an improvement of FGOALS-g3 in simulation of NWP monsoon precipitation.

Figure 20. JJA mean (left column) precipitation (shadings; mm day$^{-1}$), (right column) horizontal wind (arrows; m s$^{-1}$), and specific humidity (shadings; g kg$^{-1}$) at 850 hPa. (a) and (b) are observational results from GPCP and ERA-Interim, respectively. (c) and (d) are FGOALS-g3 results. (e) and (f) are the biases between FGOALS-g3 and the observations. Red contours in (a), (c), and (e) denote topography above 2,500 m. Values on the top right in (c) and (d) are pattern correlation coefficients, and in (e) and (f) are root-mean-square errors. The black boxes in (a), (c), and (e) denote the meiyu/baiu/changma region. Dotted shadings in (e) and (f) denote biases exceeding 1% significance level.
The performance of FGOALS-g3 on simulating the East Asian summer monsoon (EASM) was further examined. For the climatological mean of precipitation in East Asia (Figure 20a), FGOALS-g3 has evident dry biases over southeastern China and the Korean Peninsula (Figure 20c). The meiyu rain band over the Yangtze River valley (western part of black box in Figure 20a) is largely missing in the FGOALS-g3 simulation (Figure 20c), whereas rainfall is overestimated in the eastern Tibetan Plateau and SCS. The pattern correlation coefficient (PCC) of rainfall in the East Asian domain is only 0.67. Such rainfall biases already existed in FGOALS-g2 (Zhou et al., 2014), indicating limited improvement in EASM rainfall in the new version. However, the low-level EASM circulation in FGOALS-g3, in contrast to the rainfall deficit, is stronger than the observations (Figure 20f), with an enhanced WNP Subtropical High (WNPSH), similar to the biases of FGOALS-g2. Thus, the rainfall biases cannot be explained by those of the circulation. Low-level moisture in FGOALS-g3 is evidently underestimated throughout nearly all of the East Asian region, especially over the continent, consistent with the lower rainfall. However, more rainfall over the eastern Tibetan Plateau and SCS can be attributed to the stronger monsoon circulation in FGOALS-g3 (Figure 20f).

Given that the WNPSH is the dominant system in the EASM, the interannual variability of the EASM was evaluated by comparing the anomalous patterns of June–August (JJA) precipitation and 850 hPa wind associated with a WNPSH index between FGOALS-g3 and the observations. The WNPSH index is defined as a meridional shear of zonal wind between the domain 22–32°N/110–140°E and 5–15°N/100–130°E.

Figure 21. JJA precipitation (shadings; mm day$^{-1}$) and 850-hPa wind (arrows; m s$^{-1}$) anomalies regressed onto the WNPSH index (zonal wind difference between 22–32°N, 110–140°E, and 5–15°N, 100–130°E) from (a) GPCP and ERA-Interim and (b) FGOALS-g3 and (c) the difference between (a) and (b). Dotted shadings in (c) denote biases exceeding 5% significance level. (d) Lead-lag correlation coefficients between the Niño3.4 index (sea surface temperature in 5°S to 5°N, 170–120°W). Dashed lines denote 5% significance levels based on t test. Values in (b) and (c) are pattern correlation coefficients and root-mean-square errors, respectively, for the precipitation and wind anomalies.
following Wang and Fan (1999). FGOALS-g3 simulates well the EASM interannual variability, especially for the circulation anomalies with a PCC of 0.96 in the East Asian domain (Figure 21b), which is better than FGOALS-g2 with a PCC of 0.89 (Zhou et al., 2014). The precipitation pattern is also reproduced and characterized by dry anomalies in the SCS and WNP and relatively wet anomalies in the maritime continent and meiyu/baiu/changma region (the black box in Figure 20a). The biases in anomalous circulation are very small, whereas the positive biases in rainfall are evident over the SCS, while negative biases characterize the meiyu/baiu/changma region (Figure 21c). Considering the similar biases of the rainfall interannual anomalies to those of the climatology (Figure 20e), the underestimation of moisture by FGOALS-g3 (Figure 20f) may also contribute to the biases in the rainfall interannual variability (Figure 21c).

Interaction between the EASM and ENSO is one of the most important sources of monsoon interannual variability. Here, the lead-lag correlation coefficient between the Niño3.4 index and JJA WNPSH index is analyzed. It shows that FGOALS-g3 can capture the interaction that an anomalous anticyclone over the WNP is driven by a decaying El Niño from the previous year, which then drives a La Niña in the next winter (Figure 21d). The effect of decaying El Niño on the summer WNPSH is underestimated in FGOALS-g3, whereas the effect of WNPSH on the developing La Niña is overestimated (Figure 21d).

4. Summary and Discussion

By upgrading the atmosphere, ocean, and land model components, as well as the coupler, FGOALS-g3 was developed, which was used to conduct the main experiments designed for CMIP6. The performance of FGOALS-g3 was evaluated based on the 700-yr piControl, six-member historical, and four-member SSPs runs. The results indicate that there are many significant improvements in FGOALS-g3 compared with FGOALS-g2.

First, the simulated climate mean states of many different components, such as sea/land surface temperatures, seasonal cycles of soil moisture and Arctic sea ice concentration (not shown), air temperatures, and geopotential heights are improved. These improvements may be attributed to the reduction of systematic cold biases in FGOALS-g2, due to increasing the resolution, improving the parameterization of physical processes in the component models, and tuning the model repeatedly and carefully for a better piControl run. Beside the parameters in GAMIL3 and LICOM3, the coupling intervals of ocean model component are tuned for a better ENSO and smaller drift in piControl run. The results of this run indicate a smaller climate drift in FGOALS-g3 than in FGOALS-g2, with a more reasonable estimation of the globally averaged climate mean surface temperature for the preindustrial era of 13.7°C (Figure 1).

Second, FGOALS-g3 captures well some characteristics of climate variability at different scales, for example, the E/W ratios for OLR and U850 in MJO (Figure 11), quadrature phase relationship between convection and zonal wind in MJO (Figure 12), spatial distribution and phase locking of ENSO and IOD (Figures 13 and 14), and the dominant timescale of AMO (Figure 17). In addition, the EASM interannual variability and interaction between EASM and ENSO are well simulated, perhaps related to the strong ENSO and/or interannual variability in FGOALS-g3.

Third, FGOALS-g3 better models the evolution of globally averaged temperature than FGOALS-g2 during the historical period, including closer-to-observation warming trends during 1910-1940 and 1970-2005 and the cooling trend from 1940-1970 (Figure 18 and Table 3). The improvement in simulating the warming trends is mainly due to the external forcing changes (Nie et al., 2019), while the cooling trend was associated with the internal variability. Except the SSP1-2.6 scenario, the other scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5) show continuous warming with the values of 1.8°C, 3.2°C, and 3.5°C by 2100 relative to 1960-1990, respectively.

Fourth, unlike other CMIP6 models, the anthropogenic groundwater exploitation forcing from 1965-2014 was added to FGOALS-g3, which mainly includes the withdrawal from groundwater pumping and widespread done to supplement human water demand. It has shown that the irrigation resulting from groundwater consumption may increase local evapotranspiration and decrease the temperatures near the surface and in the lower troposphere by affecting soil moisture content (Zeng et al., 2017; Zou et al., 2014). Increased water vapor resulting from groundwater irrigation can also induce local convection and further alter atmospheric water balances (Haddeland et al., 2006; Lo & Famiglietti, 2013).
anthropogenic groundwater exploitation may be more apparent in the severe groundwater extraction region (e.g., northern India, northern China plain, and central United States), although further analysis of the groundwater exploitation is needed to quantify its impacts on the FGOALS-g3 simulations.

Moreover, there are still some obvious biases in FGOALS-g3, and some of these are similar to its previous version, such as the zonal mean ocean temperature biases (Figure 3), underestimations of MJO eastward propagation (Figures 12 and 13), weaker monsoon intensity in the Northern Hemisphere (Figure 19), and biases in EASM rainfall (Figure 20). Some of these biases are even larger than in FGOALS-g2 (e.g., ENSO amplitude-period and rainfall RMSE). Another notable bias of FGOALS-g3 is its performance in simulating the spatial pattern of the PDO (Figure 15). Compared with the observation, biases are also witnessed in simulating fluctuations of the associated Aleutian low-pressure system, indicating crucial role of air-sea interactions over the North Pacific for the PDO. However, the PDO is a combined phenomenon influenced by different processes and the root cause of it is still unclear (Newman et al., 2016). An understanding of the model’s performance in simulating the PDO deserves dedicated research in the future. Therefore, FGOALS-g development needs to be continued. In addition, the specific reasons for the many improvements in FGOALS-g3 need to be further investigated, especially with regard to the cooling trend during 1940–1970.

Acknowledgments

The University of Delaware temperature data were provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado USA (https://www.esrl.noaa.gov/psd/). This research was jointly funded by the National Natural Science Foundation of China (Grants 41622503, 41775101, 1605061, 41530426, and 91958201) and a National Key Research Project (Grant 2018YFB0200805). We thank Stephen Griffies and three anonymous reviewers for the helpful comments that improved the manuscript. The simulated data sets used in this study are archived at the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences, and are available for research purposes through ESGF-node (https://esgf-node.llnl.gov/projects/cmip6/); for details please contact ljl@mail.iap.ac.cn referencing this paper. The coupled model source codes could be obtained after filling out the related memorandum (http://www.lasg.ac.cn/news/202004/122000425_553389.html), and its atmospheric model codes could be downloaded from the site (https://doi.org/10.5281/zenodo.3774655).

References

Adler, R. F., Huffman, G. J., Chang, A., Ferraro, R., Xie, P., Janowiak, J., et al. (2003). The Version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979–present). Journal of Hydrometeorology, 4(11–12), 4023–4045. https://doi.org/10.1175/1525-7541(2003)004<1147:tgppg3>2.0.CO;2

Ahn, M. S., Kim, D., Sperber, K. R., Kang, I. S., & Hendon, H. (2017). MJO simulation in CMIP5 climate models: MJO skill metrics and process-oriented diagnosis. Climate Dynamics, 49(11–12), 4023–4045. https://doi.org/10.1007/s00382-017-3558-4

Allan, R., & Ansell, T. (2006). A new globally complete monthly historical gridded mean sea level pressure dataset (HadSLP2): 1850–2004. Journal of Climate, 19(22), 5816–5842. https://doi.org/10.1175/JCLI3937.1

Bao, Q., Lin, P. F., Zhou, T. J., Liu, Y. M., Yu, Y. Q., & Wu, G. X. (2013). The Flexible Global Ocean–Atmosphere–Land System model, Spectral Version 2: FGOALS-g3. Advances in Atmospheric Sciences, 30(3), 561–576. https://doi.org/10.1007/s00376-012-2113-9

Briegleb, B., & Light, B. (2007). A Delta–Eddington multiple scattering parameterization for solar radiation in the sea ice component of the Community Climate System Model. NCAR Technical Note.

Cai, W., & Cowan, T. (2013). Why is the amplitude of the Indian Ocean Dipole overly large in CMIP3 and CMIP5 climate models? Geophysical Research Letters, 40, 1200–1205. https://doi.org/10.1002/grl.50208

Canuto, V. M., Howard, A., Cheng, Y., & Dubovik, M. S. (2001). Ocean turbulence. Part I: One-point closure model—Momentum and heat vertical diffusivities. Journal of Physical Oceanography, 31(6), 1413–1426. https://doi.org/10.1175/1520-0485(2001)031<1413:OTIPMC>2.0.CO;2

Canuto, V. M., Howard, A., Cheng, Y., & Dubovik, M. S. (2002). Ocean turbulence. Part II: Vertical diffusivities of momentum, heat, mass, and passive scalars. Journal of Physical Oceanography, 32(1), 240–264. https://doi.org/10.1175/1520-0485(2002)032<0240:OPVOPI>2.0.CO;2

Chen, K. M., Zhang, X. H., Lin, X. Z. J., & Lin, W. Y. (1997). A coupled ocean–atmosphere model for climate change study, Part I: The model’s configuration and performance. Acta Oceanologica Sinica, 19(3), 21–32. (In Chinese)

Chen, L., Yu, Y. Q., & Zheng, W. (2016). Improved ENSO simulation from climate system model FGOALS-g1.0 to FGOALS-g2. Climate Dynamics, 47(7–8), 2617–2634. https://doi.org/10.1007/s00382-016-2988-8

Comiso, J. C. (2017). Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS, Version 3. Boulder, Colorado USA: NASA National Snow and Ice Data Center Distributed Active Archive Center. https://doi.org/10.5067/7Q8HCWCSI40R

Covey, C., Achutaran, K. M., Cubasch, U., Jones, P., Lambert, S. J., Mann, M. E., et al. (2003). An overview of results from the Coupled Model Intercomparison Project. Global and Planetary Change, 37(1–2), 103–133. https://doi.org/10.1016/S0921-8181(02)00193-5

Craig, A. P., Jacob, R., Kauffmann, B., Bettge, T., Larson, J., Ong, E., et al. (2005). CPLE: The next extensible, high-performance parallel coupler for the Community Climate System Model. International Journal for High Performance Computing Applications, 19(3), 309–327. https://doi.org/10.1177/109434205056117

Craig, A. P., Vertenstein, M., & Jacob, R. (2012). A new flexible coupler for earth system modeling developed for CCSM4 and CESM1. International Journal for High Performance Computing Applications, 26(1), 31–42. https://doi.org/10.1177/1094342011428141

Cunningham, S. A., Kanow, T. O., Rayner, D., Barringer, M. O., Johns, W. E., Marotzke, J., et al. (2007). Temporal variability of the Atlantic meridional overturning circulation at 26.5ºN. Science, 317(5840), 935–938. https://doi.org/10.1126/science.1141304

Dee, D., Uppala, S., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society, 137(656), 553–597. https://doi.org/10.1002/qj.828

Ebying, V., Bony, S., Meehi, G. A., Senior, C. A., Bjorn, S., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 5 (CMIP5) experimental design and organization. Geoscientific Model Development, 9(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Ferreira, D., Marshall, J., & Heimbach, P. (2005). Estimating eddy stresses by fitting dynamics to observations using a residual-mean ocean circulation model and its adjoint. Journal of Physical Oceanography, 35(10), 1891–1910. https://doi.org/10.1175/JPO2785.1

Ganachaud, A., & Wunsch, C. (2003). Large-scale ocean heat and freshwater transports during the world ocean circulation experiment. Journal of Climate, 16(4), 696–705. https://doi.org/10.1175/1520-0442(2003)016<0696:LSOHATP>2.0.CO;2

Gao, J., Xie, Z., Wang, A., & Luo, Z. (2016). Numerical simulation based on two-directional freeze and thaw algorithm for thermal diffusion model. Applied Mathematics and Mechanics, 37(11), 1467–1478. https://doi.org/10.1007/s10483-016-2106-8

Gao, J., Xie, Z. H., Wang, A. W., Liu, S., Zeng, Y. J., Liu, B., et al. (2019). A new frozen soil parameterization including frost and thaw fronts in the Community Land Model. Journal of Advances in Modeling Earth Systems, 11(3), 659–679. https://doi.org/10.1029/2018MS001399
Legates, D. R., & Willmott, C. J. (1990). Mean seasonal and spatial variability in gauge-corrected, global precipitation.

Li, L. J., Lin, P. F., Yu, Y. Q., Wang, B., Zhou, T. J., Liu, L., et al. (2013). The Flexible Global Ocean

Lin, J. L., Kiladis, G. N., Mapes, B. E., Weickmann, K. M., Sperber, K. R., Lin, W. Y., et al. (2006). Tropical intraseasonal variability in 14

Larson, J., Jacob, R., & Ong, E. (2005). The model coupling toolkit: A new Fortran90 toolkit for building multiphysics parallel coupled

Madec, G., & Imbard, M. (1996). A global ocean mesh to overcome the north pole singularity.

Guo, Z., & Zhou, T. (2014). An improved diagnostic stratocumulus scheme based on estimated inversion strength and its performance in

Hurtt, G., Chini, L., Sahajpal, R., Frolking, S., Bodirsky, B. L., Calvin, K., et al. (2017). Harmonization of global land use scenarios (LUH2):

Liu, L., Xie, S. P., Zheng, X. T., Li, T., Du, Y., Huang, G., & Yu, W. D. (2014). Indian Ocean variability in the CMIP5 multi

Lipscomb, W. H., Hunke, E. C., Maslowski, M., & Jakacki, J. (2007). Ridging, strength, and stability in high resolution sea ice models.

Liu, L., Wang, B., Dong, L., Liu, L., Shen, S., Hu, N., et al. (2013). Evaluation of grid-point atmospheric model of IAP LASG Version 2

Hunke, E. C., & Dukowicz, J. K. (1997). An elastic

IPCC (2001). In E. Watson, T. J. Houghton, & Y. Ding (Eds.), (p. 68). New York, NY: Cambridge University Press.

Hunke, E. C., & Dukowicz, J. K. (1997). An elastic

Haddeland, I., Lettenmaier, D. P., & Skaugen, T. (2006). Effects of irrigation on the water and energy balances of the Colorado and Mekong

Guo, Z., & Zhou, T. (2014). An improved diagnostic stratocumulus scheme based on estimated inversion strength and its performance in

Gent, P. R., & McWilliams, J. C. (1990). Isopycnal mixing in ocean circulation models.

Hewitt, C. D., & Hargreaves, J. S. (2006). A simple parameterization of global land cover transition rates: Application to the united

IPCC (2007). Climate change 2007: The physical science basis. In S. Solomon, et al. (Eds.), (p. 572). Cambridge, UK: Cambridge University Press.

IPCC (1995). In T. J. Houghton, et al. (Eds.), Climate change 1995: The science of climate change (p. 572). Cambridge, UK: Cambridge University Press.

IPCC (2001). In E. Watson, T. J. Houghton, & Y. Ding (Eds.), Climate change 2001: The scientific basis (p. 882). Cambridge, UK: Cambridge University Press.

IPCC (2007). Climate change 2007: The physical science basis. In S. Solomon, et al. (Eds.), (p. 996). Cambridge, UK and New York, NY: Cambridge University Press.

IPCC AR4 climate models. Part I: Convective signals.

IPCC (2007). Climate change 2007: The physical science basis. In S. Solomon, et al. (Eds.), (p. 996). Cambridge, UK and New York, NY: Cambridge University Press.

IPCC (1995). In T. J. Houghton, et al. (Eds.), Climate change 1995: The science of climate change (p. 572). Cambridge, UK: Cambridge University Press.

IPCC (2017). Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. In V. R. Field, et al. (Eds.), (p. 1010). Cambridge, UK: Cambridge University Press.

Hurtt, G., Chini, L., Sahajpal, R., Frolking, S., Bodirsky, B. L., Calvin, K., et al. (2017). Harmonization of global land use scenarios (LUH2):

Hunke, E. C., & Dukowicz, J. K. (1997). An elastic

Haddeland, I., Lettenmaier, D. P., & Skaugen, T. (2006). Effects of irrigation on the water and energy balances of the Colorado and Mekong

Guo, Z., & Zhou, T. (2014). An improved diagnostic stratocumulus scheme based on estimated inversion strength and its performance in

Gent, P. R., & McWilliams, J. C. (1990). Isopycnal mixing in ocean circulation models.

Hewitt, C. D., & Hargreaves, J. S. (2006). A simple parameterization of global land cover transition rates: Application to the united

Hewitt, C. D., & Hargreaves, J. S. (2006). A simple parameterization of global land cover transition rates: Application to the united

Gent, P. R., & McWilliams, J. C. (1990). Isopycnal mixing in ocean circulation models.
Yu, R. C. (1994). A two-step shape-preserving advection scheme. Advances in Atmospheric Sciences, 11(4), 479–490. http://doi.org/10.1007/BF02658169

Yu, Y. Q., Tang, S. L., Liu, H. L., Lin, P. F., & Li, X. L. (2018). Development and evaluation of the dynamic framework of an ocean general circulation model with arbitrary orthogonal curvilinear coordinate. Chinese Journal of Atmospheric Sciences, 42(4), 877–889 (in Chinese). https://doi.org/10.3878/j.issn.1006-9895.1805.17284

Yu, Y. Q., Yu, R. C., Zhang, X. H., & Liu, H. L. (2002). A flexible global coupled climate model. Advances in Atmospheric Sciences, 19(1), 169–190. https://doi.org/10.1007/s00376-002-0042-8

Yu, Y. Q., & Zhang, X. H. (1998). A modified air-sea flux anomaly coupling scheme. Chinese Science Bulletin, 43, 866–870. https://doi.org/10.3321/j.issn:0023-074X.1998.08.019

Yu, Y. Q., Zhang, X. H., & Gao, Y. F. (2004). Global coupled ocean–atmosphere general circulation models in LASG/IAP. Advances in Atmospheric Sciences, 21(3), 444–455. https://doi.org/10.1007/BF02915571

Yu, Z. P., Liu, H. L., & Lin, P. F. (2017). A numerical study of the influence of tidal mixing on Atlantic meridional overturning circulation (AMOC) simulation. Chinese Journal of Atmospheric Sciences, 41(5), 1087–1100 (in Chinese). https://doi.org/10.3878/j.issn.1006-9895.1702.16263

Zeng, Y. J., Xie, Z. H., Liu, S., Xie, J. B., Jia, B. H., Qin, P. H., & Gao, J. Q. (2018). Global land surface modeling including lateral groundwater flow. Journal of Advances in Modeling Earth Systems, 10(8), 1882–1900. https://doi.org/10.1029/2018MS001304

Zeng, Y. J., Xie, Z. H., Yu, Y., Liu, S., Wang, L. Y., Jia, B. H., & et al. (2016). Ecohydrological effects of stream–aquifer water interaction: A case study of the Heihe River basin, northwestern China. Hydrology and Earth System Sciences, 20(6), 2333–2352. https://doi.org/10.5194/hess-20-2333-2016

Zeng, Y. J., Xie, Z. H., Yu, Y., Liu, S., Wang, L. Y., Zou, J., & et al. (2016). Effects of anthropogenic water regulation and groundwater lateral flow on land processes. Journal of Advances in Modeling Earth Systems, 8, 1106–1113. https://doi.org/10.1002/2016MS000646

Zeng, Y. J., Xie, Z. H., & Zou, J. (2017). Hydrologic and climatic responses to global anthropogenic groundwater extraction. Journal of Climate, 30(1), 71–90. https://doi.org/10.1175/JCLI-D-16-0209.1

Zhang, L. X., Zhou, T. J., Klingaman, N. P., Wu, P. L., & Roberts, M. J. (2018). Effect of horizontal resolution on the representation of the global monsoon annual cycle in AGCMs. Advances in Atmospheric Sciences, 35(8), 1003–1020. https://doi.org/10.1007/s00376-018-7273-9

Zhang, T., & Sun, D. Z. (2014). ENSO asymmetry in CMIP5 models. Journal of Climate, 27(11), 4070–4093. https://doi.org/10.1175/JCLI-D-13-00454.1

Zhang, X. H., Bao, N., Yu, R. C., & Wang, W. Q. (1992). Coupling experiments based on an atmospheric and an oceanic GCM. Chinese Journal of Atmospheric Sciences, 16, 129–144. (in Chinese)

Zhou, T. J., Chen, X. L., Dong, L., Wu, B., Man, W. M., Zhang, L. X., & et al. (2014). Chinese contribution to CMIP5: An overview of five Chinese models’ performances. Journal of Meteorological Research, 28(4), 481–509. https://doi.org/10.1007/s13351-014-4001-y

Zhou, T. J., Chen, Z. M., Zou, L. W., Chen, X. L., Yu, Y. Q., Wang, B., & et al. (2020). Development of Climate and Earth System Models in China: Past achievements and new CMIP6 results. Journal of Meteorological Research, 34(1), 1–19. https://doi.org/10.1007/s13351-020-9164-0

Zou, J., Xie, Z. H., Yu, Y., Zhan, C. S., & Sun, Q. (2014). Climatic responses to anthropogenic groundwater exploitation: A case study of the Haihe River Basin, Northern China. Climate Dynamics, 42(7-8), 2125–2145. https://doi.org/10.1007/s00382-013-1995-2

Zou, J., Xie, Z. H., Zhan, C. S., Qin, P. H., Sun, Q., Jia, B. H., & Xia, J. (2015). Effects of anthropogenic groundwater exploitation on land surface processes: A case study of the Haihe River Basin, Northern China. Journal of Hydrology, 524, 625–641. https://doi.org/10.1016/j.jhydrol.2015.03.026