Performance Evaluation of Multi-Model Based Early Winter Precipitation Prediction over the Tibetan Plateau (Postprint)

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Date: 2023-08-25T00:00:00+00:00

Abstract

Based on the current mainstream climate operational model systems (BCC_{CSM} 1.1, ECMWF_{System} 5, NCEP_{CFSv2}, TCC_{MRI}-CGCM 3), this study evaluates the prediction performance of multiple models for early winter precipitation over the Tibetan Plateau from the perspective of deterministic forecasting. The results indicate that multiple models can reproduce the spatial distribution pattern of early winter (November–December) precipitation over the Tibetan Plateau, but there is a general overestimation of precipitation magnitude. Among them, the model from BCC can reflect the spatiotemporal evolution characteristics of the primary modes of regionally uniform and north-south opposite precipitation patterns, while the EC model overestimates the dominant role of the first mode. Historical hindcasts of precipitation by multiple models show predominantly positive skill, with the BCC model demonstrating the best forecast skill, while TCC only performs well for predictions in the northern Tibetan Plateau. Analysis from the perspective of predictability sources reveals that the equatorial central-eastern Pacific sea surface temperature index (Niño 3.4) and the positive phase of the Indian Ocean Dipole (IOD) serve as good indicators for enhancing model prediction skill. The ability of the BCC model to predict the anomalous trend of early winter precipitation over the plateau in 2018 lies in its capability to predict the key circulation patterns that influence precipitation anomalies over the Tibetan Plateau.

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Full Text

Evaluation of Multi-Model Prediction Performance for Early Winter Precipitation over the Tibetan Plateau

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Abstract: Based on current mainstream climate operational model systems (BCC_{CSM} 1.1, ECMWF_{System} 5, NCEP_{CFSv2}, and TCC_{MRI}-CGCM3), this study evaluates the prediction performance of multiple models for early winter precipitation over the Tibetan Plateau from a deterministic forecasting perspective. Results indicate that all models can reproduce the spatial distribution pattern of early winter precipitation over the Tibetan Plateau, but consistently overestimate precipitation magnitude. Among them, the BCC_{CSM} 1.1 model can reflect the dominant role of the regionally uniform precipitation mode, while the ECMWF_{System} 5 model overestimates the first mode' s dominance. Multi-model historical hindcasts show predominantly positive skill, with the BCC_{CSM} 1.1 model demonstrating optimal forecast skill. The TCC_{MRI}-CGCM3 model performs well only in the northern Tibetan Plateau. Analysis from a predictability source perspective reveals that positive phases of equatorial central-eastern Pacific sea surface temperature (Niño 3.4) and the Indian Ocean Dipole (IOD) serve as excellent indicators for enhancing model prediction skill. The BCC_{CSM} 1.1 model can predict the anomalous trend of early winter precipitation over the Tibetan Plateau because it possesses certain predictive capability for the key circulation patterns affecting precipitation anomalies.

Keywords: precipitation; prediction performance; model assessment; Tibetan Plateau

Introduction

The Tibetan Plateau, known as Earth' s "Third Pole" and the "Asian Water Tower" [?], is influenced by the East Asian monsoon, South Asian monsoon [?], and westerly belt [?]. Although winter precipitation accounts for a small proportion of the annual total, it exhibits extreme intensity with large interannual and intra-seasonal variability, frequently causing severe snow disasters along the eastern foothills and southern margin of the Bayan Har Mountains [?]. The winter of 2017/2018 witnessed historically record-breaking snowfall magnitude and duration across the Tibetan Plateau, resulting in the most severe snow disaster in nearly a decade and significantly impacting alpine pastoral livestock production and transportation. Research indicates that dynamic components in water vapor flux play a crucial role in Tibetan Plateau winter snowfall [?].

Studies have highlighted the Indian Ocean Dipole (IOD) and El Niño-Southern Oscillation (ENSO) as important indicators for early winter snow cover over the Tibetan Plateau [?]. [?] demonstrated that IOD anomalies can trigger convective activities over the western Indian Ocean and generate a cyclonic circulation anomaly over the central Tibetan Plateau through wave train excitation, facilitating moisture transport from the tropics to the plateau interior and causing snow cover anomalies. [?] further verified the independent and combined effects of IOD and ENSO on early winter snowfall anomalies over the Tibetan Plateau. During positive IOD phases, the Eurasian (EU) teleconnection wave train is influenced, creating anomalous upward motion and decreased tropospheric mid-lower layer temperatures over the plateau, providing dynamic and thermodynamic conditions for early winter snowfall anomalies [?]. [?] estimated future snowfall changes over the Northern Hemisphere based on the CMIP5 intercomparison project, projecting increased daily snowfall amounts and heavy snowfall event frequency over the Tibetan Plateau by 2050, presenting new challenges for future snow disaster prevention.

At the synoptic scale, typical circulation patterns for eastern Tibetan Plateau winter snowfall include north-ridge-south-trough, Ural Mountain ridge, and stepped trough types [?]. [?] found that interannual variability of heavy snowfall events over the eastern Tibetan Plateau primarily results from unstable wave trough airflow development associated with Eurasian mid-high latitude large-scale weather system activities and circulation adjustments. [?] attributed winter snowfall variations in northern Tibetan Plateau to the North Atlantic Oscillation (NAO), Arctic Oscillation (AO), and East Asian westerly jet. Most previous research has focused on extreme characteristic changes and mechanism attribution, with relatively limited work on model evaluation or numerical simulation.

With recent rapid development of climate numerical models, they have become powerful tools for short-term climate prediction. China developed the second-generation global atmospheric general circulation spectral model BCC_{AGCM} with improved snow cover parameterization and physical processes [?]. Building upon this, the National Climate Center established the medium-resolution (110 km) BCC_{CSM} 1.1 climate system model incorporating global carbon cycle and dynamic vegetation [?], and developed the second-generation short-term climate prediction model system BCC_{CSM} 1.1m [?], effectively improving East Asian summer monsoon circulation and precipitation forecast capabilities [?]. The European Centre for Medium-Range Weather Forecasts (ECMWF) established a high-resolution climate prediction system based on persistent sea surface temperature anomaly forcing in the early 1990s, and developed a 51-member ocean-atmosphere coupled ensemble prediction system in 2017. The U.S. Climate Prediction Center (NCEP/CPC) launched the second-generation coupled system CFSv2 in 2011, featuring new cloud radiation, land surface, ocean, and sea ice processes, demonstrating improved prediction of global tropical precipitation and surface temperature compared to its predecessor. The Japan Meteorological Agency (JMA) coupled atmospheric circulation model (MRI-AGCM) with ocean circulation model (MRI.COM). Currently, model-based research remains limited for mid-high latitude Northern Hemisphere regions, particularly regarding simulation performance over the Tibetan Plateau.

The Tibetan Plateau experiences severe cold, with surface temperatures dropping below zero by November, primarily featuring solid precipitation (snowfall) and frequent snow disasters during early winter (November-December). This study utilizes historical hindcast data from current mainstream seasonal climate prediction models to investigate whether multi-models can simulate the primary spatiotemporal variation characteristics of early winter precipitation over the Tibetan Plateau, evaluate inter-model prediction performance through error metrics, and analyze predictability sources to provide scientific references for winter climate prediction and snow disaster prevention.

1 Data and Methods

1.1 Data Description

This study employs current mainstream climate models, including the seasonal climate prediction model BCC_{CSM} 1.1 from the National Climate Center (NCC), the ECMWF_{System} 5 ocean-atmosphere coupled model ensemble prediction system from the European Centre for Medium-Range Weather Forecasts, the second-generation fully coupled system CFSv2 from the U.S. National Centers for Environmental Prediction (NCEP), and the atmospheric-oceanic circulation coupled model TCC_{MRI}-CGCM3 from the Tokyo Climate Center (TCC). We uniformly select early winter hindcast data from November initializations for each model year. Based on model raw output fields, we calculate model forecast circulation anomaly fields using historical hindcast period averages.

Model field multi-year average calculation periods: BCC_{CSM} 1.1 (1991-2018), ECMWF_{System} 5 (1981-2018), NCEP_{CFSv2} (1999-2018), and TCC_{MRI}-CGCM3 (1981-2018). Through bilinear interpolation, model data are interpolated from grid points to stations for comparison with observation fields. Verification data include monthly precipitation station observations from the China Meteorological Administration' s National Information Center, from which we extract 89 stations with continuous observation sequences over the Tibetan Plateau (Fig. 1). Due to sparse observation networks in western Tibet, this study focuses on verification results for the central-eastern region, covering 1961-2018. Reanalysis data are obtained from the NCEP/NCAR monthly geopotential height and sea surface temperature fields at 2.5°$×$2.5° resolution. Early winter precipitation is defined as cumulative precipitation from November to December, with observations referenced to the 1981-2010 average.

1.2 Methods

1.2.1 Verification and Evaluation Methods We employ three evaluation metrics—Anomaly Correlation Coefficient (ACC), Temporal Correlation Coefficient (TCC), and Root Mean Square Error (RMSE)—to objectively and quantitatively assess model prediction performance from a deterministic forecasting perspective.

The Anomaly Correlation Coefficient (ACC) reflects spatial similarity between forecast and observation fields, calculated as:

$$ACC_j = \frac{\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)(\Delta y_{ij} - \Delta\bar{y}_j)}{\sqrt{\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{N}(\Delta y_{ij} - \Delta\bar{y}_j)^2}}$$

where Z represents the 500 hPa geopotential height field.

The Temporal Correlation Coefficient (TCC) characterizes model prediction capability at each grid point, yielding forecast skill spatial distribution, calculated as:

$$TCC_i = \frac{\sum_{j=1}^{M}(x_{ij} - \bar{x}_i)(\Delta y_{ij} - \Delta\bar{y}_i)}{\sqrt{\sum_{j=1}^{M}(x_{ij} - \bar{x}_i)^2 \sum_{j=1}^{M}(\Delta y_{ij} - \Delta\bar{y}_i)^2}}$$

Both ACC and TCC range between [-1, 1], with values closer to 1 indicating higher forecast skill.

For multi-dataset comparison, we calculate RMSE of model fields relative to observations using:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$$

where x and y represent the two datasets being compared.

1.2.2 Statistical Methods Statistical methods employed include trend analysis, correlation analysis, and Empirical Orthogonal Function (EOF) decomposition.

1.2.3 Climate Index Calculation Method The Eurasian pattern (EU) teleconnection index reflects anti-correlation between geopotential height over western Europe and Siberia, and positive correlation with northeastern China and Japan [?]. The EU index is calculated as:

$$EU = -\frac{1}{4}[Z(55°N, 20°E) + Z(55°N, 75°E) + Z(40°N, 145°E) + Z(30°N, 100°E)]$$

2 Results

2.1 Comparison of Multi-Model Hindcast Capabilities

Early winter precipitation over the Tibetan Plateau increases from northwest to southeast (Fig. 2a), with most areas receiving less than 10 mm in the northwest and high-value regions exceeding 50 mm in the southeast—areas prone to frequent winter snow disasters. The standard deviation of early winter precipitation similarly shows a northwest-to-southeast gradient (Fig. 2b), with larger magnitudes corresponding to greater variability. High-value areas are located on both sides of the Hengduan Mountains, indicating large interannual variability in early winter precipitation, particularly since the late 1990s with frequent and substantial oscillations.

We analyze historical hindcast results from BCC_{CSM} 1.1, ECMWF_{System} 5, NCEP_{CFSv2}, and TCC_{MRI}-CGCM3 (hereafter referred to as BCC, ECMWF, NCEP, and TCC) to evaluate model capability in characterizing basic features of early winter precipitation, including climatology and dominant spatial variability modes. Figure 3 presents multi-year average early winter precipitation from model hindcasts. Compared with observations, all four models reproduce the northwest-dry/southeast-wet pattern but overestimate precipitation magnitude, particularly in the high-precipitation southeast where model-observation biases are substantial. All models show positive biases, with BCC and ECMWF exhibiting larger deviations west of the Hengduan Mountains and in the Kunlun Mountains-Qaidam Basin region. NCEP and TCC overestimate observations across most plateau areas but contain small underestimation zones, with TCC showing smaller overall deviations.

The ability to simulate dominant precipitation modes is crucial for reflecting model prediction performance. EOF decomposition of observed early winter precipitation yields three modes (Fig. 4) with cumulative variance contributions of 51.4%. The modes are mutually independent and represent primary early winter precipitation characteristics. The first mode explains 32.7% variance, showing a nearly regionally uniform distribution with only a small reversed loading area on the southeastern plateau. The second mode exhibits a north-south reverse pattern, with the Qilian Mountains-Qaidam Basin opposite to other regions. The third mode shows a tripole pattern with an east-west "positive-negative-positive" distribution from north to south across eastern Tibet, with the Three-River-Source region (Yellow River, Yangtze River, Lancang River) opposite to other areas.

Applying EOF decomposition to model hindcasts from November initializations reveals that models can reproduce the first two modes but not the third. For the first mode, BCC, ECMWF, and NCEP show spatial correlation coefficients with observations significant at the 95% confidence level, with model variance contributions around 33.7-42.9%. ECMWF most closely matches observations (33.7%), while BCC significantly overestimates the first mode' s dominance (42.9%). Except for NCEP, all models show significant correlations between first mode time coefficients and observations. For the second mode, TCC best captures the spatial pattern, with correlation significant at the 95% level, while other models show weaker performance. For the third mode, models fail to represent the tripole distribution, showing weak simulation capability in eastern Tibet despite some consistency in western loading vectors. Temporal correlations for second and third modes are weak across all models, indicating limited capability in capturing interannual variations of these spatial patterns.

In summary, BCC demonstrates optimal simulation performance for dominant early winter precipitation modes, accurately characterizing both regionally uniform and north-south reverse patterns with temporal evolution consistent with observations. TCC also captures both spatial patterns well but overestimates variance contribution of the first mode. NCEP shows simulation capability for regionally uniform and tripole patterns.

2.2 Historical Hindcast Skill Assessment

Root Mean Square Error (RMSE) measures model performance through deviations between predicted and observed values. RMSE results (Fig. 5) show higher values in southern than northern Tibetan Plateau, confirming higher prediction skill in the north. Southern plateau margins show particularly large RMSE, corresponding to high-precipitation areas. BCC exhibits the smallest RMSE, followed by ECMWF, with NCEP and TCC showing larger errors, particularly NCEP in southern and northwestern regions.

Temporal Correlation Coefficient (TCC) distribution (Fig. 6) indicates predominantly positive forecast skill across models. BCC shows the largest significant positive correlation area, demonstrating high forecast skill. Previous research indicates BCC has high forecast capability for EU teleconnection-affected regions [?], and the Tibetan Plateau lies within the area influenced by this teleconnection's southern branch path, contributing to enhanced model forecast skill. TCC shows significant positive correlations across central-western Tibet, indicating good prediction capability for these regions. NCEP exhibits significant positive correlations only in northern Tibet, with negative correlations in southern and Hengduan Mountain areas–opposite to BCC' s pattern, suggesting complementary reference value for these two models in practical applications.

Interannual SST variability in the Indian Ocean and Pacific Ocean represents important climate prediction signals, with ENSO events being the most crucial predictability source for seasonal prediction. Research shows second-generation models demonstrate significantly improved ENSO forecast correlation skill compared to first-generation versions [?]. To examine relationships between model prediction performance and SST anomaly backgrounds, we analyze scatter plots of ACC skill against Niño 3.4 and IOD indices for BCC and TCC (Fig. 7). When Niño 3.4 and IOD are in positive phases, model predictions show predominantly positive skill, with BCC performing optimally. Conversely, during negative phases, probabilities of positive and negative skill become comparable, indicating increased prediction uncertainty. Particularly when Niño 3.4 is negative, models show reduced predictive capability. Thus, positive phases of both indices favor positive skill for these models, while negative phases increase uncertainty and degrade performance, with BCC being more dependent on Niño 3.4 phase variations.

2.3 Assessment of Historically Typical Years

We select historically typical anomaly years from the 58-year record to test multi-model prediction effectiveness for extreme precipitation and evaluate predictive capability for extreme events. The 2017/2018 early winter precipitation broke historical records, causing severe snow disasters. Observations show precipitation high-value areas in southeastern Tibet, with most regions receiving more than double the climatological values (Fig. 8). Model predictions for 2018 early winter precipitation and anomaly percentage (Fig. 9) reveal that BCC overestimates northwestern plateau precipitation while underestimating southeastern areas. ECMWF overestimates across the entire plateau, most significantly in the southwest. TCC predictions are closest to observations, with deviations controlled within 50%, demonstrating predictive capability for both precipitation distribution patterns and high-value centers. NCEP shows obvious biases, with large deviations in the southwestern plateau.

Atmospheric circulation is the primary factor directly affecting precipitation anomalies. The 500 hPa geopotential height anomaly field from NCEP reanalysis (Fig. 10a) shows a "negative-positive-negative" wave train pattern across Asia, with an exceptionally strong European ridge and significant positive height anomalies over Scandinavia. A positive anomaly center in northeastern Asia favors Okhotsk Sea blocking high development, while negative anomalies extend from polar-Siberian regions southward to southwestern China, with a stronger East Asian trough and the Tibetan Plateau under negative height anomaly control—corresponding to EU teleconnection negative phase characteristics [?]. The EU index reached its third lowest value in 58 years (Fig. 10b).

Multi-model predictions for the 2018 early winter 500 hPa height anomaly field (Fig. 11) show that BCC predicts mid-latitude wave train structures (Fig. 11a), with a "negative-positive-negative" distribution from the Atlantic to East Asia: negative anomalies over eastern Atlantic, positive anomalies over Scandinavia-Eastern European Plain, and negative anomalies over Lake Baikal and southward. The similarity coefficient between predicted and observed Northern Hemisphere height anomaly fields is 0.42, significant at the 95% confidence level. While BCC shows high prediction skill for the wave train structure that directly enhances precipitation forecast performance, its negative skill over the Balkhash Lake-Baikal region directly affects plateau height field anomalies and degrades precipitation forecast performance. Other models also show wave trains but with distinct differences in intensity and center location, exhibiting negative or significantly reduced skill in this region—further demonstrating that improving mid-latitude winter prediction performance is crucial.

The 2018 early winter SST anomaly monitoring (Fig. 12) shows significantly warmer equatorial central-eastern Pacific, positive anomalies near the Bering Sea, North Atlantic Tripole (NAT) positive phase characteristics, uniformly warm North Indian Ocean, and west-positive/east-negative patterns in the South Indian Ocean. Model SST predictions (Fig. 13) consistently capture significant positive SST anomalies in the equatorial Pacific and NAT positive phase structure, particularly for BCC and TCC. BCC simulations are closest to observations for South Indian Ocean dipole SST patterns, North Atlantic SST, and Niño 3.4 warm phase characteristics. Combined with previous results showing high prediction skill for both 2018 Tibetan Plateau precipitation and mid-high latitude wave train structures, we infer that models enhance overall prediction performance by improving forecast skill for key region SSTs and accurately capturing SST teleconnection effects on extratropical regions.

3 Conclusions

Using four operational models from domestic and international sources, we evaluate multi-model prediction performance for early winter precipitation variability and anomalies over the Tibetan Plateau. Main conclusions are:

1) All models reproduce the northwest-dry/southeast-wet precipitation pattern but consistently overestimate magnitude. Models show good simulation capability for the regionally uniform precipitation dominant mode, with BCC optimally simulating spatiotemporal evolution characteristics of precipitation modes.

2) Multi-models demonstrate consistently good forecast skill for low-latitude tropical circulation but poor skill in mid-latitude regions, predominantly negative skill. Forecast skill significantly improves during positive Niño 3.4 or IOD phases, with BCC showing higher dependence on Niño 3.4 index variations.

3) For the 2018 historically typical extreme year, TCC predictions are closest to observations with deviations within 50%, attributable to its high prediction skill for mid-high latitude wave train structures and key region SSTs. We infer that prediction models enhance overall performance by improving forecast skill for key region SSTs and accurately capturing SST teleconnection effects on extratropical regions.

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Note: Figure translations are in progress. See original paper for figures.