

Impact of SST Nudging on CFSR Analysis and Seasonal ENSO Forecasts

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Abstract

Ocean reanalysis (ORA) systems often constrain their sea surface temperature (SST) by strongly nudging the top ocean model layer toward external SST analyses. Different SST analyses may be adopted in operational ORA due to practical configuration limitations. However, impacts of switching SST datasets for nudging on ORAs and forecasts have rarely been examined. In February 2020, the Climate Forecast System Reanalysis (CFSR) switched from the long-used NOAA OISSTv2 dataset to NCEP's Near-Surface Sea Temperature (NSST). This study investigates how this change influenced CFSR SST and two seasonal forecast systems that rely on it for ocean initial conditions: CFSv2 and CCSM4.

The switch introduced a sharp discontinuity in CFSR SST, with negligible differences relative to OISSTv2.1 before 2020 but a large bias afterward. Errors exceeded -1°C along western boundary currents and the Antarctic Circumpolar Current and about $-0.2 - 0.5^{\circ}\text{C}$ in tropical upwelling zones. These biases propagated almost undamped into forecasts initialized from CFSR. At 0-month forecast lead, both CFSv2 and CCSM4 exhibited cold anomalies in the eastern tropical Pacific, which intensified and spread westward toward the dateline within four months. ENSO composites show that forecasts after 2020 had systematically cold biases during boreal fall and winter, impacting the strength of ENSO. This cooling trend reversed an earlier warm bias associated with a known CFSR discontinuity around 1999 and led to overly cold La Niña forecasts in 2024, even during high-skill ENSO seasons. These findings highlight that changing the SST dataset for ORA can introduce nonstationary errors affecting real-time forecasts.

1. Introduction

Sea surface temperature (SST) is an important variable for understanding and predicting the coupled interactions between the atmosphere and ocean. Changes in SST directly influence both weather and climate patterns by regulating heat exchange across the ocean–atmosphere interface and by regulating the location of deep convection in tropical latitudes.

Many factors contribute to SST variability. For example, the upper ocean thermal structure, particularly variations in thermocline depth along the equator in the central and eastern Pacific, plays a crucial role. Thermocline fluctuations in the central and eastern tropical Pacific modulate SSTs through vertical advection and thereby provide oceanic memory for predictability on seasonal to interannual time scale associated El Niño–Southern Oscillation (ENSO; Zebiak and Cane 1987; Jin 1997; Meinen and McPhaden 2000).

Previous studies have demonstrated that improved subsurface analyses, particularly more realistic upper-ocean heat content and thermocline depth, can enhance seasonal forecast skill for coupled climate phenomena such as ENSO and the Indian Ocean Dipole (e.g., Balmaseda et al. 2013; Fujii et al. 2015; Mayer et al. 2024). Recognizing this, ocean reanalysis (ORA) systems have been developed to provide dynamically consistent, time-evolving three-dimensional estimates of the ocean state by assimilating *in situ*, ship, and satellite observations into numerical ocean models. These ocean analysis

systems play a critical role in climate monitoring and prediction both by reconstructing historical ocean variability and by providing ocean initial conditions for coupled forecast models (Xue et al. 2017).

A key analyzed variable from ORAs is SSTs. To constrain ORA SST, ORA systems often nudge the model SST towards independent external SST analysis products (Donlon et al. 2012; Penny et al. 2019), which merge satellite radiances with buoy and ship observations using optimal interpolation or variational techniques to produce gap-free global spatial and temporal coverage (Reynolds et al. 2007; Huang et al. 2015). However, uncertainties exist among SST analyses because of differences in observational inputs, analysis techniques, and satellite retrieval methods (Yasunaka and Hanawa 2011; Kennedy et al. 2011; Yang et al. 2021). For example, SST uncertainty can arise from how satellite infrared (IR) and microwave (MW) radiances are converted to temperature, especially in *in situ* data-sparse regimes—western boundary currents, high latitudes, and coastal zones—where satellite calibration remains difficult (Penny et al. 2019; O’Carroll et al. 2019).

While it is ideal to use a single SST dataset for nudging to maintain temporal consistency, the data used is sometimes changed because of operational constraints. The Climate Forecast System Reanalysis (CFSR), for instance, nudged its SSTs toward HadISST (Rayner et al. 2003) from 1979 through October 1981, and then to a higher-resolution SST—NOAA’s daily OISSTv2 (Reynolds et al. 2007) maintained at NCEP—from November 1981 to January 2020 (Saha et al. 2010; Xue et al. 2011). After OISSTv2 was discontinued from NCEP’s production suite, the CFSR transitioned to another internally generated near-surface SST (NSST) (Li et al. 2007) beginning in February 2020 (https://www.emc.ncep.noaa.gov/emc/pages/numerical_forecast_systems/sst.php). Given a change in the analysis used for SST nudging, it is necessary to quantify differences between NSST and daily OISSTv2, and to assess how the changes affect both the analyzed ocean state and on the forecasts that are initiated from it.

Continuing with CFSR as an example, historical hindcasts initialized from CFSR have exhibited a well-documented regime shift in Niño-3.4 SST forecast bias: colder before 1999 and warmer afterward, linked to discontinuities in subsurface temperature in the eastern Pacific (Kumar et al. 2012; Barnston and Tippett 2013; Xue et al. 2013; Becker et al. 2022). While these historical biases have been extensively studied, real-time predictions issued during 2024 tell an opposite story: CFSv2, CCSM4, and CESM1 forecasts with June–November initializations from CFSR all favored La Niña during fall through winter 2024/25, while the observations ended up verifying as ENSO-neutral because of its short duration (Fig. 1). A large cold bias exceeding 0.5°C was also evident even in shorter lead forecasts initialized in late summer through fall. This is unusual because dynamical models typically exhibit their highest ENSO skill for late summer–fall initializations (Ehsan et al. 2024). The sign reversal and onset of a large magnitude bias raise the possibility that the NSST replacement altered the background ocean state used for initialization, thereby degrading the performance of ENSO prediction.

To investigate this possibility, this study assesses how the NSST transition in CFSR affects the ocean state estimate and subsequent forecasts, with emphasis on ENSO prediction skill. Section 2 describes

the data and methods; section 3 diagnoses the SST error introduced by the change in the analysis; section 4 traces the propagation of that error into global forecasts and ENSO skill; and section 5 summarizes the main conclusions.

2. Data and methods

CFSR provides the oceanic initial conditions for NCEP's operational CFSv2 seasonal prediction system and extends from January 1979 to the present (Saha et al. 2014). In CFSR, the guess state is produced using a coupled forecast, in which the NCEP Global Forecast System (GFS) atmosphere and the Modular Ocean Model version 4 (MOM4) are integrated simultaneously, exchanging surface fluxes and SST once per hour (Saha et al. 2010). After coupled integration providing the first guess for analysis, atmospheric and oceanic data assimilation components operate separately. The ocean component employs a three-dimensional variational scheme to assimilate subsurface temperature profiles and SST.

As part of the assimilation, the top model level (5m depth) is strongly nudged to external SST analysis data, providing a strong constraint on the ocean-atmosphere interface, and compensating for potential model drift caused by errors in surface fluxes (Xue et al. 2011). Three SST analyses have been used in sequence: HadISST1.1 (January 1979–October 1981; Rayner et al. 2003), Daily OISSTv2 (November 1981–January 2020; Reynolds et al. 2007) and NSST from February 2020 onward (Li et al. 2007). Following the definition by Minnett and Kaiser-Weiss (2012), HadISST and OISSTv2 represent an intermediate-depth temperature ($\sim 0.2\text{m}$), while NSST representative of the foundation temperature (i.e., temperature free of diurnal cycle), similar to U.K. Met Office OSTIA (Good et al. 2000). Intermediate-depth SST analyses such as HadISST and OISSTv2 assimilate only infrared (IR) satellite retrievals together with in-situ ship and buoy data. Foundation-temperature products, like NSST, in contrast, also ingest microwave (MW) retrievals. Because MW sensors can sample through clouds and tend to report slightly cooler daytime temperatures than clear-sky IR observations, foundation products exhibit a small cool bias relative to intermediate-depth analysis datasets (Good et al. 2020; Yang et al. 2021).

In this analysis, the NOAA Daily OISST v2.1 dataset (OISSTv2.1; Huang et al. 2021) is adopted as a reference SST field. For the period 1981–2015, OISSTv2.1 is identical to the earlier Daily OISSTv2 analysis (Reynolds et al. 2007) that provided the SST nudging source for CFSR; beginning in 2016, algorithm upgrades were introduced to reduce the cold bias detected in OISSTv2 analysis. Daily OISSTv2.1 is very similar to OSTIA, as shown in Figure S1 in the supplementary information, where the Niño-3.4 index from OISSTv2.1 closely matches that from OSTIA. In contrast, the NSST product exhibits notable differences from both OISSTv2.1 and OSTIA. Subsurface temperature analysis is evaluated with respect to EN4 2.2 global ocean temperature and salinity objective analysis dataset produced by the Met Office Hadley Center (Good et al. 2013).

Assessing how the OISST to NSST transition in CFSR influenced SSTA forecasts is nontrivial – particularly in the tropical Pacific, where SST variability reflects influence from multiple interacting processes such as local air–sea coupling, extratropical forcing, and inter-basin exchanges (Alexander et

al. 2002; Chang et al. 2006; Di Lorenzo et al. 2010; Luo et al. 2017). These competing influences can obscure the specific contribution of ocean initial conditions (ICs) errors within any single coupled model. An alternative strategy is to identify common features that multiple, independent forecast systems share when they start from the same ocean ICs. If different models exhibit similar spatial and temporal SSTA errors, those errors are most likely inherited from the common ocean state rather than from model-specific physics. Because of proximity to the ICs, shorter forecast lead times tend to help better identify dataset discontinuities in the ICs, while forecasts at longer lead times diverge due to subsequent dynamical processes and air-sea feedback, and can obscure the influence of initial conditions.

Following this idea, we analyze three models from the North American Multi-Model Ensemble (NMME; Kirtman et al. 2014, Becker et al. 2022)—NCEP CFSv2, the Community Climate System Model version 4 (CCSM4; Gent et al. 2011, Infanti and Kirtman 2016) and RSMAS-CESM1(Becker et al. 2022), which are all initialized with CFSR ocean fields. Forecasts are initialized at the beginning of each month. In this study, a 0-month lead is referred to as the mean for the same month of initialization; a 1-month lead as the following month, and so on. Forecast anomalies are verified against OISSTv2.1. Because CESM1 data are not available prior 1991 (Becker et al. 2025), the primary comparison of SST forecasts focuses on CFSv2 and CCSM4.

We focus on examining monthly mean data. All monthly anomalies are relative to the individual data set's 1991–2020 climatology. Because NSST only has a few years, its SST anomalies are defined as departures from OISSTv2.1 climatology. In this study, error is defined as the difference between a data-set anomaly and the corresponding anomaly from the designated reference. For example, NSST error denotes the NSST anomaly minus the OISSTv2.1 anomaly, whereas CFSR subsurface-temperature error denotes the CFSR anomaly minus EN4 temperature anomaly.

The SST anomaly in Niño-3.4 region (170° – 120° W, 5° S– 5° N) is used to represent ENSO status. ENSO events are defined when Niño-3.4 is above $+0.5^{\circ}\text{C}$ or below -0.5°C for a minimum of five consecutive overlapping seasons. There are 31 ENSO events (1982, 1983, 1984, 1986, 1987, 1988, 1991, 1994, 1995, 1997, 1998, 1999, 2000, 2002, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2014, 2015, 2016, 2017, 2018, 2020, 2021, 2022, 2023) within our analysis period (1982–2024).

3. Impact of the NSST replacement on CFSR SST

Because the surface layer of CFSR is strongly nudged to an external SST analysis, changing the source can leave an imprint on the CFSR SST analysis. The magnitude of the imprint depends on the differences between the two sources of SST analyses. To gauge the potential impact of replacing OISSTv2 with NSST, we first compare the two data sets over February 2020–December 2024.

Figure 2a shows the mean difference between NSST and OISSTv2.1. NSST is markedly colder in the mid- to high latitudes—exceeding 1°C near western-boundary currents such as the Gulf Stream, Kuroshio, and Antarctic Circumpolar Current (ACC). These regions are dominated by vigorous mesoscale eddies, which complicate satellite retrievals. In the tropics NSST is cooler by about 0.2 – 0.5°C , particularly in upwelling

zones (Pacific and Atlantic cold tongues, southern coast of Arabian Peninsula). By contrast, SSTs in the Indo-Pacific warm pool are similar or slightly warmer in NSST. Root-mean-square error (RMSE) between NSST and OISSTv2.1 monthly anomalies (Fig. 2b) is largest ($> 0.9^{\circ}\text{C}$) in the western-boundary currents and ACC, and around 0.4°C in upwelling regions, indicating that the error also fluctuates substantially in space.

The difference between NSST and OISSTv2.1 is more than twice the maximum inter-product spread reported by Yang et al. (2021). One possible explanation is that NSST represents the foundation temperature, whereas OISSTv2.1 represents the intermediate-depth temperature at ~ 0.2 m depth. To test this, we repeated the calculation using OSTIA—which, like NSST, also represents foundation temperature. The differences between OSTIA and NSST are nearly identical to those between OISSTv2.1 and NSST (see Fig. S2 in the supplementary information). This similarity indicates the fact that NSST being foundation temperature is unlikely the source of the cold bias and further work is needed to understand its origins.

Given the bias structure described above, it is reasonable to expect that replacing OISSTv2 with NSST will introduce a systematic shift in the CFSR SSTs, which will subsequently cause biases in CFSv2 and CCSM4 coupled forecasts. To test this hypothesis, we compute CFSR SSTA errors for three epochs: 1982–98, 1999–2019, and 2020–24. The first two periods bracket the well-documented 1998/99 discontinuity in CFSR subsurface temperature (Xue et al. 2011; Kumar et al. 2012;). When CFSR was strongly nudged toward OISSTv2 (i.e., before 2020), SSTA errors relative to OISSTv2.1 were negligible across most basins (Figs. 3a-b). After the switch to NSST in February-2020, however, the error pattern closely mirrors the NSST bias relative to OISSTv2.1: cold anomalies in mid-to-high latitude western-boundary currents and in tropical upwelling zones, and warm anomalies in the Indo-Pacific warm pool (Fig. 3c). The mid-latitude cold error is slightly weaker than those in NSST, whereas the equatorial Pacific error is slightly stronger. This contrast is consistent with the idea that extratropical SST anomalies tend to be damped by atmospheric heat fluxes (Frankignoul and Hasselmann 1977; Barsugli and Battisti 1998), while equatorial SST variability is strongly modulated by ocean-dynamical processes such as thermocline feedback (Bjerknes 1969; Jin 1997). Although CFSR SST is strongly nudged to external SST analysis, the weakly coupled configuration of the assimilation system allows the local heat-flux and dynamical adjustments to partly modify, though not erase, the imprint of the new SST boundary condition.

The temporal evolution of zonally averaged CFSR SSTA error (Fig. 4) reinforces this conclusion. Before February 2020, CFSR SST tracks OISSTv2.1 closely. Immediately after the NSST switch, a pronounced cold bias develops poleward of about 30° , consistent with the NSST bias pattern, confirming that the new SST analysis is the primary cause of the systematic shift in the CFSR SST error that begins in 2020.

4. Impact of the NSST replacement on SST forecasts and ENSO prediction

Systematic errors in CFSR SST initial conditions may propagate into seasonal forecasts that rely on this analysis—namely the NCEP CFSv2 and NCAR CCSM4—and can thereby influence predictions of major climate modes such as ENSO.

We begin with 0-month-lead forecasts, which most directly reflect the influence of IC errors. Because SST modulates surface heat and moisture exchange, any bias at initialization time should manifest immediately in the forecast. Figures 5a-b show the evolution of zonal-mean SSTA error from 1982 to 2024. Both models contain two visible discontinuities: one around 1999 and the other in 2020. The first is the well-documented sign reversal near the equator, which occurred around 1999. The discontinuities in CFSv2 and CCSM4 during this period have been reported in the literature and have been linked to nonstationary changes in CFSR subsurface analysis error ((e.g., Kumar et al., 2012; Barnston and Tippett, 2013; Xue et al. 2011; 2013). Consistent with evaluations using TAO mooring observations (Xue et al. 2011), CFSR subsurface temperature error (departure relative to EN4) in the eastern Pacific thermocline exhibits a pronounced transition from a predominately cold to a warm bias beginning approximately in 1999. This subsurface discontinuity has been attributed to a sudden reduction in the easterly trade wind bias associated with the introduction of Advanced TIROS Operational Vertical Sounder (ATOVS) radiance assimilation (Wang et al. 2011; Xue et al. 2011; Zhang et al. 2012).

The second error, we hypothesize, stems from the transition from OISSTv2 to NSST. Figure 6 displays the mean 0-month-lead bias for three periods—1982–98, 1999–2019, and 2020–23. In the first two periods the bias is confined to the central–eastern Pacific cold tongue (cold in 1982–98, warm in 1999–2019) and remains $< 0.1^{\circ}\text{C}$ elsewhere except in western-boundary currents. After 2020 the pattern changes abruptly: cold errors $> 0.5^{\circ}\text{C}$ appear in mid- and high-latitude western-boundary currents and in tropical upwelling zones, while a warm bias covers much of the Indo-Pacific warm pool. The spatial resemblance to the CFSR SSTA error also suggests that the NSST IC error is the primary factor contributing to SST forecast error

To assess whether post-NSST forecast errors differ significantly from those in previous years, we conducted a two-sided t -test comparing forecasts after the NSST implementation with those from 2000–2019. We excluded the 1982–1998 period because ATOVS radiance data were not assimilated during those years. Figure 7 shows the evolution of the annual mean SST forecast errors at lead times of 0, 2, 4, and 6 months.

In both CFSv2 and CCSM4, substantial cold SSTA errors emerge in the eastern tropical Pacific at lead-0 and then intensify and expand westward toward the Date Line, peaking around the 4-month lead. Notably, the amplitude and persistence of cold errors are greater in CCSM4 than in CFSv2, with CCSM4 exhibiting anomalies exceeding -0.5°C between 150°W and 110°W at the 2-month lead, a pattern that persists through the 6-month lead. Despite their use of entirely different atmospheric and ocean models, both forecast systems exhibit very similar cold bias patterns in the eastern tropical Pacific, strongly suggesting that the common CFSR ocean analysis is a key driver of the errors. In contrast, discrepancies between the models in the western Pacific imply that additional factors such as atmospheric physics,

convective parameterizations, and subsequent air–sea coupling may contribute more prominently to forecast uncertainty in that region.

Earlier work suggested that subsurface IC errors strongly influence CFSv2 and CCSM4 SST skill in the tropical Pacific (Kumar et al. 2012; Xue et al. 2013). One can, therefore, argue that the recent cold SST bias could also be attributed to CFSR subsurface error in equatorial Pacific. To quantify the relative contribution between CFSR SST IC and subsurface IC, we analyze scatterplots relating monthly CFSR SST IC errors to lead-0 SST forecast errors averaged over the equatorial eastern Pacific [160°–90° W, 5° S–5° N] to examine whether the error pathway changed in recent years (Fig. 8).

The analysis indicates that the relationship between SST IC and forecast errors are quite different in the most recent period compared to earlier decades. In the two earlier periods, SST IC errors are modest ($< 0.2^{\circ}\text{C}$), and their correlations with forecast errors are only moderate (~ 0.5 – 0.6), indicating limited sensitivity. During 1982–1998, regression slopes of 2.8 in CFSv2 and 4.1 in CCSM4 indicate a three- to four-fold amplification of difference between CFSR SST error and forecast error at lead-0 (Fig. 8c). The SST forecast error is consistent with strong subsurface cold bias during the period (Fig. 5c), in agreement with the thermocline feedback theory. From 1999 to 2019, the sign of the relationship reverses: CFSR develops a warm bias at depth while surface errors remain small, resulting in forecasts that predominantly inherit a warm bias (Fig. 8d). This behavior indicates that subsurface IC errors were the dominant source of forecast errors during both earlier periods, although the sign of the bias shifted from cold (1982–1998) to warm (1999–2019).

In contrast, the 2020–24 period exhibits a distinctly different pattern. The thermocline bias becomes negligible (Fig. 5c), while surface SST IC errors are sizable and predominantly negative (Fig. 8b). Regression slopes near 0.9 and nearly unit correlation coefficients indicate that both models communicate the NSST-driven surface anomaly almost undamped into their lead-0 forecasts (Fig. 8a-b). The analysis suggests that the NSST-induced surface bias—not subsurface IC error—is now the principal source of short-lead SST forecast error. The earlier periods highlight the complementary case: when SST bias is small, thermocline error dominates. The results underscore that although the quality of subsurface IC remains crucial, a large SST IC bias can override subsurface influences and rapidly degrade forecast skill.

We next examine the influence of the NSST bias on ENSO prediction skill using Niño-3.4 forecast error composites from CFSv2 and CCSM4 (Fig. 9). Thirty one ENSO events are stratified into three eras—1982–98, 1999–2019, and 2020–24. For the first two periods, the shaded envelopes represent the central-75% spread of individual-event errors (light blue for 1982–98 and pink for 1999–2019), while the four post-2020 events are plotted individually in green.

During 1982–98 the forecasts are systematically too cold throughout the ENSO life cycle, consistent with the pervasive cold thermocline bias in the CFSR subsurface ICs (Fig. 5c). In 1999–2019 the sign of bias reverses: a persistent warm bias appears, mirroring the switch to a warm subsurface IC error. In both periods the largest departures emerge in JAS(0) at lead-0, reflecting the seasonally modulated

growth also reported by Kumar et al. (2012). CFSv2 generally exhibits larger error amplitudes than CCSM4. This behavior changes sharply after NSST is adopted. From 2020–23, when the CFSR subsurface bias was minimal (Fig. 5c), Nino34 errors are negative for all the four ENSO events, with the cold error peaking in OND(0) and persisting or intensifying into DJF(1)–JFM(1). This cold bias reaches 1°C at both 2-month and 4-month leads.

The persistent cold bias during ENSO development could make the forecast models prone to overestimate the strength of La Niña events, as seen in the 2024 forecast highlighted in the introduction. Figure 10a shows that in August–November 2024, NSST errors exceeding -0.6°C develop in the eastern equatorial Pacific between August and November 2024, and then weaken after December. CFSR SST errors closely resemble the NSST error (Fig. 10b). Small negative subsurface temperature errors are only confined to the upper ~ 20 m and share the same seasonality as the surface bias. Meanwhile subsurface errors below 50 m are very small (Fig. 10c). This analysis indicates that the overly cold La Niña prediction in late 2024 (Fig. 1) stems primarily from the surface-analysis cold bias in SST, not from subsurface analysis IC error.

5. Summary and discussion

ORAs often constrain their SST analysis by strongly nudging the top ocean model layer toward independent SST analyses to avoid model drift. Beginning in February 2020, CFSR transitioned from the NOAA OISSTv2 to the near-surface SST (NSST) foundation product developed at NCEP/EMC, following OISSTv2's discontinuation from NCEP operations. This study quantifies the imprint of the NSST replacement as an external SST nudging source on CFSR SST fields, traces its propagation into forecast systems initialized from CFSR (CFSv2, CCSM4), and evaluates the implications for ENSO prediction.

NSST exhibits pronounced cold biases relative to OISSTv2.1, particularly in mid- to high-latitudes near western boundary currents and the ACC, where annual mean biases exceed 1°C . Biases of $0.2\text{--}0.5^{\circ}\text{C}$ are also evident in tropical upwelling regions, and root-mean-square errors exceed 0.4°C in these areas. The difference between NSST and OISSTv2.1 is larger than the typical spread across modern SST analyses (Yang et al. 2021). This analysis suggests there is a need to revise NSST or operationally implement a new SST dataset that corresponds more closely with other well-established SST datasets (OISSTv2.1 or OSTIA).

The transition to NSST caused a sharp discontinuity in CFSR SST, with negligible differences relative to OISSTv2.1 before 2020 and an immediate large-scale bias thereafter. The error pattern mirrors that of NSST, with large cold bias in extratropical and equatorial upwelling regions and weak warm anomalies in the Indo-Pacific warm pool.

These NSST-induced CFSR SST errors propagate directly into initialized forecasts. A comparative analysis over three periods (1982–1998, 1999–2019, and 2020–2024) shows that 0-month lead forecasts from both CFSv2 and CCSM4 reproduce the NSST error pattern with cold anomalies exceeding 0.5°C in large scale mid-latitudes and the tropical upwelling regions. Notably, the cold anomalies in the

eastern tropical Pacific amplify and migrate westward toward the dateline by the four-month lead. The coherence of errors across CFSv2 and CCSM4, despite their independent model configurations and coupling schemes, demonstrates a shared origin in the ocean ICs.

Both equatorial subsurface temperature and SST ICs are important factors driving SST evolution in the coupled forecast systems. To isolate the role of SST IC error from that of subsurface temperature error, we compared correlations between CFSR initial-state errors and forecast errors across the three periods. Comparison across three epochs reveals a nonstationary evolution of forecast error. In the post-2020 period, SST forecast errors show a strong, near-undamped correspondence with NSST-induced CFSR surface errors, in contrast to earlier decades, when subsurface bias amplification was dominant. Niño-3.4 forecast composites also reveal a regime-dependent evolution: cold biases in 1982–1998, warm biases in 1999–2019, and a return to cold starts post-2020. Post-2020 forecasts consistently show negative Niño-3.4 errors peaking in OND (0) and persisting into DJF (1), despite the reduction of thermocline errors in recent years. The 2024 real-time plumes illustrate this behavior: CFSv2, CCSM4, and CESM1 all produced false La Niña alarms during initial months in boreal summer–fall, typically the most skillful months for dynamical ENSO prediction. CFSv2, CCSM4, and CESM1 are core components of the operational NMME. Their shared NSST-induced biases might degrade ENSO forecast skill by introducing a systematic cold bias into the NMME ensemble mean forecasts, increasing the risk of too cold forecasts, including the possibility of La Niña false alarms.

Earlier studies pointed out that all NMME models tend to produce spurious SST trend errors that are more positive than observed (Shin and Huang 2019; L’Heureux et al. 2022). CFSv2 and CCSM4 have the most positive trend errors at short leads, which is likely due to the initialization discontinuities in CFSR subsurface temperature. Incidentally, the introduction of NSST, combined with the diminished warm subsurface biases after 2015, may partially offset these historical positive trend errors, benefitting forecasts with a colder initial condition. However, the apparent improvement is misleading, as it replaces one systematic error with another, also known as error compensation, which is endemic in climate models and their representation of ENSO (e.g. Bellenger et al., 2014; Bayr et al., 2019). Post-2020 trend assessments must account for this artificial correction to avoid misinterpreting forecast performance.

The present analysis has focused on ENSO, but the pronounced forecast SST errors in other ocean basins—including the mid-to-high latitudes and tropical Atlantic—warrant further investigation, particularly for long-lead forecasts.

Finally, our results raise concerns about the use of stationary bias corrections in real-time operational forecasting. The NSST replacement introduced non-stationary IC errors that are not accounted for by traditional mean-bias removal schemes. Applying fixed climatological adjustments may inadvertently translate time evolving biases into artificial climate signals. Accurate model validation, therefore, requires continuous evaluation of ocean reanalysis updates and their evolving influence on forecast skill.

Declarations

Competing interests

The authors declare no competing interests. They have no financial or proprietary interests in any material discussed in this article.

Data Availability Statement

The NOAA Daily Optimum Interpolation Sea Surface Temperature (OISST) v2.1 dataset (Huang et al., 2021) can be accessed from <https://www.ncei.noaa.gov/data/sea-surface-temperature-optimum-interpolation/v2.1/access/avhrr/>. The U.K. Met Office Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) dataset (Good et al., 2020) and the EN4 data set (Good et al. 2013) can be accessed at <ftp://nrt.cmens-du.eu> and <http://www.metoffice.gov.uk/hadobs/en4/data/en4-2-1>, respectively. Forecast data from the North American Multi-Model Ensemble (NMME) project, including the CFSv2, CCSM4, and CESM1 models, were obtained from the FTP site detailed in Kirtman et al. (2014) (<https://ftp.cpc.ncep.noaa.gov/NMME/>).

Disclaimer

The analysis, results, and conclusions presented here are those of the authors and do not necessarily reflect the views of NOAA or the Department of Commerce.

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Figures

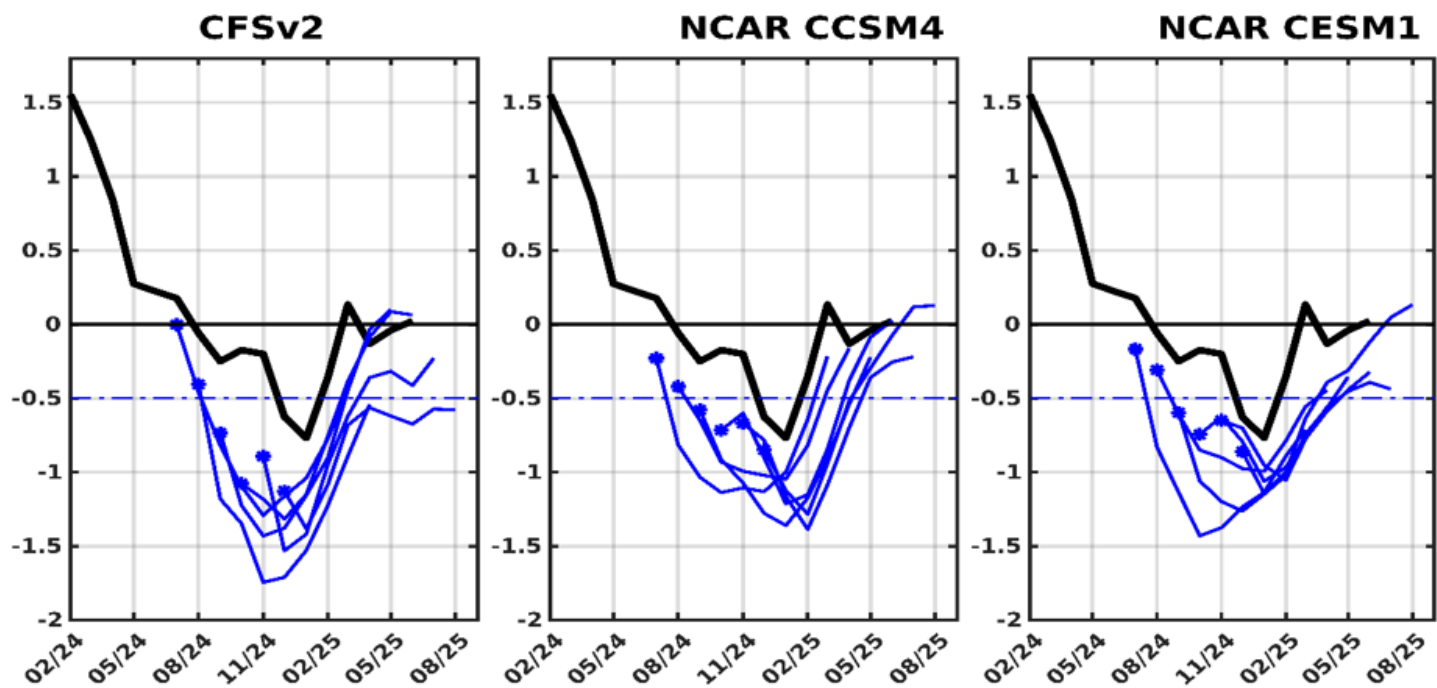


Figure 1

Monthly forecast of the Niño 3.4 from CFSv2 (left), NCAR-CCSM4 (middle), and NCAR CESM1 (right), initialized each month from June to December 2024 (blue lines). Thick black lines represent observation from OISSTv2.1 monthly data (Huang et al. 2021).

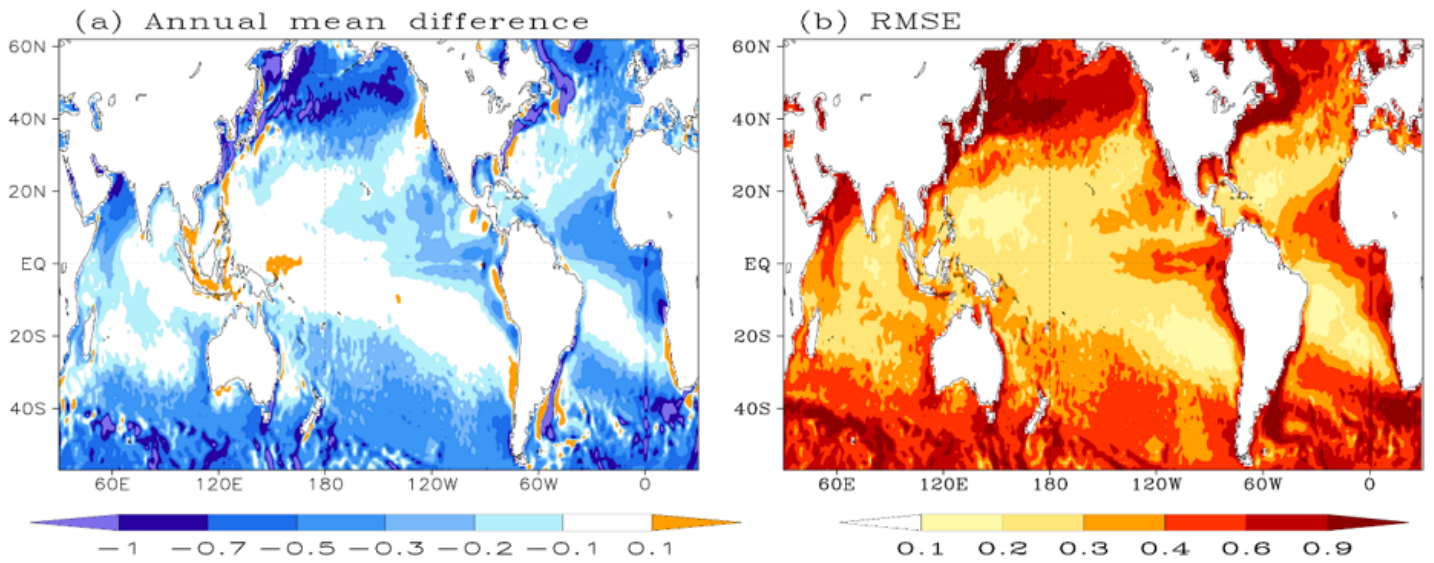


Figure 2

(a) Mean difference and (b) Root-mean-square error (RMSE) of monthly SST anomalies between NSST and OISSTv2.1 over the period February 2020 to December 2024.

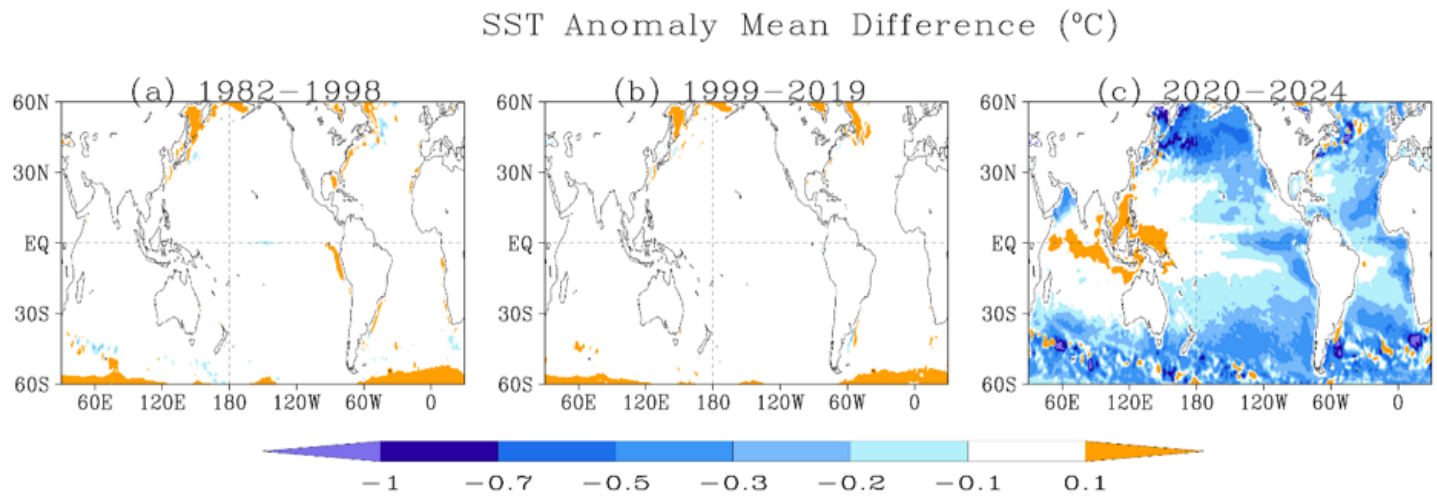


Figure 3

Annual mean SST anomaly differences between CFSR and OISSTv2.1 for the periods (a) 1982–1998, (b) 1999–2019, and (c) 2020–2024.

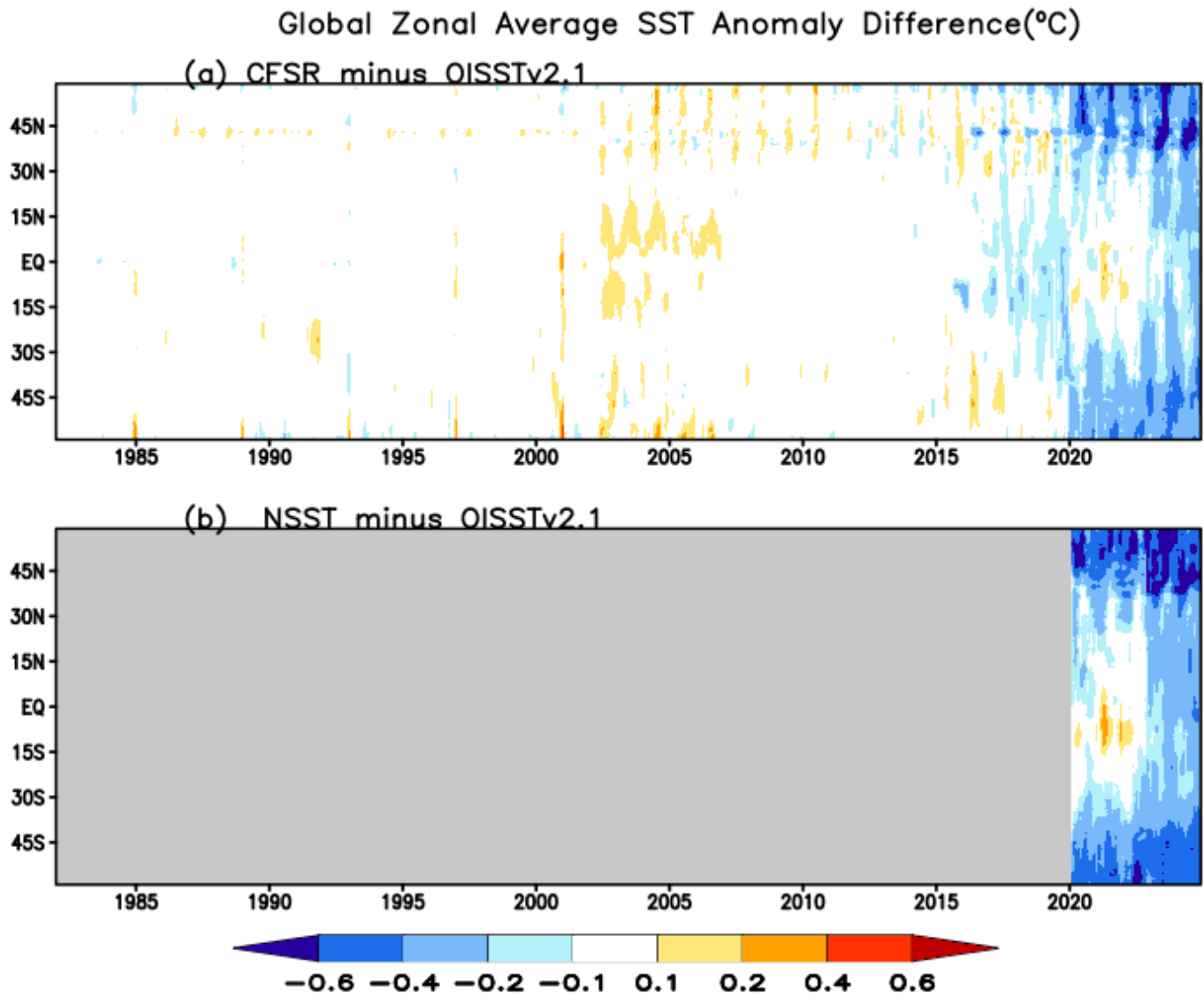


Figure 4

Zonal-mean monthly SST anomaly differences between (a) CFSR and OISSTv2.1, and (b) NSST and OISSTv2.1 during 1982–2024. Units are in °C.

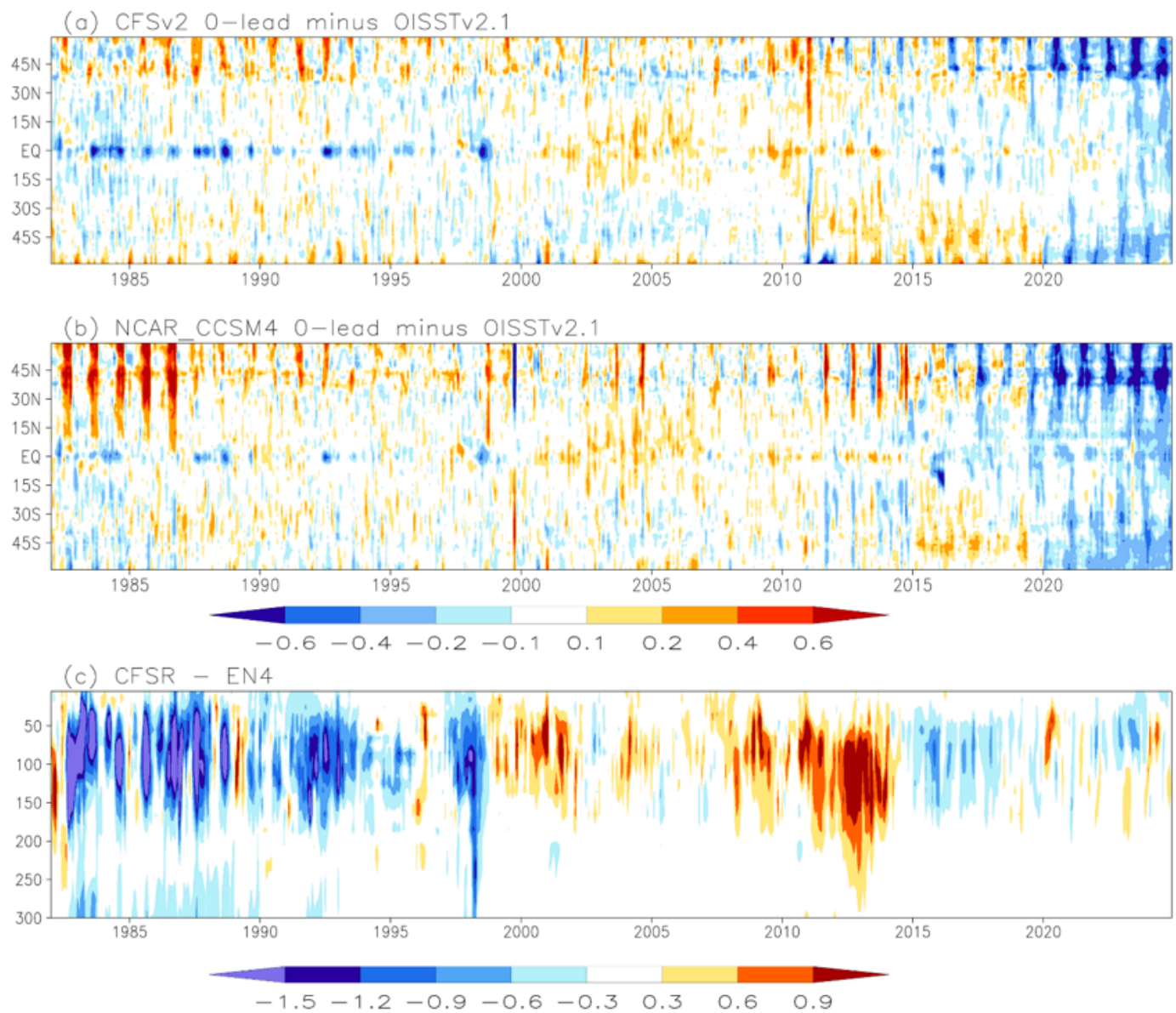


Figure 5

Time series of global zonal-mean monthly SST-anomaly differences relative to OISSTv2.1 for (a) CFSv2 0-month-lead forecasts and (b) NCAR CCSM4 0-month-lead forecasts during 1982–2024. Panel (c) shows subsurface-temperature-anomaly differences between CFSR and EN4, averaged over 160°–90°W, 2°S–2°N. All anomalies are in °C.

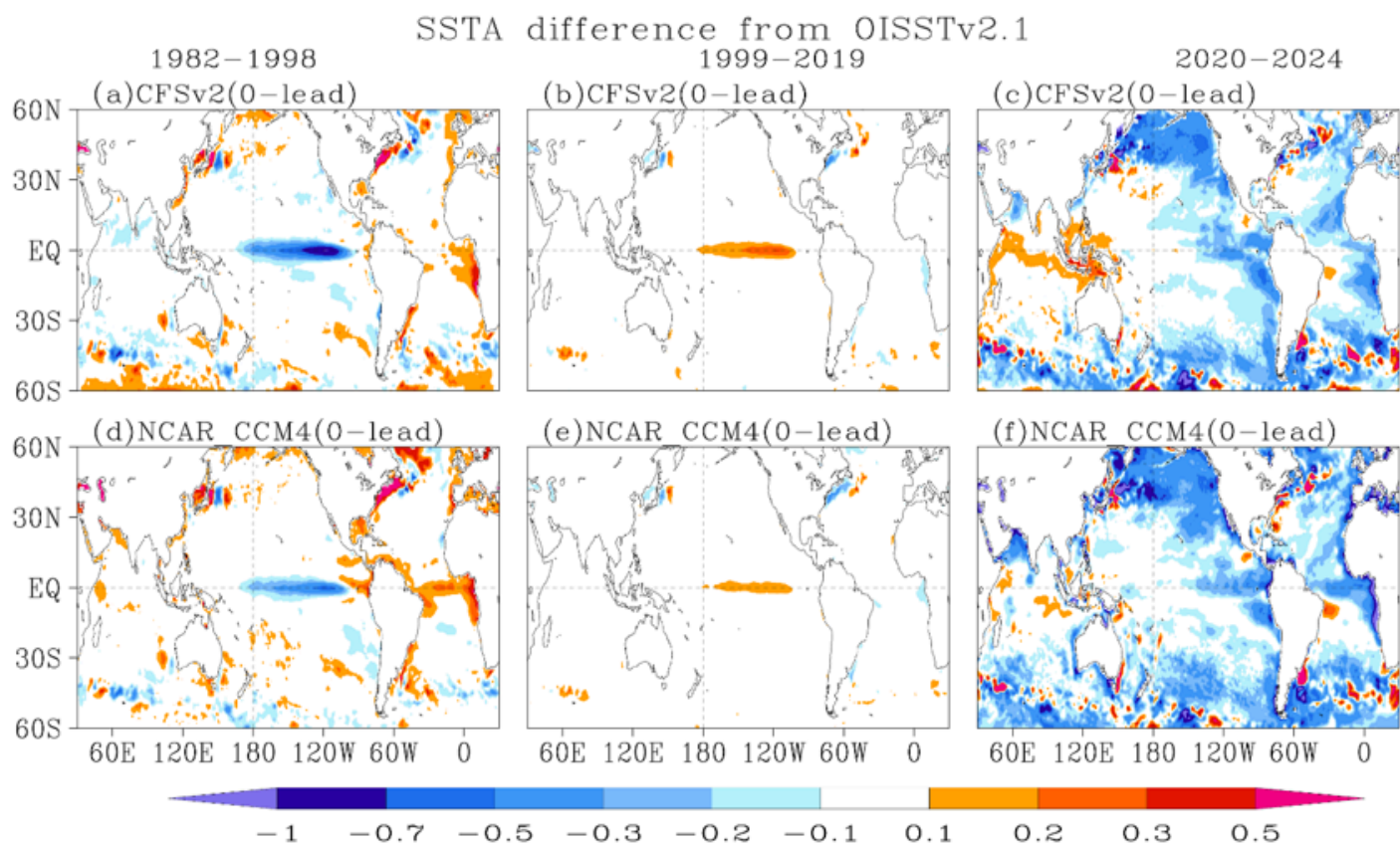


Figure 6

Mean SSTA-anomaly differences (°C) between 0-month-lead forecasts and OISSTv2.1 for CFSv2 during (a) 1982–1998, (b) 1999–2019, and (c) 2020–24. Panels (d)–(f) show the corresponding differences for NCAR CCSM4.

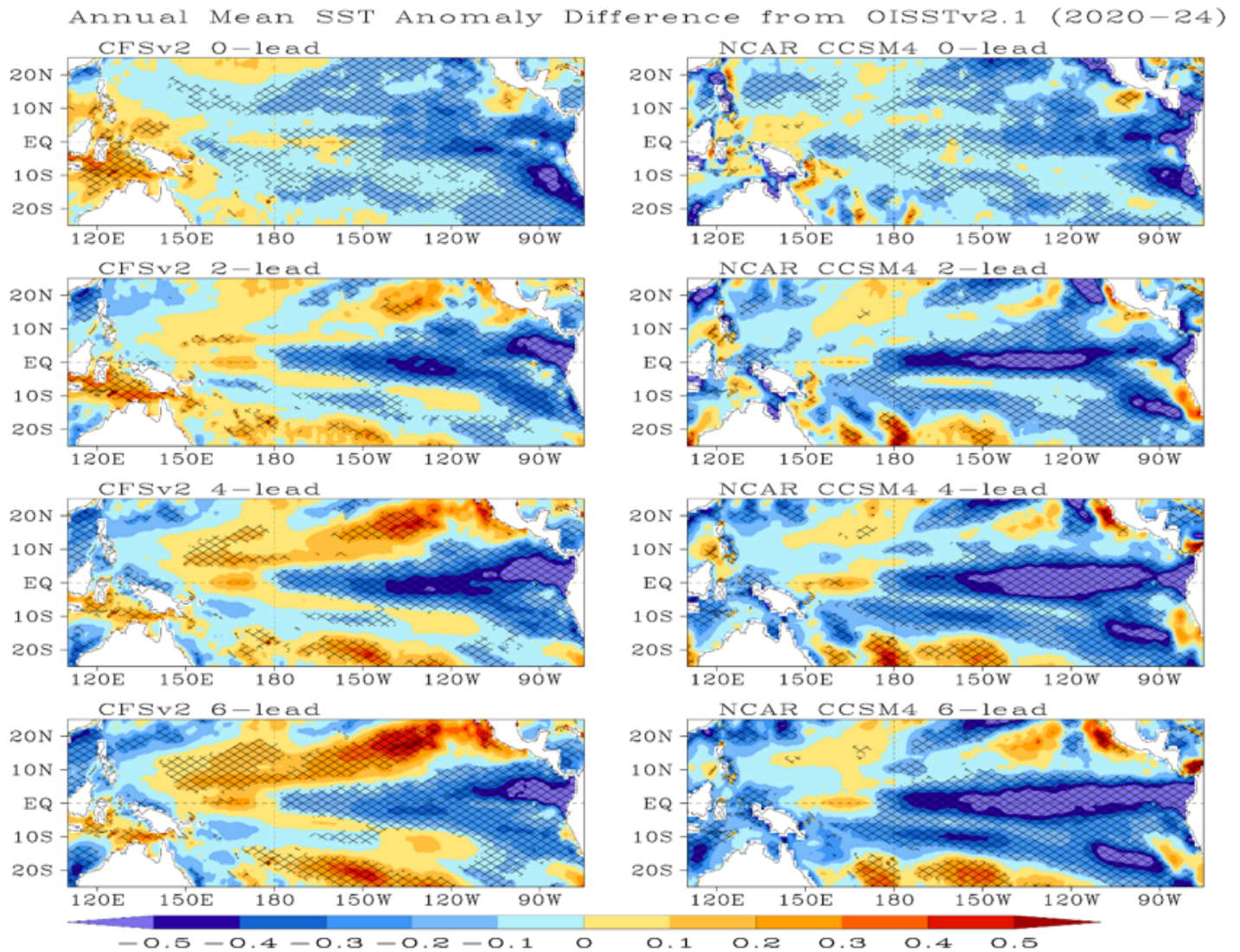


Figure 7

Left-hand panels: spatial distribution of annual-mean SST-anomaly differences (shaded, °C) between CFSv2 forecasts and OISSTv2.1 for 2020–24 at 0-, 2-, 4-, and 6-month leads. Hatched areas denote regions where the 2020–24 departures differ from those in 1999–2019 at the 95% confidence level based on a two-sided Student's t-test. Right panels are the same as left panels except for NCAR CCSM forecasts.

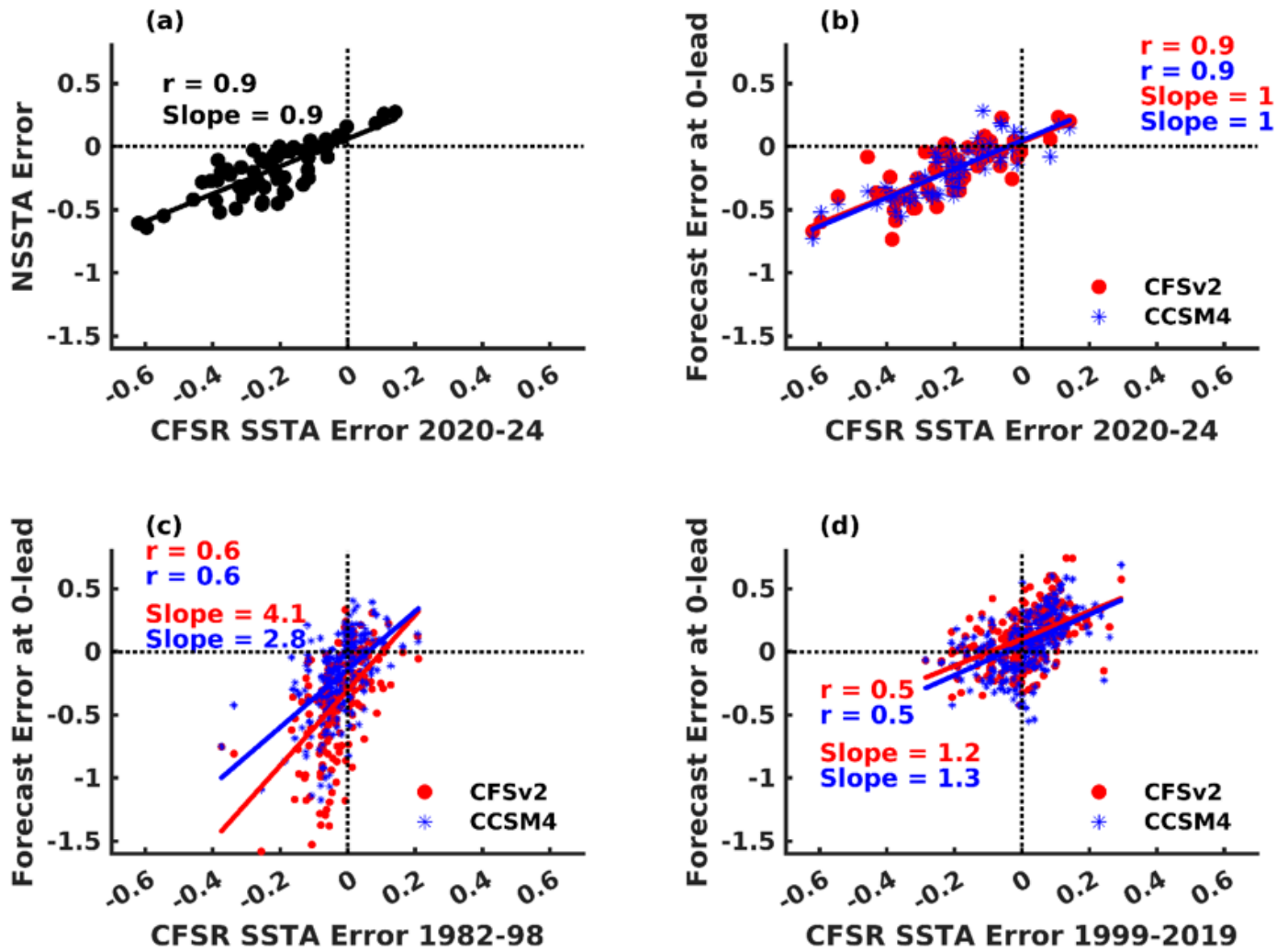


Figure 8

Scatterplots showing the relationship between CFSR SSTA error average in equatorial eastern Pacific (160°–90°W, 5°S–5°N, unit in °C) and: (a) concurrent NSST SST-anomaly error for 2020–24, (b) CFSv2 0-month-lead forecast SST-anomaly error for 2020–24, (c) CFSv2 0-month-lead forecast error for 1982–98, and (d) CFSv2 0-month-lead forecast error for 1999–2019. The correlation coefficient (r) and the least-squares regression slope of the two variables are given in each panel.

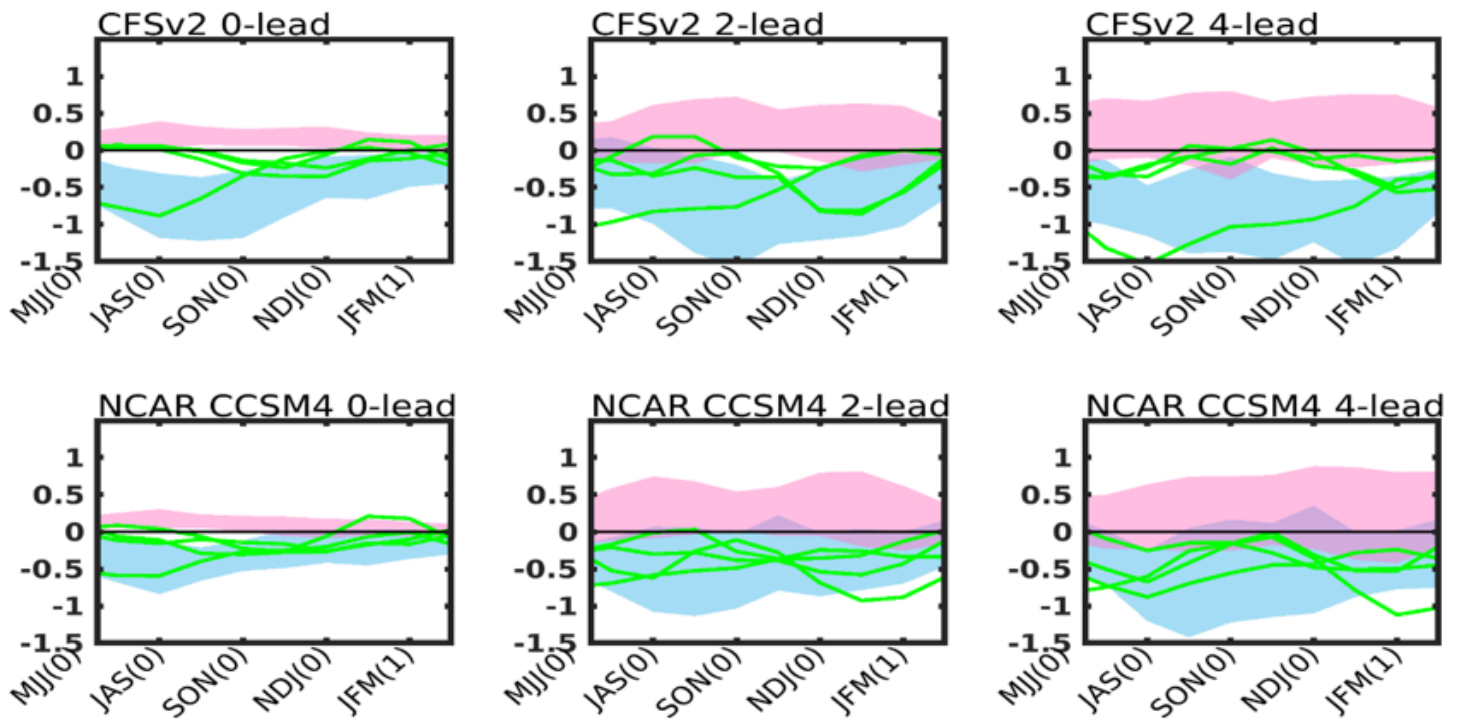


Figure 9

Time evolution of Niño-3.4 SST-anomaly forecast error (forecast minus OISSTv2.1) composited over ENSO cycle. Upper panels: CFSv2 errors at 0-, 2-, and 4-month leads. Blue and (red) shaded envelopes show the central 75% of event values for the 1982–98 and 1999–2019 respectively. (0) represent the year where ENSO peak and (1) the following year. Green lines display time evolution of individual NINO34 forecast error for ENSO events during 2020-23. ENSO years included are 1982, 1983, 1984, 1986, 1987, 1988, 1991, 1994, 1995, 1997,

1998, 1999, 2000, 2002, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2014, 2015, 2016, 2017, 2018, 2020, 2021, 2022, 2023.

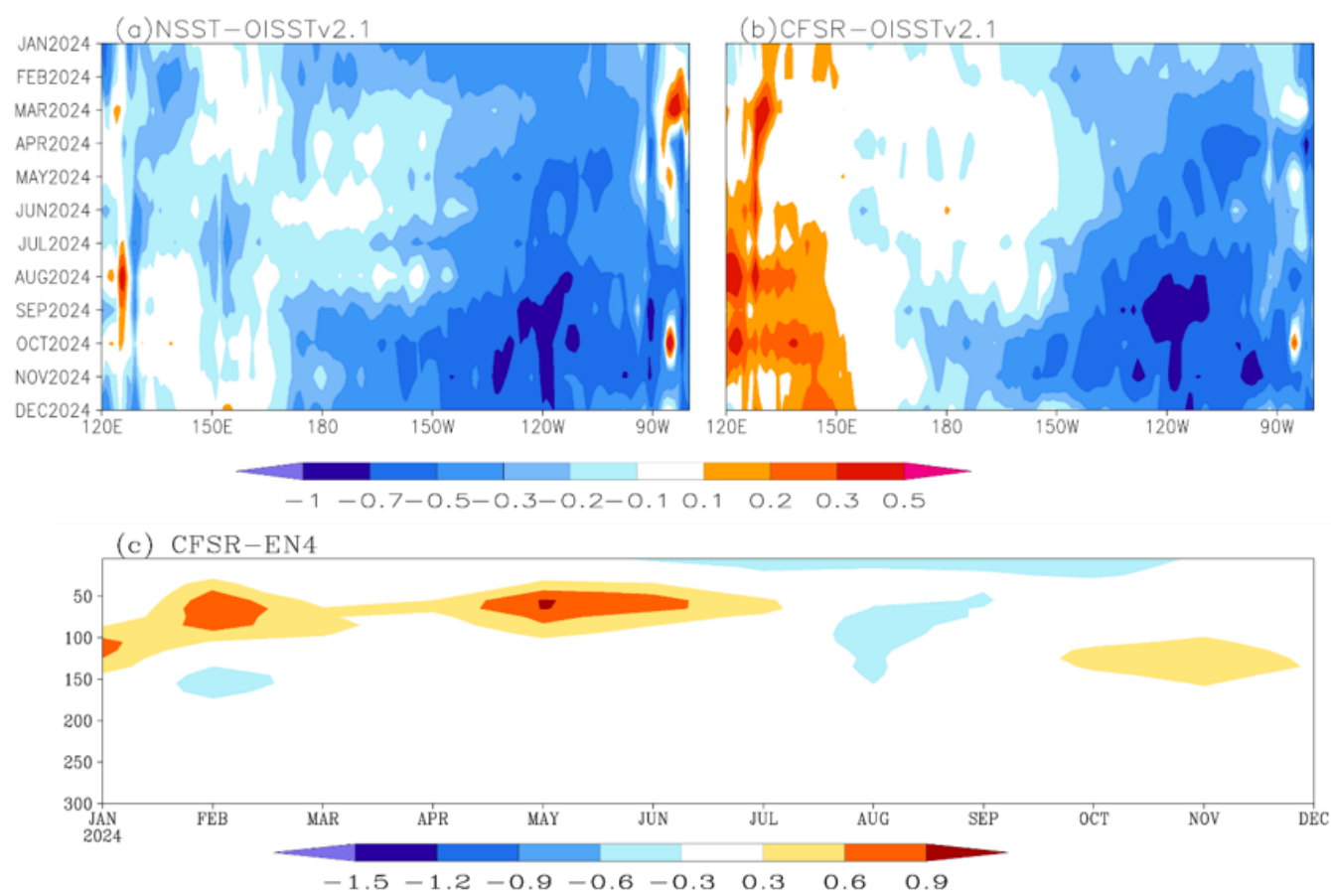


Figure 10

Hovmöller (longitude–time) diagrams along the equator (2°S–2°N): (a) SST-anomaly error of NSST relative to OISSTv2.1, (b) SST-anomaly error of CFSR relative to OISSTv2.1, and (c) subsurface (0–300 m) temperature-anomaly difference between CFSR and EN4, zonally averaged over 160°–90°W. All anomalies are referenced to the 1991–2020 climatology, and units are °C.

Supplementary Files

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