

Extending the limits of online state-independent bias corrections in climate models

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Key points

- A previous empirical climatological correction method is modified to more effectively reduce mean state bias
- Bias in corrected variables (winds and specific humidity) are reduced by 50-80 percent in an online correction experiment
- Precipitation is not degraded by the mean state correction and blocking frequency bias is reduced in the Northern Hemisphere

Abstract

At seasonal-to-subseasonal timescales, forecasts are less strongly tied to their initial conditions, resulting in “climate drift,” where models drift towards their preferred mean state. This mean state is often biased from the observed atmosphere due to pervasive challenges of numerical modeling, including coarse model resolution and imperfect representations of physics. In theory, systematic model biases can be estimated empirically and corrected using an additional tendency term. A recent study (Scinocca & Kharin, 2024) was able to largely reduce mean state bias in a climate model using a nudging that relaxed the model climatology towards a target climatology. Here we detail a new variant of climatological nudging that pushes the corrected model closer to the target using an integrated mean bias, which additionally reduces the sensitivity of results to the nudging timescale. In a freely-running simulation with the empirically-derived correction applied, mean state bias is reduced by 50-80% for the forced variables (wind and moisture), reducing bias beyond previous methods. In addition, we examine downstream impacts on unforced variables and find marginal improvements in precipitation patterns and surface fluxes. To our knowledge, this is the largest reported state-independent correction that does not degrade downstream diagnostics like precipitation. An example of an improved subseasonal process due to the correction is shown via an analysis of blocking frequency biases in the Northern Hemisphere. Comparing results from this method to previous results additionally provides insight into which nudging parameter choices may be model independent, and which vary with model formulation.

Plain Language Summary

Climate models are useful for simulating and learning about processes in our atmosphere that affect weather and climate. The Earth system is very complex, however, and depends on important processes that occur on length scales that are smaller than global models are able to represent. This results in models that are biased from what we observe, and some of these biases are systematic, meaning they tend to occur with a consistent pattern and magnitude. It is possible to estimate the systematic biases from the model’s difference from observations and apply that difference as a correction term while the model is running. We build on previous model correction procedures to more strongly reduce bias and end up with a reduction in model bias by 50-80%. Other aspects of the model that are not corrected directly are mostly unchanged, with some small improvements in spatial precipitation pattern. The corrected model has many potential

uses, including investigating where model biases come from, looking for processes that are correct for the wrong reasons, and improving forecast skill.

1 Introduction

Improving the accuracy of subseasonal-to-seasonal (S2S) weather forecasts with forecast horizons of weeks to months is of great relevance to society. Longer skillful forecasts can help farmers plan for anomalous temperatures and precipitation events during the growing and harvest seasons, governments prepare for natural disasters, and water managers plan around projected drought or flood conditions. S2S forecasts are particularly difficult, as they lie in the gap between skillful short-term deterministic forecasts and seasonal forecasts that can rely on ocean conditions and statistical models (Vitart & Robertson, 2018). The S2S forecast horizon has been identified as a promising opportunity for research development due to the large gap between current forecast skill and potential unrealized skill, which could bring large societal benefit (Brunet et al., 2015; White et al., 2022).

No forecast model perfectly represents the observed climate; imperfections in physics parameterizations and numerical errors from finite resolution lead to systematic biases in the simulation of the Earth system. As the forecast horizon extends into subseasonal timescales or longer, systematic mean biases result in model drift as the model strays away from the observed initial condition towards its preferred biased state. Drifts of the background state affect the simulated timing, location, and development of weather systems. In the extratropics, for example, the background state influences the amplitude and phase of Rossby waves (Hoskins & Karoly, 1981; Sardeshmukh & Hoskins, 1988). A biased Rossby wave setup has been shown to negatively impact simulation of blocking events (Kleiner et al., 2021) and teleconnections from the tropical Pacific (Henderson et al., 2017; Tseng et al., 2020; Wang et al., 2020), among other phenomena.

Systematic model biases are unavoidable for global models due to difficulty in simulating subgrid processes. Improving physics parameterizations can reduce model bias, but require a lengthy retuning process and occasionally result in trade-off scenarios, where fixing a bias in one region degrades a process in a different area (Kim et al., 2011). Instead, a quicker fix can be to estimate the model bias empirically; for systematic biases

due to coarse topography or missing physics, there may be a pattern to the errors that can be estimated and then removed.

Such empirical corrections are typically performed by estimating the model’s bias from a target, and then applying that difference as a correction. Offline bias correction is routinely done as a post-processing step for operational forecasts and has been shown to improve subseasonal forecasts and regional climate change simulations through down-scaling (Mouatadid et al., 2023; S. Zhang et al., 2024). This is a useful, relatively cheap strategy, but does not require physical consistency between the post-processed output variables (Maraun et al., 2017). In addition, for longer timescales, the original simulation may miss some processes entirely due to the biased mean state, making it difficult to correct during post-processing.

Online bias correction (also called runtime bias correction) is more physically consistent, as the correction tendencies are applied during model simulation, allowing the model physics and dynamics components to feed back on the corrections each time step. Online bias correction has been explored in various forms for decades (Leith, 1978; Del-Sole & Hou, 1999; Guldberg et al., 2005; Kleiner et al., 2021), and recently there have been multiple comprehensive studies that thoroughly examine the impact of bias correction methods and parameter choices on bias reduction and subseasonal processes (Chapman & Berner, 2024; Scinocca & Kharin, 2024; Krinner et al., 2026; Champouillon et al., 2026). These papers all found improvements in mean state bias after empirical correction, and some found improvements in variability, subseasonal processes, or subseasonal forecast skill.

Here we focus on correcting the state-independent (climatological) component of systematic model bias online. Recent work has used similar ideas to correct the state-dependent component by training a machine learning model to predict the correction increment based on current model state (Watt-Meyer et al., 2021; Chen et al., 2022; Chapman & Berner, 2025), and these results are quite promising. However, Chapman and Berner (2025) found that their overall correction was improved after calculating the state-independent component separately, so the machine learning model only had to predict the state-dependent bias. Thus, it is a worthy goal to reduce model bias as much as possible using a state-independent correction so that subsequent state-dependent corrections can be the most successful.

Previous state-independent correction studies find a range of total bias reduction, with the most successful methods able to reduce total RMSE by up to 60% for reported variables (Scinocca & Kharin, 2024; Krinner et al., 2026). This raises a question of whether this is a natural limit or whether bias could be further reduced. Using the Lorenz 63 model, it can be shown that an empirical state-independent correction may not be able to correct biases in the mean state for some systems (see Appendix A). How much of the systematic biases exhibited by climate models is empirically correctable is unknown. An aspect of this study is to quantify the amount of bias that can be corrected with a state-independent corrector using a correction designed to minimize climatological bias.

In this study, we propose an extension to previous correction approaches that reduces model bias beyond previous methods. We examine its impacts on downstream variables, determining that the main processes in the model are not strongly degraded (and often also improved) by the corrected mean state. We then provide an example of how the bias-corrected model could be useful for investigating subseasonal processes via blocking in the Northern Hemisphere. Since previous studies find that results vary depending on which model is used, which variables are corrected, and which correction parameters are chosen, we additionally attempt to synthesize previous methods to reveal what modeling choices seem to be universally important, and which choices seem to be sensitive to exact implementation.

1.1 Empirical correction

Most empirical correction methods are derived from the assumption that by correcting short-term model errors, the long-term climate drift will also be reduced. Methods vary in how they derive the empirical correction tendencies, but most use a two-step strategy to first generate a set of state-independent tendencies (*tendency generation step*) and then apply those tendencies as a state-independent forcing in a freely-running simulation (*correction step*). The tendencies are applied as an additional physics tendency, such that the model’s physics and dynamics will adjust and respond to the additional forcing. It is important to note that empirical corrections are usually not designed to conserve mass or moisture since the tendencies are purely derived from the difference between the model and observed target state.

Empirical corrections tend to use a form of data assimilation, including nudging, to generate the correction tendencies; in these methods, the model is forced to closely track the target dataset such that the forcing at each time step can be assumed to be due to model errors from that time step and not confounded by accumulated errors from model drift. From a long running simulation, the short-term forcings can then be collected and combined into a climatology of correction tendencies.

1.2 Instantaneous nudging

Nudging is essentially a Newtonian relaxation towards a target state and has been used for decades for a variety of purposes, including simple data assimilation, testing the sensitivity of physics parameterizations, and constraining large-scale dynamics in tracer experiments (Ramamurthy & Carr, 1987; Jeuken et al., 1996; K. Zhang et al., 2014). We define nudging as a relaxation towards a target with a timescale τ :

$$\frac{\Psi^{i+1} - \Psi^i}{\Delta t} = N(\Psi^{i+1}) - \frac{1}{\tau} (\Psi^{i+1} - \Psi_{ref}^{i+1}) \quad (1)$$

where Ψ is the model state, the increment i indicates the model time step, $N(\Psi)$ includes all the dynamics and physics tendencies from the control model, Ψ_{ref} is the nudging target, and τ is a parameter that sets the nudging timescale. The second term on the right represents the nudging tendencies which are archived every nudging update step; Chapman and Berner (2024) used 6 hours as a nudging update frequency as it could reasonably capture the diurnal cycle within the constraints of target reanalysis availability, and this tends to be a typical choice.

We define instantaneous nudging as using an instantaneous value for the nudging target Ψ_{ref}^i and current model state Ψ^i . In empirical correction methods using instantaneous nudging, the nudging tendencies from each update step are averaged to create a climatology, respecting day of year and time of day, and then smoothed to reduce higher frequency sampling noise. The climatological tendencies are then applied as a state-independent forcing during the freely-running correction step as:

$$\frac{\Psi^{i+1} - \Psi^i}{\Delta t} = N(\Psi^{i+1}) - \frac{1}{\tau} \left(\overline{\Psi^{i+1} - \Psi_{ref}^{i+1}}^C \right) \quad (2)$$

where $\overline{\Psi}^C$ signifies a climatological average with a seasonal smoothing, respecting the time of day.

By applying a climatological average of 9 years of instantaneous nudging tendencies as state-independent correctors, Chapman and Berner (2024) were able to reduce model bias in state variables and downstream diagnostic variables by 30-50%. They also tested a more complex data-assimilation strategy (an ensemble adjustment Kalman filter) to generate their correction tendencies and found that the simpler nudging was just as or more effective for most metrics. In a similar procedure, Chang et al. (2019) used the Incremental Analysis Update data assimilation procedure (Bloom et al., 1996) as the basis for their climatological correction tendencies, with similar reduction in climatological bias in the GEOS model.

Since the nudging is modulated by a relaxation timescale τ (typically 6 hours in these studies), the correction tendencies will not be able to completely push the model towards the target, suggesting that some state-independent bias remains after the nudging. In addition, with only 30-40 years of nudging tendencies possible due to the observational record, the climatological tendencies themselves could be conflated with noise from interannual variability; any noise included in the tendencies themselves could reduce actual correction skill when applied over a longer period.

Krinner et al. (2026) attempted to improve bias beyond the relaxation timescale by repeating the nudging procedure across multiple iterations. They applied the correction tendencies from one nudging run as a state-independent forcing in a second nudging run, so that the total correction tendencies would sum to a more optimal set of correction tendencies. Two iterations improved their bias reduction, but they found signs of overcorrection after three iterations. The fact that two iterations could improve bias implies that some state-independent bias remains after an instantaneous nudging procedure.

1.3 Climatological nudging

In addition to capturing noise from interannual variability, it is not guaranteed that the average of instantaneous tendencies derived from short-term drift will be the same as the tendencies best suited to correct climatological drift. Scinocca and Kharin (2024) (hereafter SK24) revised the nudging method to instead force the model climatology towards a target climatology. Their method, dubbed “Climatological Adaptive Bias Correction of Climate Models” (CABCOR), uses a long-running nudging simulation to con-

continuously update the model climatology. This method has the benefit of no longer assuming that near instantaneous model errors represent long-term model drift; the nudging itself is designed to eventually converge towards tendencies that correct biases on the climatological timescale. The converged nudging tendencies can then be applied as a state-independent forcing that (if actually converged) should match the behavior during the nudging step. SK24 showed that the CABCOR method largely improved bias compared to the instantaneous nudging strategy, even when the instantaneous nudging parameters were manually optimized to result in the lowest bias.

An issue with all forms of nudging is that results can be sensitive to several parameter choices that are not obvious and often arbitrarily chosen. Importantly, results are highly sensitive to the nudging timescale τ ; one might wish to force the model as closely as possible to the target with a short nudging timescale, but these strong nudging tendencies can oppose the dynamical tendencies in undesired ways (Kruse et al., 2022). SK24 found a strong dependence on nudging timescale, where a decrease in nudging timescale resulted in reduced bias during the tendency generation step. However, once applied during the correction step, the resulting bias for the strongest nudging timescales was found to be larger than correcting with a weaker τ . Only after allowing the tendencies to converge for 500 years were the correction biases with a 12-hour nudging timescale similar to those with a 24-hour timescale, and still larger than biases during the tendency generation step.

As with the instantaneous nudging approach, the climatological nudging is modulated by the nudging timescale chosen, which means the nudging timescale of 24 hours used in SK24 would still allow model drift within the relatively weak relaxation timescale. The optimal choice of nudging timescale may be dependent on model, variable, and vertical level (S. Zhang et al., 2026). Champouillon et al. (2026) suggested that the optimal implementation may vary for each region or process one is interested in, yet choosing optimal parameters is a computationally expensive procedure. Ideally one could find a way to reduce the dependence on this parameter choice.

The empirical correction method defined here builds on the climatological correction described in SK24, but modifies the implementation to reduce the importance of the nudging timescale by altering how the correction tendencies are updated. The new update method is designed to continue updating the correction tendencies until there

is zero mean climatological bias. We find that the nudging timescale in this method instead determines the time to convergence, allowing us to choose parameters that reach tendency convergence more efficiently. Section 2 describes the implementation used in this study. Section 3 presents the impact of the correction on mean state bias, diagnostics, and variability, using blocking frequency bias as an example of an improved sub-seasonal processes. A discussion of the method and insights into empirical bias correction in general concludes the paper.

2 Methods

We first describe the model, data, and analysis techniques used, followed by the key modifications in our implementation beyond the climatological correction from SK24. Implementation details that were determined to not significantly affect results are described in the appendix for completeness.

2.1 Model and Data

The simulations diagnosed here use the Finite Volume Community Atmosphere Model version 6 (CAM6-FV) of the Community Earth System Model (CESM) version 2.1.5 (Danabasoglu et al., 2020). CAM6 is run at approximately 2x1.5 degree resolution with 26 vertical levels on a hybrid sigma-pressure coordinate and with a 30-minute timestep. The climatological nudging strategy can be used with analogous namelist parameter options to the standard nudging toolbox in CAM (https://ncar.github.io/CAM/cam6.3-users-guide/users_guide/index.html), and can be run out of the box from the CAM fork at https://github.com/sweidy/CAM/releases/tag/climo_nudge_v1.0. Examples of namelist and compset configurations used for this study are listed in Weidman (2026), but the method is expected to be independent of resolution and compset.

SK24 use climatology SSTs and forcings throughout the tendency generation step. We instead use prescribed SSTs, ice, and forcings from 1980-2010 in a cyclical way. Every 30 years, the model restarts at 1980 with initialization files from the previous year of simulation (2010) and continues until 2010 again. Performing the nudging with climatological SSTs gives similar results, so in the future, this may be preferable due to ease of implementation.

The target dataset used in this manuscript is MERRA2 (Gelaro et al., 2017). MERRA2 is regridded to the CAM6 grid using the regridding reanalysis software from MUSICA-Tools (<https://github.com/NCAR/IPT>), which adjusts the regridded reanalysis to align with CAM6-specific topography; this alignment was deemed critical for obtaining reasonable convective behavior over steep orography. The target climatology is the MERRA2 climatology from 1980-2010 with 6-hourly frequency. The MERRA2 climatology was additionally smoothed with a 31-day rolling mean to isolate the seasonal cycle. Methods were also tested using ERA5 (Hersbach et al., 2020) as the target dataset with broadly similar behavior. Thus, we expect the method to be independent of target.

Bias calculations are performed by comparing model output to MERRA2 for most variables; precipitation biases are additionally compared to the Global Precipitation Climatology Project monthly dataset (Adler et al., 2003), since using different precipitation datasets can dramatically change results (Chapman & Berner, 2024; Sun et al., 2019). Top-of-atmosphere fluxes and total cloud fraction are compared to the CERES EBAF-TOA Ed4.2.1 climatological values (Loeb et al., 2018, 2024). Unless otherwise noted, mean model biases are calculated as the seasonal difference between 30-year model simulations forced with SSTs from 1980-2010 and the MERRA2 climatology.

2.2 Climatological nudging with integrated control

As in the CABCOR method, the model climatology is nudged towards the target climatology, rather than nudging to instantaneous states:

$$\frac{\Psi^{i+1} - \Psi^i}{\Delta t} = N(\Psi^{i+1}) - \frac{1}{\tau} \left(\Psi_M^{i+1} - \overline{\Psi_{ref}^{i+1}}^C \right) \quad (3)$$

where Ψ is the model state, Ψ_{ref} is the target state, and the overbar represents a climatological mean. The model climatology Ψ_M is updated continuously during the tendency generation step as the model adjusts to the nudging. To reach an initial tendency convergence, we start with the CABCOR update method. For the model's current day and time of year, the model climatology used by the nudging is updated as:

$$\Psi_M^{i+1} = (1 - \rho)\Psi_M^i + \rho\Psi_I^{i+1} \quad (4)$$

where Ψ_M is the stored model running mean, Ψ_I is the instantaneous model state, and ρ is an update weight that can be tuned to incorporate the climatological timescales of interest, but is not critical to results (see Appendix B). Essentially, this strategy relaxes

the model climatology towards the target climatology with nudging timescale τ . The model state is only nudged for horizontal winds U and V and specific humidity Q ; this choice is discussed further in Section 3.4.

To reduce the dependence on τ and further reduce mean bias, we implement an integrated control on the nudging tendencies convergence. Once the model climatology has approximately stabilized, the nudging tendency switches to being updated with an integrated mean bias. This modifies Equation 4 to:

$$\Psi_M^{i+1} = \Psi_M^i + \rho \left(\Psi_I^{i+1} - \overline{\Psi_{ref}^{i+1}}^C \right) \quad (5)$$

The effect of this new update scheme is to reduce the dependence on nudging timescale: as long as there is a nonzero model bias, the nudging tendency should continue change. In a sense, the integrated control is a similar idea to using the sum of multiple nudging iterations as in Krinner et al. (2026). However, the integrated control is designed to update continuously throughout the tendency generation step, rather than through a discontinuous manual update for each iteration.

We perform the nudging up to 300 years, after which the integrated mean bias has approximately converged for the nudging timescales chosen. Sensitivity to convergence time is described in Section 3.2. There are still small year-to-year fluctuations in the tendencies due to changing historical SSTs and forcings. We reduce the impact of these fluctuations by taking an average over 30 years of nudging, respecting time of day, before applying the tendencies as a state-independent correction. By construction, the correction tendencies are already smoothed across the seasonal cycle (see Appendix B). There is one correction scalar for each 6-hour period, day of year, state variable, and grid point. We apply the correction field as a tendency through its corresponding 6-hour period such that the tendency is applied at the same strength as in the tendency generation step.

3 Results

One goal of modifying the climatological correction procedure from SK24 by adding the integrated control is to determine how strongly a state-independent correction can reduce mean bias. First, we examine how the integrated control impacts mean bias compared to previous methods, then determine the broad sensitivity of parameter choices on total bias reduction. The parameters that most effectively reduce mean bias are then

used in separate correction experiment to investigate how the correction impacts model behavior.

3.1 Comparing correction methods

We quantify the amount of bias reduction at each vertical level with a global metric by looking at the RMSE in the corrected model, normalized by the control RMSE, as in Kleiner et al. (2021):

$$\text{Average Normalized Error} = \frac{\langle (\bar{X}_{corr} - \bar{X}_{obs})^2 \rangle^{1/2}}{\langle (\bar{X}_{cont} - \bar{X}_{obs})^2 \rangle^{1/2}} \quad (6)$$

where X_{corr} is a variable X at a single vertical level in the corrected run, X_{cont} is from the control run, and X_{obs} is from the observations, with the overbar signifying the seasonal mean. The angle brackets signify an area-weighted horizontal average. An average normalized error of 1 would mean no change in RMSE, while values closer to 0 have a larger reduction in RMSE, compared to the control. A bootstrap procedure with $n = 500$ is performed to determine uncertainty of the average normalized error; for each bootstrap, a sample climatology from 30 randomly selected years with replacement is calculated for the control, corrected, and target datasets, with average normalized error calculated from the sample climatologies.

Figure 1 shows the DJF average normalized error for U,V,Q and T; a similar plot for JJA is shown in Figure S1, with similar behavior. Shading encloses the 5-95th percentiles of average normalized error from the bootstrap. The climatological nudging with the integrated control is shown in blue. For the corrected variables (U,V and Q), RMSE is reduced by 50-80%. Moisture is the most improved, followed by zonal wind and then meridional wind. Most of the improvement is in the mid- to upper-troposphere, with less improvement near the surface and in the stratosphere. Although temperature is not directly corrected, its RMSE is also moderately reduced at most levels except for near 800 hPa. Krinner et al. (2026) found a similar slight degradation in T around 850 hPa in their correction runs when they only corrected U and V wind.

Figure 1 also shows the average normalized error of the instantaneous nudging described in Chapman and Berner (2024) and the CABCOR method from SK24. All methods here use a nudging timescale of 1 day; for the instantaneous nudging, Chapman and Berner (2024) reported the largest correction using a 6-hourly timescale, but we found reduced bias with $\tau = 1$ day, which is plotted here for consistency between methods.

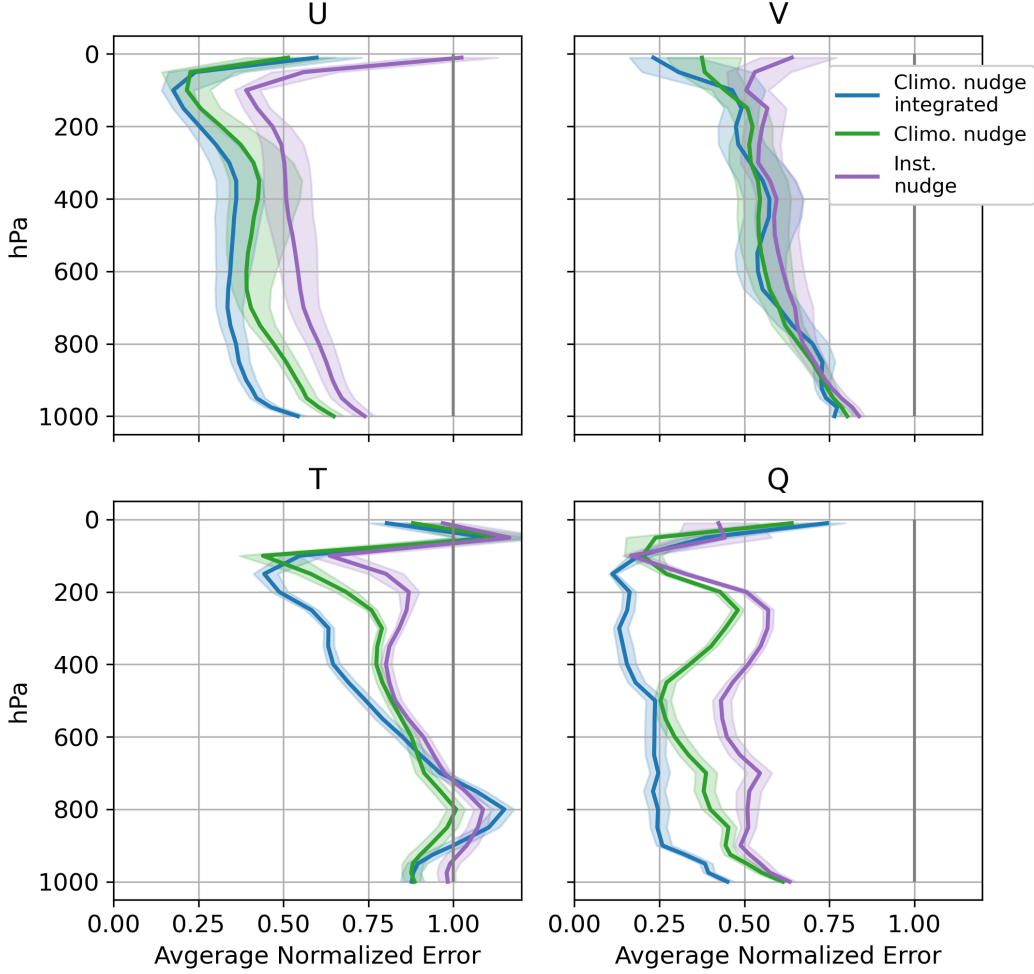


Figure 1. 30-year DJF global RMSE in the corrected model normalized by the control RMSE, plotted for each vertical level and state variable. The blue line is the climatological nudging method with an integrated control, the green line is the CABCOR correction as in Scinocca and Kharin (2024), and the purple line is corrected by the instantaneous nudging method as in Chapman and Berner (2024). All methods use $\tau = 24$ hours. Shading indicates the 5th and 95th percentiles from bootstrapping with $n = 500$.

The CABCOR method uses identical parameter choices to the correction plotted in blue, but without the integrated control.

Both climatological nudging methods reduce bias more than the instantaneous nudging procedure, but the addition of the integrated control further reduces bias for U and Q beyond the CABCOR approach. This improvement is most significant in moisture and at lower levels. Meridional wind bias is reduced by a similar amount for all three methods.

3.2 Dependence on τ and convergence length

Both the CABCOR and integrated control methods in Figure 1 use a convergence length of 240 years, but for the CABCOR method, total bias is essentially unchanged if the tendencies are applied as a correction after 180, 210, or 240 years (see Figure S3). This suggests that the tendencies have converged and will not improve, even with longer time to convergence. The integrated control is able to correct systematic bias that is not correctable by converged tendencies from the CABCOR method. The question still remains whether these parameter choices are the best we can do.

Figure 2 shows the bias reduction dependence on τ and length of convergence of the tendency generation step. For the weakest τ , an increase in convergence time reduces bias as the tendencies continue to converge towards optimal values. This is most evident for Q in DJF, and for both U and Q in JJA (see Figure S2). Additionally, stronger τ reduces bias. For $\tau = 6$ hours, the bias is already very low after the shortest convergence times, and does not largely improve beyond 180 years of convergence. The trend of reduced bias with shorter τ or increased convergence length is not exactly monotonic, especially for V, but this nonmonotonicity is found in regions with higher uncertainty from the bootstrap estimates in Figure 1.

These findings differ from SK24, which found longest time to convergence for the strongest τ thus chose to use $\tau = 24$ hours. Other studies also determined $\tau = 24$ hours to be an optimal parameter choice (Krinner et al., 2026; Champouillon et al., 2026). However, the key difference between our method and SK24 is the addition of the integrated control. In this case, τ is not exactly the same as a relaxation timescale, and instead adjusts how quickly the integrated mean bias accumulates, since, regardless of nudging timescale, the mean bias will continue to change as long as there is nonzero bias. From Equation

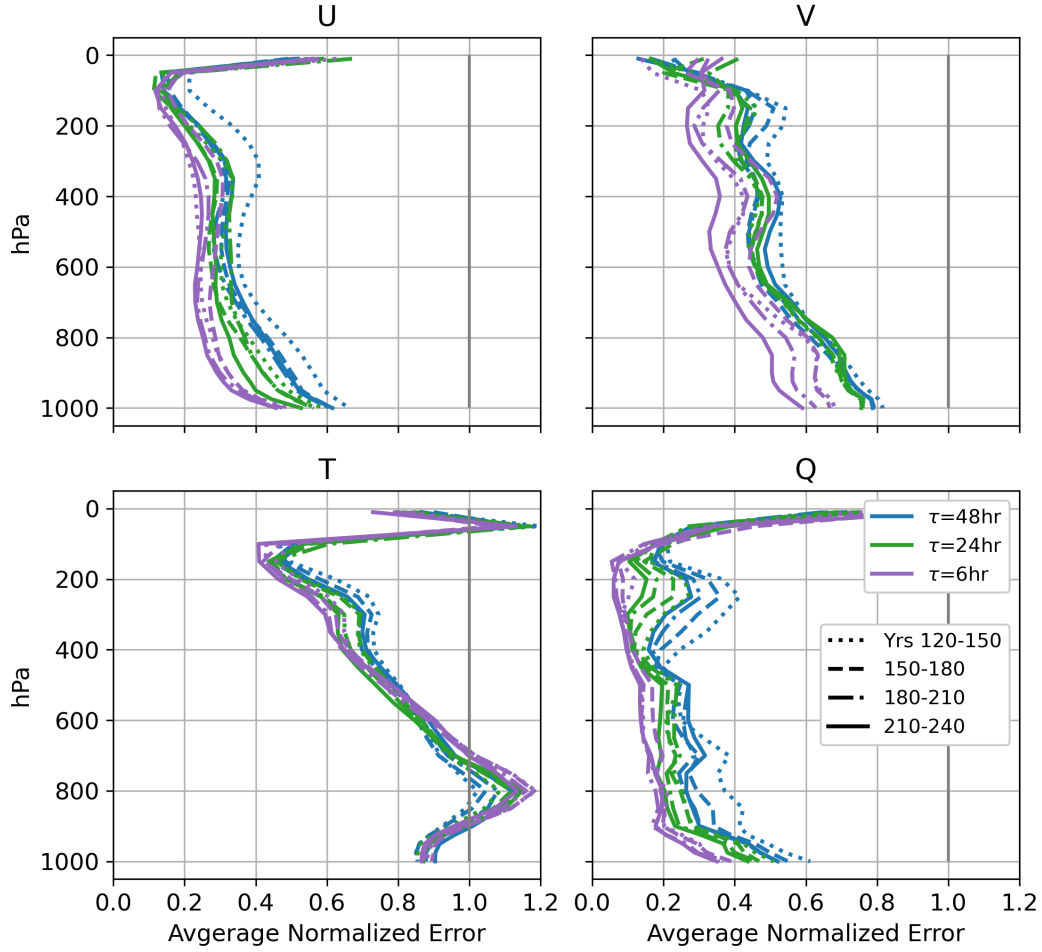


Figure 2. 30-year DJF average normalized error of the corrected model as in Figure 1 but comparing different nudging timescales τ (colors) and length of convergence (line styles) when using the integrated control.

3, it can be seen that if the model climatology difference is able to continue adjusting (growing) as long as there is nonzero bias, the numerator will grow compared to constant τ , reducing dependence on nudging timescale. Thus, when using the integrated control, τ simply adjusts how quickly the climatological nudging takes to converge.

We demonstrate the tendency convergence time with τ in Figure 3 by projecting the correction tendencies for each τ onto the primary empirical orthogonal function (EOF) of DJF tendencies, calculated from the $\tau = 6$ tendencies. Details of the EOF calculation are described in Appendix C. EOF1 explains over 90% of the variance in tendencies. The amplitude of the principal component (PC) for the $\tau = 6$ case grows with convergence length before leveling off around year 300, implying that even though the average normalized error is similar after year 180, the tendencies continue to adjust to correct lingering biases. The convergence length varies across variables and across levels (not shown), but approximate convergence by year 300 for $\tau = 6$ hours is fairly representative.

The pseudo PCs of the tendencies for shorter τ , projected onto the primary EOF from $\tau = 6$, have not yet converged by year 300 (except for Q for $\tau = 12$), but instead grow in amplitude towards the converged values from $\tau = 6$. We expect the rate of PC amplitude growth to be inversely proportional to τ ; this is approximately true for V, where the slope of PC amplitude for $\tau = 12$ is approximately double that for $\tau = 24$, and so on. This proportionality is not as clean for U and Q, but the rates of convergence still decrease for larger τ . The PC for the CABCOR method does not change with increased convergence length, confirming that the tendencies have already converged.

If the tendencies with different τ are converging on the same correction fields but with different times to convergence, then from a computational efficiency standpoint, it seems ideal to use the strongest τ because it requires the shortest time to convergence. With the goal of reducing the state-independent bias as strongly as possible, we conclude that the tendencies from the $\tau = 6$ case have converged to their optimal values around year 300, and use the tendencies averaged from years 270-300 as state-independent correctors in the following experiments. Results are similar when applying tendencies that have converged for 240 or 270 years. Horizontal maps of the full converged tendency fields are shown in Figures S4 and S5.

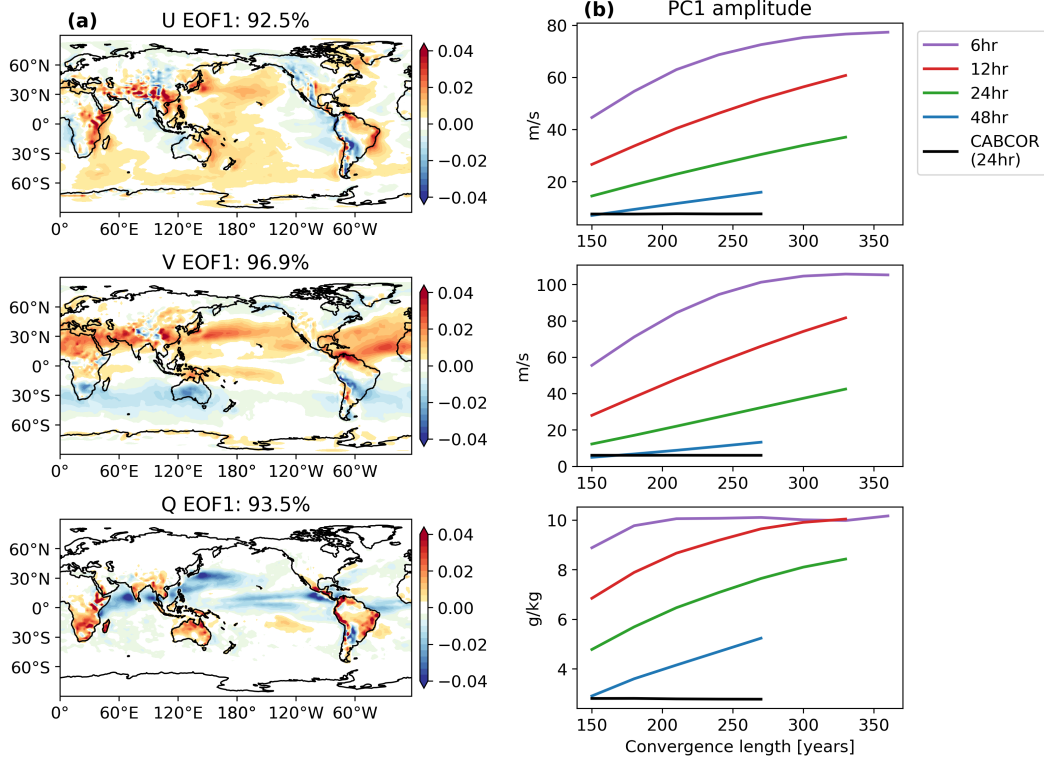


Figure 3. (a) EOF1 of the DJF mean correction tendency for U, V, and Q at model level 21 (near 700 hPa) for the $\tau = 6$ hour case. Percent explained variance by the EOF is displayed in the title. (b) Projection of the tendencies onto the EOF shown in the left column at each convergence time for cases with differing τ .

3.3 Reduction in mean bias for $\tau = 6$

The 30-year DJF zonal mean bias of zonal wind, meridional wind, specific humidity, and temperature in the control simulation, years 270-300 of the tendency generation step for $\tau = 6$ hours, and the corrected simulation, are shown in Figure 4. A similar plot for JJA is shown in Figure S6. The bias from the tendency generation step is slightly lower than the freely-running corrected experiments, especially for U in the tropical stratosphere. This implies the correction tendencies are not completely converged in the stratosphere, where we expect the longest time to convergence due to its long adjustment timescale. Hitchcock and Haynes (2016) found that nudging the stratospheric dynamics had minimal influence on the troposphere, so it is plausible that remaining bias in the stratosphere will not impede most processes we are interested in.

There is a demonstrable decrease in model bias between the corrected run and the control. In the control, the jet is too far poleward, and the corrected run largely eliminates this bias in both seasons. The control run has a strong moisture deficit throughout the tropics with some excess moisture in the subtropics. The correction largely eliminates these biases. The meridional wind bias is larger in the extratropics in the corrected run, but this turns out to be due to canceling biases in the horizontal in the control simulation (see Figure 5). We do not directly correct temperature, but the wind and moisture corrections result in an indirect reduction in temperature biases, especially at the upper levels. As evident from the average normalized error plots, the temperature bias slightly increases near 800 hPa, but the overall temperature pattern is more realistic.

Horizontal maps of mean biases of the control and corrected runs are shown in Figures 5 and S7 for DJF and JJA, respectively, with additional levels in Figures S8 and S9. Again, it is clear that the subtropical jet biases are largely reduced, as the correction shifts the jet equatorward to match the observed jet in both seasons, and tropical zonal wind biases are also reduced. The horizontal cross section demonstrates that the magnitude of meridional wind biases are larger in the control, though they cancel out in the zonal mean. The control model has a dry bias across the tropics, with some regions of elevated moisture in the subtropics, but the correction removes these biases. Visually, the correction does a remarkable job at reducing seasonal biases, as it is designed to do.

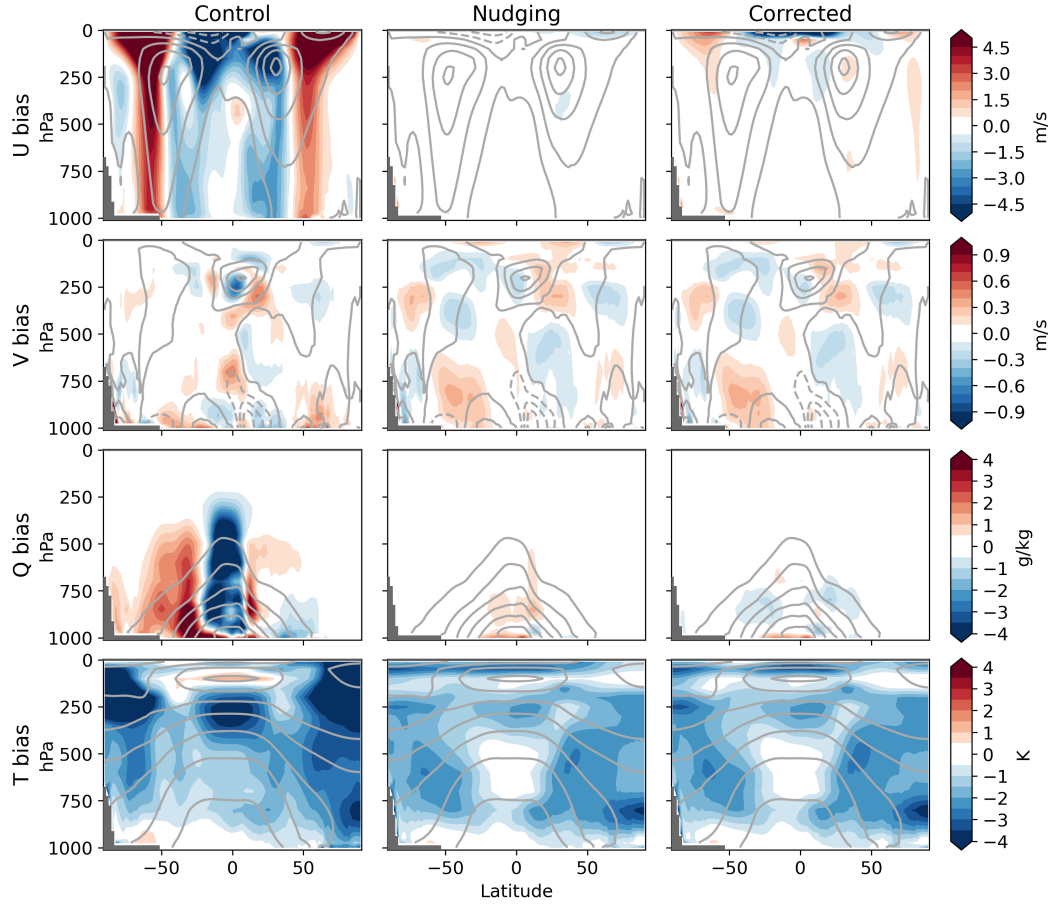


Figure 4. 30-year DJF zonal mean bias in the control model (left), years 270-300 of the tendency generation (nudging) step (center) and corrected model (right) for horizontal wind, meridional wind, specific humidity, and temperature. Grey contours are the 30-year MERRA2 climatology. Regions where the pressure level is below the model surface are masked in dark grey.

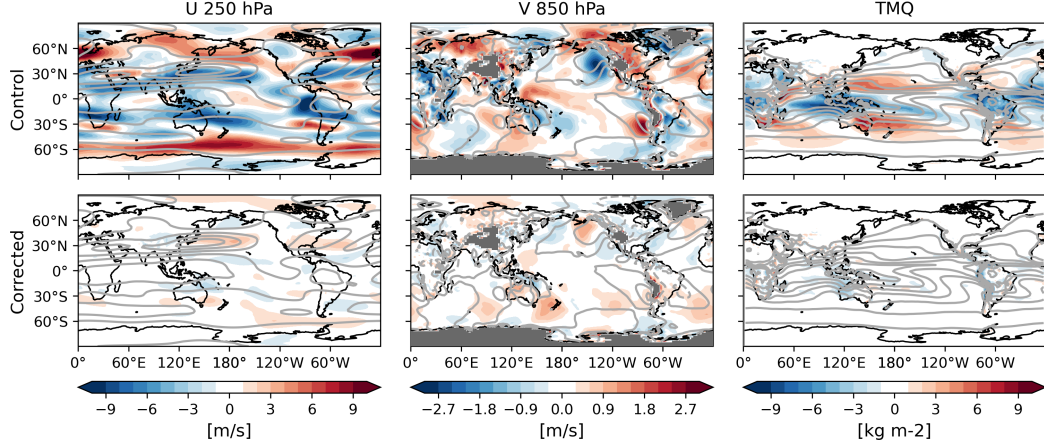


Figure 5. 30-year DJF mean of bias in the control model (top) and corrected model (bottom) for zonal wind at 250 hPa, meridional wind at 850 hPa, and integrated total column moisture. Grey contours are the 30-year MERRA2 climatology. Regions where the pressure level is below the model surface are masked in dark grey.

3.4 Diagnostic variables

The correction method is designed to reduce mean bias for the prognostic variables used in the nudging, here U,V, and Q. Ideally, the reduction in mean state bias can also reduce bias in other diagnostic variables, though this is not guaranteed. For variables that are dependent on the model's physics parameterizations (such as precipitation), the parameterizations are tuned by model development centers to best represent the observed climate, using the model's control mean state. Degradation in diagnostic behavior after mean bias correction can reveal compensating biases in the control model.

Supplementary Figures S10 and S11 show the biases of several diagnostic variables related to radiation and surface coupling in the control and corrected simulations. In general, the bias of these diagnostics does not largely change after the correction, with the exception of reduced latent heat flux bias over the ocean, potentially due to the improved moisture field, and somewhat increased total cloud fraction bias in the tropics, mostly due to an increase in high cloud fraction. The minor changes in bias of diagnostics is encouraging that the model remains healthy and can simulate a reasonable climate of these variables with the additional correction tendency applied.

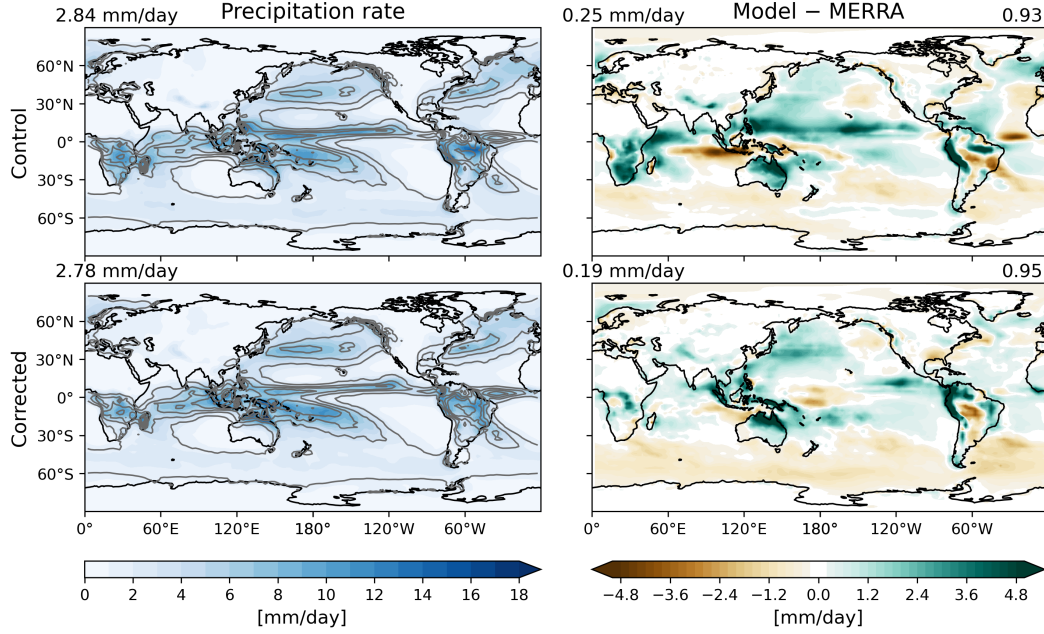


Figure 6. (left) DJF mean precipitation for the control (top) and corrected (bottom) simulation. (right) DJF precipitation bias compared to the bias-corrected MERRA2 dataset. Grey contours show the MERRA2 DJF precipitation. Spatially-averaged precipitation rate or precipitation rate bias is shown in the top left corner of each plot. Pattern correlation for each model with the MERRA2 precipitation is displayed at the top right corner of the corresponding bias map.

Figure 6 shows the DJF precipitation bias for the control and corrected model, compared to the MERRA2 bias-corrected precipitation. We do not expect a perfect representation of MERRA2 precipitation with an improved mean state since MERRA2 precipitation was diagnosed using the GEOS model with a different convection parameterization, and has additionally been post-processed to better match satellite and gauge-based observations (Reichle & Liu, 2014). Precipitation bias compared to the GPCP climatology is shown in Figure S13, but results are similar between both datasets (partially because MERRA2 precipitation uses GPCP as a target in its post-processing algorithm).

Both the control and corrected model have a positive precipitation bias, but the mean precipitation amount is decreased after the correction to bring the model closer to the target. The correction shifts the regions of strongest convection in the tropics: in the control, there is a region of positively biased precipitation in the central Pacific and

the northern branch of the ITCZ. In the corrected simulation, the southern branch of the ITCZ is slightly enhanced, though more strongly over the Maritime Continent land, partially overcorrecting for a dry bias in the control model. The correction damps extratropical precipitation, which reduces bias in the Northern Hemisphere but results in a negative precipitation bias in the Southern Hemisphere. The pattern correlation in the corrected model compared to MERRA2 is slightly higher than the control model, but improvement in pattern correlation is larger in the tropics: between 25°S and 25°N, the pattern correlation is 0.97 for the corrected run, compared to 0.90 for the control.

Although precipitation is dependent on convection scheme tuning, it still is useful to see whether the dynamical and moisture corrections have an impact on precipitation behavior. The correction does not seem to significantly degrade precipitation with our chosen parameters. However, when performing the same correction procedure but correcting temperature instead of moisture, the precipitation field becomes unrealistically low due to a strong damping of convection (see Figure S14, where correcting U,V and T decreases total precipitation by 0.5 mm/day compared to the control). The degradation of precipitation is the primary reason why we chose to only correct U, V, and Q, even though correcting temperature directly reduces overall temperature bias by 80%.

For CAM, we find that correcting temperature strongly damps precipitation. Some studies find similar issues when nudging Q, rather than T. This seems to be a model-dependent issue: models in the E3SM suite report very similar damped precipitation characteristics when they nudged Q but not T (Sun et al., 2019; S. Zhang et al., 2022, 2026). Corrections applied in the LMDZ model only force wind, reportedly due to damped precipitation, but it is unclear whether that is due to T or Q or both (Krinner et al., 2026; Champouillon et al., 2026). Other papers using the CESM suite reported similar damped precipitation when nudging T (K. Zhang et al., 2014), though Chapman and Berner (2024) found best results when only nudging winds. SK24 and previous work using the CMC suite correct all of wind, temperature, and moisture, though they do not report impacts on precipitation. Merryfield et al. (2026) also used the CMC model and found moderately damped precipitation when correcting all of U,V,T and Q, but this was in a coupled simulation, so could have different behavior than the atmosphere-only version in SK24.

We hypothesize that negative impacts on convection after empirical correction is a model-dependent issue. For CAM, nudging temperature seems to reduce overall precipitation in both the tropics and extratropics, potentially because the nudging tendencies are acting to stabilize the atmosphere to convection. Many of the above studies warn against adding strong temperature or moisture tendencies, especially at the same time, because it could create unrealistic behavior in the convection scheme. We choose to nudge moisture here because we find reduced bias in both moisture and temperature compared to only nudging winds, and the precipitation behavior is moderately improved by applying a moisture tendency. Average normalized error when only correcting winds is shown in Figure S15, demonstrating similar bias reduction for U and V but unimproved Q and T. Although the impact of the correction on precipitation is likely model-dependent, CESM2 is a widely-used model, and reduced bias in CAM can already benefit a range of studies.

3.5 Variability

3.5.1 Transients

By construction, the correction should not inherently affect variability, since it is designed to adjust the climatology by the same applied tendency for each time-of-day and day-of-year, independent of model state. The other physics and dynamical tendencies in the original model are still active, so the variability around the mean state should be similar. However, it is possible that the new mean state of the corrected model is more or less variable. Previous work have found both improvements and degradations after applying a state-independent correction, with some studies finding an increase in high frequency transients and some finding a damping (Chapman & Berner, 2024; Chang et al., 2019; Champouillon et al., 2026).

Figure 7 shows eddy kinetic energy associated with transients ($\text{EKE}, \overline{v'^2 + u'^2}$) at 250 hPa, moisture flux by the transients ($\overline{v'q'}$) at 850 hPa, and heat flux by the transients ($\overline{v'T'}$) at 850 hPa for the corrected model, the corrected model difference from MERRA2, and difference from the control, averaged over DJF. The transients are calculated as daily anomalies taken from the monthly mean climatology. Starting with the corrected difference from MERRA2, we see that transient eddies are damped in the jet region compared to the target. The difference from the control model reveals that for eddy kinetic

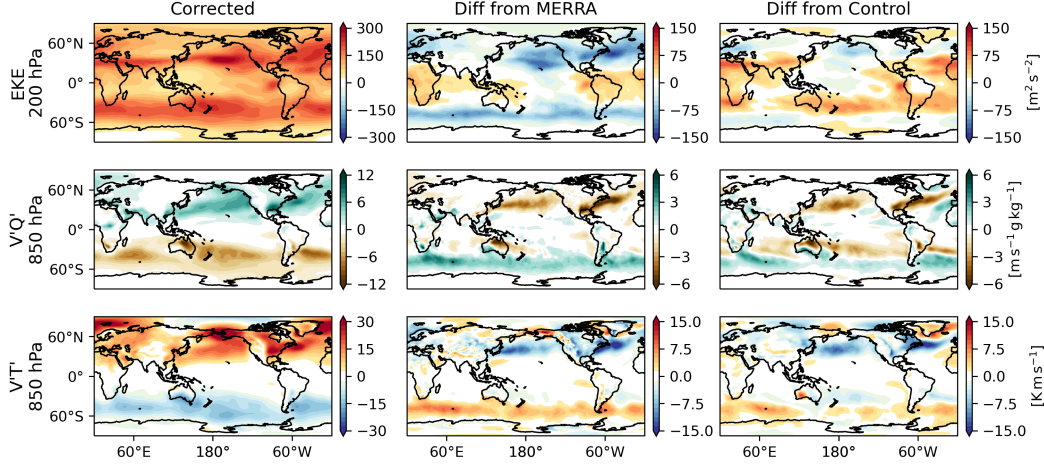


Figure 7. (left) DJF average EKE at 250 hPa, $V'Q'$ at 850 hPa, and $V'T'$ at 850 hPa for the corrected model, calculated from 1980-2010. (middle) Difference in DJF transients in the corrected model from the MERRA2. (bottom) Difference in DJF transients in the corrected model from the control simulation.

energy, EKE slightly decreases poleward of the jet, but increases equatorward, most evidently in the Southern Hemisphere. This aligns with the shifted jet in the corrected model that better tracks with the reanalysis; EKE is already biased low in the control model, but the correction shifts the location of that bias.

The biases in moisture and heat fluxes by the transients tell a different story. Here, the corrected model difference from MERRA2 looks very similar to its difference from the control, especially in the Northern Hemisphere. This implies a compensating error in the control model: moisture and heat transport look reasonable in the control simulation, but when the background fields are more realistic, the transients become biased. We hypothesize that this is due to an unrealistically strong moisture and temperature gradient in the control model compensating for a weaker eddy activity. When the moisture and temperature gradients are corrected, the weaker eddy activity bias is revealed.

3.5.2 Blocking

The primary processes that we are interested in are those at the S2S timescales. One example of an S2S process that has been shown to be dependent on background state is atmospheric blocking (Kleiner et al., 2021). The bias correction method used to di-

agnose blocking frequency in Kleiner et al. (2021) is similar to the climatological nudging described here, but required running the model in perpetual January mode. In addition, the bias correction here applies the converged nudging tendencies as a state-independent correction, reducing any potential issues with damping relevant timescales due to the nudging setup. We can now validate the results from the original study using a GCM with a full seasonal cycle.

We use the Scherrer blocking index (Scherrer et al., 2006) as in Kleiner et al. (2021); results in the original study were found to be independent of blocking index used. In short, the index finds days in which two criteria are met between 35° and 75°N. To count as a block, 500-hPa geopotential height (Z500) must be:

1. higher than geopotential height 15° to the south, and
2. more than 150 m higher than geopotential height 15° to the north.

These conditions must be met for at least 5 consecutive days.

Blocking frequency as a function of longitude for DJF in the Northern Hemisphere is plotted in Figure 8. A day is considered blocked if a block exists at any latitude within 35° - 75°N, and the fraction is computed by dividing by total number of DJF days. Figure 8 also shows the spatial pattern of blocking frequency bias compared to MERRA2. The control model exhibits a common bias amongst CMIP models in that it has fewer blocked days over the Northern Atlantic, while its blocking frequency over the Bering Strait is biased lower than the CMIP6 ensemble mean (Lohmann et al., 2024). The corrected model improves the spatial pattern of blocking frequency, increasing the number of blocked days in the Pacific sector and reducing the magnitude of the blocking frequency bias over the Atlantic. The blocking frequency dependence on longitude matches the reanalysis within the bootstrapped uncertainty for nearly all longitudes, improving frequency in regions where the control model blocking frequency is biased low. This is an improvement beyond the blocking frequency shown in Chapman and Berner (2024), which found reduced blocking frequency after the correction; for their setup, this resulted in an improved blocking frequency in the Atlantic, but no improvement in the Pacific.

Davini and D’Andrea (2016) proposed a linear decomposition of Z500 to diagnose how much bias in blocking frequency is due to systematic biases, and how much the blocking drives the systematic bias. The derivation of the decomposition can be found in Davini

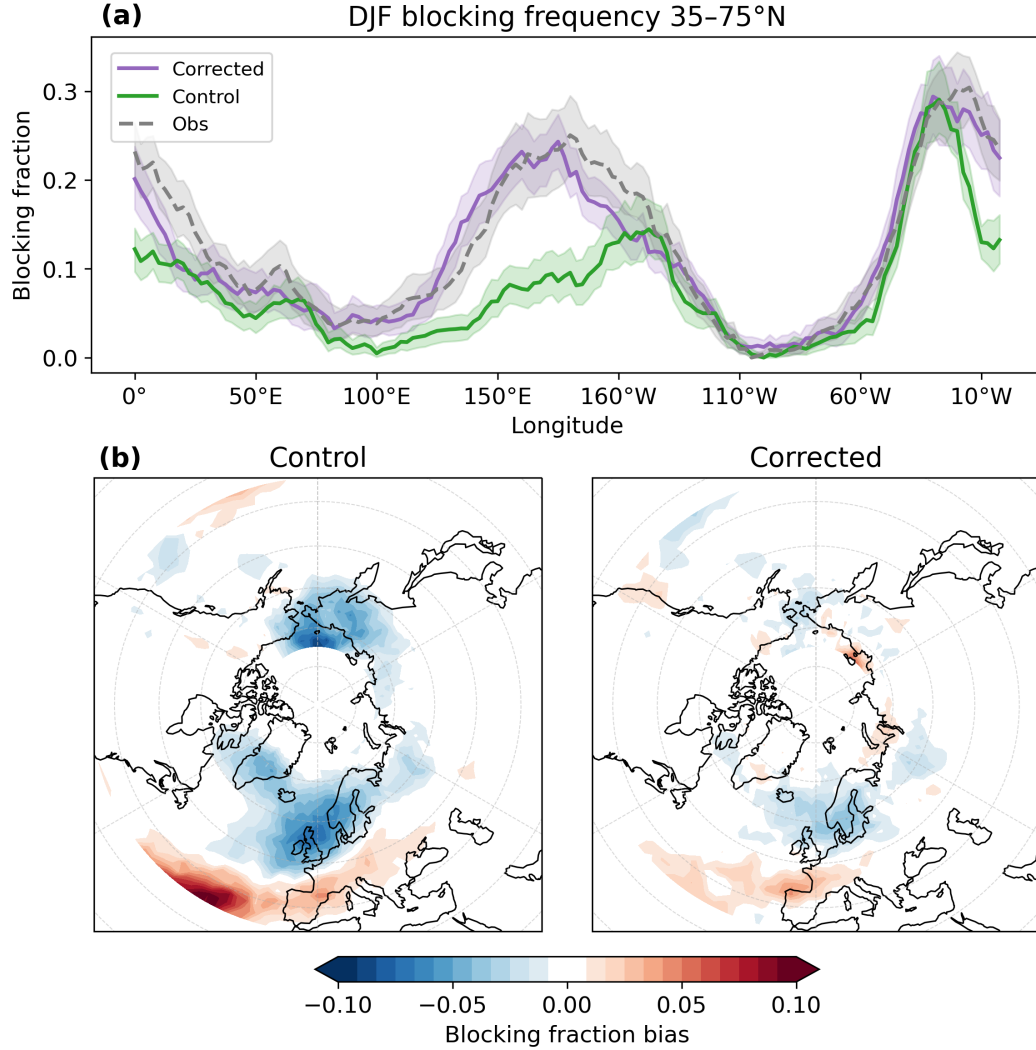


Figure 8. (a) DJF blocking frequency between 35-75°N for the control model, corrected model, and MERRA2, calculated from daily geopotential height at 500 hPa as described in the text. Shading indicates the 5th and 95th percentiles from a bootstrap with $n=500$. (b) DJF blocking frequency bias for each model compared to the reanalysis.

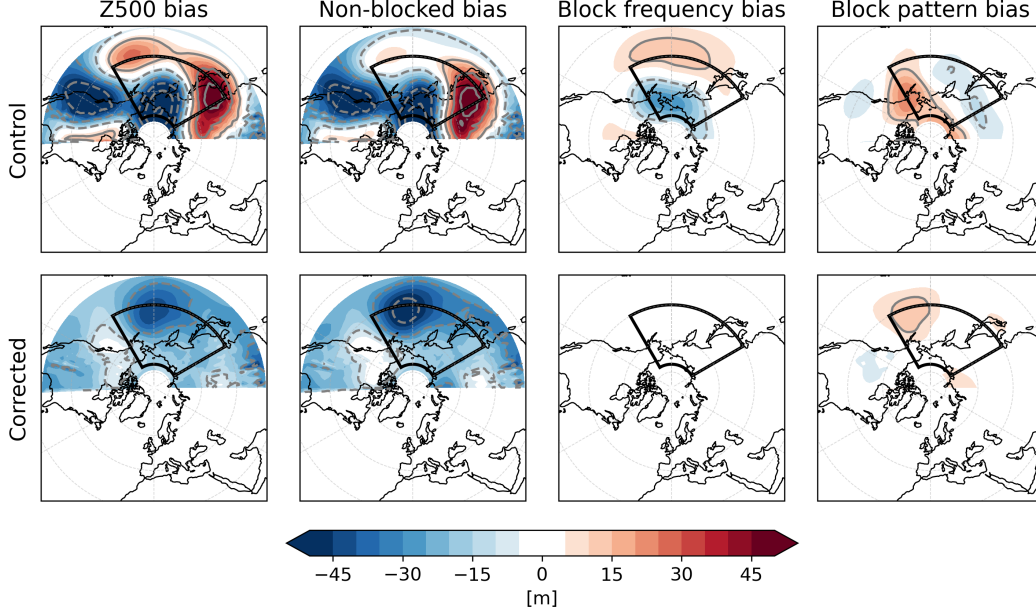


Figure 9. Decomposition of Z500 bias into blocking and non-blocking components, as described in the text, for the control model (top) and corrected model (bottom). Blocking days are defined within the black rectangle (120°- 210°E, 40°- 75°N).

and D’Andrea (2016) resulting in the following bias decomposition:

$$\begin{aligned}
 Z_m - Z_o &= (f_m - f_o)(Z_m^B - Z_m^{NB}) \\
 &+ f_o[(Z_m^B - Z_o^B) - (Z_m^{NB} - Z_o^{NB})] \\
 &+ (Z_m^{NB} - Z_o^{NB})
 \end{aligned} \tag{7}$$

where Z_m and Z_o are the model and observed Z500 climatologies, f is the blocking frequency, and Z^B and Z^{NB} refer to average Z500 during blocked and non-blocked days, respectively. The first term on the right hand side represents systematic error associated with blocking frequency bias, the second term represents bias from pattern differences during blocking events, and the final term is the Z500 bias during non-blocked days. To focus the decomposition on a region with differing blocking behavior in the control and corrected model, blocking events are calculated within a box in the Pacific region (120°- 210°E, 40°- 75°N), with bias decomposition defined by blocking days in that region only.

The bias fields of the control and corrected model for each term in Equation 7 are shown in Figure 9. For both models, the dominant source of Z500 systematic bias is from non-blocked days, with the total bias larger in the control than in the corrected model. For blocked days, the blocking frequency bias is nearly eliminated by the correction. The

blocking pattern bias is also reduced in the corrected model, but there remains some positive bias over the North Pacific Ocean, implying that the correction both increases the frequency of blocking and strengthens the Z500 anomaly during blocks. In addition, the duration of blocking events are more similar to observed in the corrected model, with an average duration of 6.8, 7.6, and 8.4 days over the Pacific blocking region for the control, corrected, and observed cases, respectively. A similar figure but for the Atlantic blocking region is shown in Figure S17, which has similar behavior.

The decomposition is purely a diagnostic of the bias defined by a specific blocking event definition, but it can reveal some interesting properties. First, most of the total climatological Z500 bias comes from non-blocked days, and the correction reduces the bias considerably. Filippucci et al. (2024) found a similar result and interpreted it to mean that the increase in blocking frequency does not strongly influence the mean field, rather the changes to the mean state from the correction are what drives the reduced blocking frequency bias. This improved blocking frequency and representation is notable since we are using a relatively coarse resolution; Davini and D’Andrea (2016) found that increasing resolution was one of the most effective (and robust) ways of improving blocking frequency representation in CMIP models, suggesting that the empirical correction may be able to compensate for systematic biases due to coarse horizontal resolution.

The exact reasons for the improvement in blocking frequency are not a focus of the study here. The goal instead is to demonstrate how an improved mean state can result in improvements in simulating an atmospheric process that is often biased in climate models. In the future, we hope to investigate other processes that depend on the background state such as the Madden-Julian Oscillation (MJO). The MJO is proposed to be sensitive to the horizontal moisture gradient (e.g. Hsu and Li (2012)), which is largely improved in our corrected model. With a corrected background state in a model with a reasonable simulation of the MJO (such as super-parameterized CAM), we can diagnose whether the representation of the MJO in the control model is due to compensating biases and evaluate the importance of the background state on process-based diagnostics; this work is ongoing.

4 Conclusions

We introduce an empirical state-independent correction based on a climatological nudging, designed to optimally reduce climatological bias while maintaining variability on timescales relevant to S2S processes. As in SK24, we find strong improvement in bias when using a climatological nudging approach, rather than an average over instantaneous nudging tendencies. Climatological nudging directly targets the climatological biases and smooths interannual noise by construction.

We build upon the approach from SK24 to further reduce bias using a correction tendency update scheme that converges towards zero mean climatological bias. The integrated control approach reduces the dependence on relaxation timescale τ , and instead allows nudging schemes with differing nudging parameters to reach the same optimal correction tendencies over time: the nudging timescale simply changes how soon the tendencies converge on optimal values. The integrated control allows for more efficient convergence of tendencies, reducing the computational expense of the tendency generation step. Applying the empirical correction for horizontal winds and moisture in CAM results in reduced bias by 50-80%, with the largest corrections in zonal wind and moisture. Diagnostic variables such as precipitation, surface fluxes, and radiative cloud properties are not strongly degraded by the correction, assuring model health. Increased bias in moisture and heat flux by transients after the correction reveals a compensating bias in the control model.

By comparing results using the integrated control and empirical correction methods from previous work in different modeling systems, we determine some parameter choices that seem to be consistent across models or methods, and some that are likely model dependent. Many of the parameter choice differences from the CABCOR method had surprisingly little impact on overall bias reduction, including the use of a seasonal window to smooth out high frequency noise in the tendencies online (see Appendix B), and the choice of using climatological or historical SSTs when generating the nudging tendencies. The main difference in parameter behavior is that SK24 found increasing time to convergence with decreased nudging timescale τ , while we found that shorter τ converged on optimal tendencies more quickly due to the integrated control. We found varied behavior in the impact of the correction on diagnostics and variability compared to previous studies; these differences are likely dependent on the choice of variables to correct

directly (here U, V, and Q) and are likely model dependent. The degradation of precipitation from correcting temperature was evident early in the tendency generation step, so negative impacts on diagnostics due to variable choice could be determined before running the model to full convergence.

Meridional wind is one of the few cases where climatological nudging with the integrated control does not improve average normalized error beyond previous methods. Meridional wind corrections hover near 40-50%, even with increased nudging timescale and convergence length. However, the nudging tendencies themselves continue to adjust until converging several decades later (Figure 3); examining horizontal maps show that the regions of largest V bias simply shift horizontally with continued convergence. The integrated control does not guarantee that global bias can be nonzero at all locations at the same time; it appears that while the full field tendencies are converging, the bias at individual grid points oscillate around 0. We hypothesize that the remaining bias is not correctable by state-independent tendencies, but instead is either 1) uncorrectable noise or 2) state-dependent bias. To correct state-dependent bias, the correction tendency must be predicted every nudging update step based on current model state. Development of a state-dependent correction that builds on the state-independent correction here is ongoing.

The continued growth of meridional wind tendencies without improved bias raises the question of how long to converge the tendencies during the tendency generation stage. The tendency convergence rates in Figure 3 vary with variable and with vertical level, but we choose to examine a typical convergence length of 300 years for all variables. It will likely be a subjective choice of when to stop converging the nudging tendencies based on use case. Previous work tested using different nudging timescales for different vertical levels and for different variables; these choices are justified based on trial and error (S. Zhang et al., 2026) or uncertainty of the observations themselves (Guldberg et al., 2005; Kharin & Scinocca, 2012). For simplicity, we used the same nudging timescale for all variables and vertical levels.

The correction method results in a freely-running simulation with an improved mean state that can be used to investigate processes that are dependent on the background state. Some processes, like blocking frequency shown here, are expected to be improved with an improved background state, and the empirical correction may be able to com-

686 pensate biases due to coarse resolution, allowing for cheaper simulation of these processes.
 687 However, it is not guaranteed that all processes will be improved, especially in the case
 688 where a process is dependent on physics parameterizations that had been tuned for the
 689 control climatology. In these cases, the corrected model can reveal areas of compensat-
 690 ing biases, and retuning the corrected model could result in more realistic parameter choices.
 691 Additionally, the corrected mean state could be useful for parameter perturbation stud-
 692 ies à la Ma and Kuang (2016), since apply a forcing along climatological timescales means
 693 that the impacts of perturbations to physics parameters would be due to the perturba-
 694 tion itself, rather than indirect effects from changes to the mean state. Another use for
 695 the correction method is to investigate regional-scale processes in a regional model us-
 696 ing the corrected fields as improved boundary conditions (Scinocca et al., 2025; Labonté
 697 et al., 2025).

698 Eventually, it is of interest to use empirical bias corrections in forecasts to deter-
 699 mine whether forecast skill is improved by a reduced model drift. Previous work has not
 700 found a robust improvement in forecast skill from correcting only atmospheric tenden-
 701 cies, potentially because the model drift occurs on timescales longer than the predictabil-
 702 ity timescale (Chang et al., 2019). For longer seasonal forecasts, it will be advantageous
 703 to be able to run a bias-corrected model with a coupled ocean. However, as the tenden-
 704 cies are currently generated with prescribed SSTs and the coupled model was tuned us-
 705 ing an uncorrected atmosphere, the model mismatch is likely to be detrimental to the
 706 forecasts (Klingaman & Demott, 2020). Although observations in the ocean are less ro-
 707 bust, a tendency correction could be applied in the ocean: Lu et al. (2020) developed
 708 a similar nudging correction method for the ocean using an ocean DA system. Merryfield
 709 et al. (2026) applied an instantaneous empirical correction to both the atmosphere and
 710 ocean and found improved forecast skill. The use of a similar climatological correction
 711 for the ocean may be useful to account for uncertainties in daily ocean observations.

712 Overall, empirical correction derived from climatological nudging is a highly effec-
 713 tive way to reduce systematic model bias, and at least in this model, does not strongly
 714 degrade downstream processes and may improve processes that are dependent on back-
 715 ground state. Of course, it is critical that climate modelers continue to improve param-
 716 eterizations and increase resolution with the goal of reducing model biases at their source,
 717 but empirical corrections open many interesting avenues of research to understand our
 718 climate system and improve our forecasts using the models and tools we already have.

Open Research Statement

Sourcemod changes to CAM for the climatological nudging with the integrated control can be found in the Zenodo repository (Weidman, 2026). The same repository contains code used for pre- and post-processing target and tendency data, along with analysis code for creating the figures. The original CESM versions are freely available online (at www.cesm.ucar.edu/models/cesm2/). Target reanalysis data was retrieved from <https://disc.gsfc.nasa.gov/datasets/>. Global Precipitation Climatology Project (GPCP) Monthly Analysis Product data was provided by the NOAA PSL, Boulder, Colorado, USA, from their website at <https://psl.noaa.gov>. CERES EBAF-TOA Ed4.2.1 data was retrieved from <https://ceres.larc.nasa.gov> (Loeb et al., 2018, 2024).

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Appendix A Correcting the Lorenz 63 model

The Lorenz 63 model presents the following equations (Lorenz, 1963):

$$\begin{aligned}\dot{x} &= -\sigma x + \sigma y \\ \dot{y} &= -xz + rx - y \\ \dot{z} &= xy - bz\end{aligned}\tag{A1}$$

Importantly, this system is symmetric about x and y , so $(x, y) \rightarrow (-x, -y)$ gives the same result. z does not have this symmetry.

For $r > 1$, there are three fixed points in this system: one at the origin, and two at $x^* = y^* = \pm\sqrt{b(r-1)}$, $z^* = r-1$, referred to as $\pm C$. Due to the x, y symmetry, the attractors at $\pm C$ are also symmetric in x and y . For a long enough integration and in a chaotic model, the trajectories do not tend to spend more time around one C attractor than the other. Thus, when we calculate a “mean state” of the model, we find that the mean in x and y are very close to 0, regardless of the parameters b, r, σ chosen. The mean state in z is close to $r-1$.

We obtain a set of time-independent correctors similar to as described in the main text, using two simulations with a small difference in r to create a known bias between the two cases. The correction tendencies obtained for x and y are close to 0, since both the “model” and “observation” runs are symmetric in x and y . The z tendency is similar to the difference in r between the model and observed runs. Thus, when we run the corrector step, we are essentially adding a constant forcing to the $\dot{z}$ equation and leaving the $\dot{x}, \dot{y}$ equations unchanged:

$$\begin{aligned}\dot{x} &= -\sigma x + \sigma y \\ \dot{y} &= -xz + rx - y \\ \dot{z} &= xy - bz + F\end{aligned}\tag{A2}$$

We calculate the fixed points again by setting $\dot{x}, \dot{y}, \dot{z}$ to 0. The new $\pm C$ fixed points are now

$$\begin{aligned}x^* = y^* &= \pm \sqrt{b(r-1) + F} \\ z^* &= r - 1\end{aligned}\tag{A3}$$

The z attractor remains unchanged. Even though F is found in the equations for the fixed points $\dot{x}, \dot{y}$, they are still symmetric, and still average to near 0. In this system, applying a constant forcing only in z will not be able to correct the mean state of the model, regardless of whether the correction tendencies are generated from instantaneous tendencies, climatological tendencies, or multiple iterations of the tendency generation step.

If instead we calculate a state-dependent correction by regressing the model state against tendencies from the tendency generation step, the bias can be corrected, since the predicted correction tendency will be different for the positive and negative x and y regimes.

Appendix B Implementation details

There are a number of parameter and implementation choices that need to be made when implementing the correction method described above. Except for the integrated control described in the main text, these choices were determined to not significantly influence results. The exact choices are enumerated here for completeness and reproducibility.

Equation 4 is repeated for clarity:

$$\Psi_M^{i+1} = (1 - \rho)\Psi_M^i + \rho\Psi_I^{i+1}\tag{B1}$$

In SK24, the model climatology Ψ_M is updated once per year for each time and day of year, and before being applied during the correction step, the tendencies are smoothed using a 21-day centered rolling mean. This reduces noise due to synoptic variability, but could break the assumption that the tendencies being applied as corrections are optimally converged, since they differ from those being applied during the tendency generation step. They also still contain short-frequency noise during the nudging itself; during development, we found that nudging with unsmoothed tendencies can result in instabilities and impede tendency convergence.

Using the update weight ρ , we incorporate a seasonal filter into the nudging itself. Here, ρ includes both a seasonal smoothing weight w and a climatological running mean timescale K . Each time the running mean is updated, all days within a 31-day seasonal window, respecting time of day, are also updated with weight:

$$\rho = \frac{w}{K} \quad (\text{B2})$$

where $w = 1$ for the current time step and decreases with a Hann taper to 0 at the edge of the seasonal window. Because this procedure is essentially a low-pass filter applied during the nudging itself, there is no need to apply a filter in post-processing before applying the converged nudging tendencies as a state-independent correction, and the tendencies applied during the nudging are the same as those applied as corrections. Since the nudging tendencies are updated more frequently than once per year and are less sensitive to noise from synoptic variability, they also converge more quickly. K is a value representing the time over which the model mean climatology is calculated, chosen here to be 50 years. Thus, after spinup, the model state for each subsequent year contributes 1/50 to the running mean Ψ_M . In the first 50 years of the simulation, K is equal to the number of simulated years (so year 1 contributes 1/1 to the running mean, year 2 contributes 1/2, and so on).

Equation B2 collapses to the CABCOR method by using a seasonal window of 1 day and a continually increasing K equal to the number of simulation years. Results are not sensitive to the length of the seasonal window or the climatological running mean window K , as long as K is long enough to average over interannual variability. In fact, the use of the online low-frequency smoothing turns out to not significantly alter results; performing a smoothing on the tendencies after the tendency generation step as done

in SK24 has similar bias reduction as shown in the main text, though with a slower time to convergence.

Since the nudging tendency depends on a running mean of the model, during the first several years of the simulation, the nudging tendencies can oscillate quite strongly. For stability, the model climatology Ψ_M is updated but not applied as a nudging during the first 5 years of the simulation, which reduces strong oscillatory behavior and the likelihood of model crashes. Also for stability, nudging is performed at all vertical levels except for the top model layer.

The target dataset is 6-hourly, but we update the running mean every 2 hours. For update time steps not equal to the reanalysis time step, we linearly interpolate the target. These choices are based on previous assessments of nudging parameters (Sun et al., 2019) and have insignificant impact on results.

Appendix C EOF calculation

Empirical orthogonal functions (EOFs) of the correction tendencies are calculated using a standard EOF decomposition on the seasonal mean tendencies with convergence length as the dimension of variability. Due to storage constraints, the tendencies from subsequent 30-year periods are stored as seasonal climatologies; this means convergence length is discretized into 30-year chunks, starting with years 120-150 as the first convergence length increment, followed by years 150-180, and so on. Convergence trajectories are visually similar when calculating the EOFs from tendencies for a single day-of-year across all convergence years. Tendencies are area-weighted by the square root of the cosine of latitude before decomposition. EOFs are calculated separately for each variable (U, V, and Q) and for each vertical level.

EOFs are calculated from tendencies from the $\tau = 6$ hours case. Pseudo principal components are calculated for the other nudging timescale cases by projecting the seasonally averaged tendency at each convergence length increment onto EOF1 with identical weighting and scaling.

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