Drivers of Future Extratropical Sea Surface Temperature Variability Changes in the North Pacific

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Key Points:

- We propose a method to diagnose the drivers of projected future changes to extratropical sea surface temperature variance
- These sea surface temperature variance changes are spatially heterogeneous in the Community Earth System Model version 2 large ensemble
- Changes in the North Pacific are largely driven by El Niño teleconnection shifts, augmented by ocean memory and stochastic forcing changes

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Abstract

Under anthropogenic warming, future changes to climate variability beyond specific modes such as the El Niño-Southern Oscillation (ENSO) have not been well-characterized. In the Community Earth System Model version 2 Large Ensemble (CESM2-LE) climate model, the future change to sea surface temperature (SST) variability is spatially heterogeneous. We examined these projected changes (between 1960-2000 and 2060-2100) in the North Pacific using a local linear stochastic-deterministic model, which allowed us to quantify the effect of changes to three drivers on SST variability: ocean "memory" (the SST damping timescale), ENSO teleconnections, and stochastic noise forcing. The ocean memory declines in most areas, but lengthens in the central North Pacific. This change is primarily due to changes in air-sea feedbacks and ocean damping, with the shallowing mixed layer depth playing a secondary role. An eastward shift of the ENSO teleconnection pattern is primarily responsible for the pattern of SST variance change.

Plain Language Summary

In this study we investigated the physical reasons why fluctuations of sea surface temperatures – i.e., variations from the seasonal cycle – change as the world warms. These changes are important because extreme fluctuations above the normal state, so-called marine heat waves, can have severe ecological and economic impacts. Combining a conceptual model with a state-of-the-art climate model, we examined the reasons why sea surface temperature variability in the North Pacific is projected to change heterogeneously: some areas experience higher variability in the future, some less. Three different processes are important: ocean memory (i.e., how long temperature anomalies persist), the remote influence of El Niño, and the random weather variations in the atmosphere. While changes in all three processes affect future sea surface temperature variability changes, geographical shifts in how El Niño affects the upper ocean's temperature are the most important.

1 Introduction

Anthropogenic emissions of greenhouse gasses are causing profound changes to the Earth's climate. Changes to the climate mean state have been studied for over half a century (e.g., Manabe and Wetherald (1967)) and are often used to set targets for reducing greenhouse gas emissions. In contrast, changes to climate variability—characterized

statistically by variance and occurrence of extreme events and of importance for regional adaptation strategies—under future warming scenarios are less well understood.

There is a substantial body of literature characterizing future changes to specific modes of climate variability such as the El Niño-Southern Oscillation (ENSO) (Cai et al., 2020; Cai et al., 2018; Geng et al., 2022; Maher et al., 2023; Timmermann et al., 1999; Wengel et al., 2021; Ying et al., 2022) and the Madden-Julian Oscillation (Bui & Maloney, 2018, 2020; Jenney et al., 2021; Rushley et al., 2019). However the broader study of climate variability changes is an emerging field with many outstanding questions (Rodgers et al., 2021; Stouffer & Wetherald, 2007; van der Wiel & Bintanja, 2021).

The recent advent of large ensemble climate model simulations offers an opportunity to robustly quantify future variance and extreme event changes (Deser et al., 2020; Li et al., 2021; Maher et al., 2019; Rodgers et al., 2021). Conducting a large number of simulations with the same climate model with identical external forcing but perturbed initial conditions allows for a clear identification of the forced signal as it changes over time, leaving only model and scenario uncertainty (Hawkins & Sutton, 2009).

In this study, we examined the projected change to sea surface temperature (SST) variability in the North Pacific and its physical drivers using the Community Earth System Model version 2 Large Ensemble (CESM2-LE), which consists of 100 ensemble member simulations (Rodgers et al., 2021). Changes to SST variability are of key importance to both physical and biological components of the climate system: SSTs couple the ocean and atmosphere via radiative and turbulent heat fluxes (Deser et al., 2010) and control many physiological processes of marine organisms (Smith et al., 2023). The occurrence of marine heatwaves, prolonged periods of anomalously high SST that result in severe ecological and socioeconomic impacts (Smith et al., 2021), is directly related to SST variability from a moving baseline perspective (Amaya et al., 2023; Oliver et al., 2021).

Strikingly, the projected change in SST variance in CESM2-LE between 1960-2000 and 2060-2100 is not spatially uniform (Figure 1c), and the aim of this study was to identify the drivers responsible for this pattern of variability change. Note that these projected changes in variance will directly translate (if the other statistical moments remain constant) to changes of threshold exceedances of upper percentiles (e.g., the 90^{th} percentile) that are often used to define marine heatwaves (e.g., Jacox et al. (2020)). Thus our results have direct applicability to the study of future marine heat wave changes. We

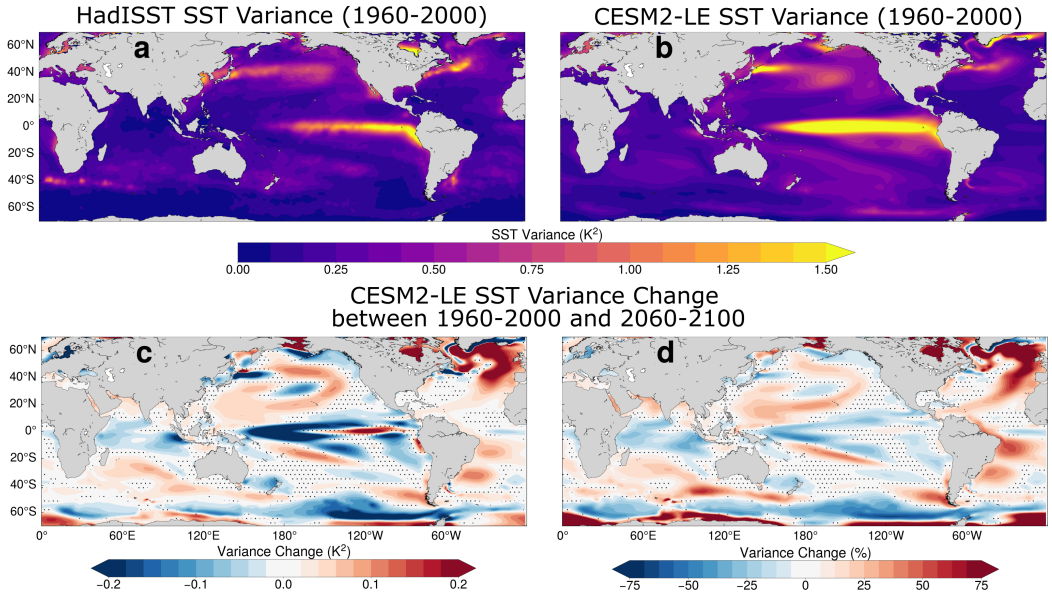

Figure 1. (a) SST variance during 1960-2000 from HadISST and (b) from CESM2-LE. (c) SST variance change in CESM2-LE between 1960-2000 and 2060-2100. (d) Relative SST variance change between those time periods. Stippled areas in (c) and (d) show where the change in variance is not significant at the 5% level.

used a local linear stochastic SST model to quantify the relative effect of changes to three drivers on the overall change in SST variance: ocean memory, ENSO teleconnections, and stochastic noise forcing.

2 Methods

2.1 Data

We used the Community Earth System Model version 2 Large Ensemble in this study. CESM2 is a coupled Earth system model with active ocean biogeochemistry (Danabasoglu et al., 2020). The model incorporates the CAM6 atmosphere model and POP2 ocean model, both on $\sim 1°$ horizontal grids, as well as coupled land, sea ice, wave, marine biogeochemical, and river runoff models. The large ensemble consists of 100 ensemble members run from 1850 to 2100 and forced by CMIP6 historical (1850-2014) and SSP3-7.0 protocols (2015-2100) (Rodgers et al., 2021). The SSP3-7.0 scenario, which has a high rate of emissions, was selected to investigate climate variability and its projected future changes. Anomalies were calculated by subtracting the ensemble mean from each ensem-

ble member. We excluded SST data from our analysis at grid points where the ensemble-mean sea ice fraction exceeded 15% for any month during the time period considered.

Additionally we used several observational and reanalysis products to compare the CESM2-LE results in the historical period (1960-2000 unless otherwise noted). We used SSTs from the Hadley Centre Global Sea Ice and Sea Surface Temperature v1.1 dataset (HadISST; Rayner (2003)); sea level pressure and 850-hPa winds from the ECMWF Reanalysis v5 (ERA5; Hersbach et al. (2020)); mixed layer depth from the Ocean Reanalysis System 5 (ORAS5; Zuo et al. (2019)), which is defined as the depth where the density exceeds the near surface density by 0.01 kg m^{-3}; turbulent surface heat fluxes from the 1° Objectively Analyzed air-sea Fluxes (OAFLUX; Yu and Weller (2007)); and radiative surface heat fluxes from OAFLUX (derived from the ISCCP-D product; Rossow and Schiffer (1999)) and Clouds and Earth's Radiant Energy Systems Energy Balanced and Filled Ed4.2 product (CERES EBAF; Kato et al. (2018)). Anomalies were calculated by subtracting the climatology for the entire time period used and then detrending with a linear fit. We excluded HadISST data from our analysis at grid points with sea ice cover (i.e., NaN values in the data) during any month from January 1960 to January 2000.

For the radiative heat fluxes, we calculated anomalies separately for OAFLUX (January 1985 to February 2000) and CERES EBAF (March 2000 to December 2022), and then combined the two sets of anomalies. We spatially smoothed this heat flux data using a moving average filter with 3-by-3-grid-cell window size. For computations requiring both heat flux and SST data, we also spatially smoothed the HadISST data in the same manner. Note that the CESM2-LE data was not smoothed.

2.2 Linear Stochastic-Deterministic Model

To quantify the effect of different drivers on SST variance, we used an extension of the original local linear stochastic climate model (Frankignoul & Hasselmann, 1977; Hasselmann, 1976) with seasonally modulated feedback and noise forcing (De Elvira & Lemke, 1982; Nicholls, 1984) and an ENSO teleconnection term (Newman et al., 2016; Newman et al., 2003; Schneider & Cornuelle, 2005). We use the formulation developed by Stuecker (2023), Stuecker et al. (2017), and Zhao et al. (2019) that includes seasonal

modulations in the feedback, noise forcing, and the ENSO teleconnection term:

$$\frac{\partial T'(t)}{\partial t} = \tilde{\lambda} T'(t) + \tilde{\beta} N(t) + \xi(t), \tag{1}$$

where T' is the SST anomaly at a given location, $\tilde{\lambda}$ is a seasonally modulated feedback coefficient, $\tilde{\beta}$ is a seasonally modulated ENSO teleconnection coefficient, N is the Niño3.4 index (the SST anomaly averaged over 5°N-5°S, 170°W-120°W), and ξ is stochastic forcing (i.e., "weather noise"). Averaged over the annual cycle, $\tilde{\lambda}$ must be negative so that SST anomalies are damped and do not grow without bound. $\tilde{\lambda}^{-1}$ has units of time and represents the decay timescale of SST anomalies, thus we refer to it hereafter to as the "ocean memory" (Shi et al., 2022).

The parameters $\tilde{\lambda}$ and $\tilde{\beta}$ are defined as

$$\tilde{\lambda} = \lambda_0 + \lambda_1 \sin(\omega_a t) + \lambda_2 \cos(\omega_a t), \tag{2}$$

$$\tilde{\beta} = \beta_0 + \beta_1 \sin(\omega_a t) + \beta_2 \cos(\omega_a t), \tag{3}$$

where ω_a is the angular frequency of the annual cycle ($2\pi/12$ months^{-1}) and λ_1, λ_2, β_1, and β_2 determine the amplitude and phase of the seasonal modulation. Physically, the seasonal modulation of these coefficients reflects seasonal changes of air-sea heat fluxes and the mixed layer heat capacity, the latter which is proportional to the mixed layer depth (Frankignoul et al., 2002; Stuecker et al., 2017). For ease of display we present these coefficients as annual averages in this report (the amplitude and phase of $\tilde{\lambda}$ and $\tilde{\beta}$ are shown in Figure S1 in the Supporting Information).

The noise term ξ represents stochastic forcing from the atmosphere. It includes all processes that are uncorrelated with local SST anomalies and remote ENSO forcing, primarily anomalous air-sea heat fluxes and anomalous Ekman advection of the SST gradient due to weather variability (Larson et al., 2018). ξ should be nearly white given the fast decorrelation timescale of the atmosphere (Hasselmann, 1976; Lorenz, 1963).

At each grid point for each ensemble member, equation 1 was fitted to the SST anomaly data using multiple linear regression (see Zhao et al., 2019). $\partial T'/\partial t$ was computed using the forward finite difference method. The noise forcing ξ was taken to be the residual from the fit. This residual is well-described by white noise (see Figure S2 in the Supporting Information), supporting the suitability of our choice of theoretical SST model.

2.3 SST Feedback Decomposition

The SST feedback coefficient $\tilde{\lambda}$ is the sum of several different atmospheric and oceanic feedbacks (Frankignoul, 1985; Haney, 1971; Patrizio & Thompson, 2021, 2022):

$$\tilde{\lambda} = \tilde{\lambda}_{\mathrm{SH}} + \tilde{\lambda}_{\mathrm{LH}} + \tilde{\lambda}_{\mathrm{SW}} + \tilde{\lambda}_{\mathrm{LW}} + \tilde{\lambda}_{\mathrm{ent}} + \tilde{\lambda}_{\mathrm{diff}} + \tilde{\lambda}_{\mathrm{other}} \tag{4}$$

where $\tilde{\lambda}_{\mathrm{SH}}$, $\tilde{\lambda}_{\mathrm{LH}}$, $\tilde{\lambda}_{\mathrm{SW}}$, $\tilde{\lambda}_{\mathrm{LW}}$ are the feedbacks associated with the sensible, latent, shortwave, and longwave components of the air-sea heat flux, respectively; $\tilde{\lambda}_{\mathrm{ent}}$ is the feedback due to entrainment as the mixed layer deepens in fall and winter; $\tilde{\lambda}_{\mathrm{diff}}$ is the feedback due to horizontal eddy diffusion, and $\tilde{\lambda}_{\mathrm{other}}$ is the feedback due to non-local and other processes not considered here.

We calculate the air-sea heat flux feedbacks given heat flux component x by fitting the following equation using multiple linear regression:

$$Q'_x(t) = \tilde{\lambda}^*_x T'(t) + \tilde{\beta}^*_x N(t) + \xi^*_x(t), \tag{5}$$

where $Q'_x(t)$ is the heat flux anomaly (defined as positive downward), $\tilde{\lambda}^*_x$ is the feedback for that heat flux component (with units $\mathrm{Wm^{-2}K^{-1}}$), and $\xi^*_x(t)$ is the noise forcing. $\tilde{\lambda}^*_x$ is related to the feedbacks $\tilde{\lambda}_x$ in equation 4 by the following:

$$\tilde{\lambda}_x = \frac{\tilde{\lambda}^*_x}{\rho c_p \tilde{H}} \tag{6}$$

where ρ is the density of seawater (1024 kg $\mathrm{m^{-3}}$), c_p is the heat capacity of seawater (4001 J $\mathrm{kg^{-1}}$ $\mathrm{K^{-1}}$), and $\tilde{H}$ is the monthly mixed layer depth climatology. To fit this equation to observations, we used the whole time period available for the heat flux data to minimize the error: January 1985 to December 2022 instead of the 1960-2000 period for fitting equation 1.

The feedback due to entrainment is

$$\tilde{\lambda}_{\mathrm{ent}} = -\frac{\tilde{w}_{\mathrm{ent}}}{\tilde{H}} \left(1 - \left\langle \frac{\partial T'_b}{\partial T'} \right\rangle \right), \tag{7}$$

where $\tilde{w}_{\mathrm{ent}}$ is the entrainment velocity climatology, the time derivative of the mixed layer depth climatology $\tilde{H}$, and T'_b is the temperature below the mixed layer, with angled brackets denoting the ensemble/time mean (see Frankignoul (1985)). If T'_b is uncorrelated with T', and assuming a mixed layer of average depth 75 meters with an annual cycle amplitude of 100 meters, $\tilde{\lambda}_{\mathrm{ent}} \approx -0.1$ $\mathrm{months^{-1}}$ when averaged over the annual cycle. Entrainment also leads to the phenomenon of "reemergence": often the SST anomaly from

the previous winter persists under the mixed layer during summer and in fall is re-entrained into the mixed layer, leading to the reemergence of SST anomalies (Alexander & Deser, 1995; Deser et al., 2003). Reemergence is not modeled in this work.

The feedback due to horizontal eddy diffusion is

$$\tilde{\lambda}_{\text{diff}} = \frac{\partial}{\partial T'}\left(\kappa \nabla^2 T'\right), \tag{8}$$

where κ is the horizontal eddy diffusivity. Assuming SST anomalies with a sinusoidal spatial structure of wavelength L, the feedback can be estimated via scaling analysis as

$$\tilde{\lambda}_{\text{diff}} \approx -\kappa \frac{4\pi^2}{L^2}. \tag{9}$$

For $L \approx 1000$ km (i.e., a length scale of ~ 160 km) and $\kappa \approx 500$ m^{2}s^{-1} (note that κ is a function of length scale and geographic location; see Nummelin et al. (2021)), $\lambda_{\text{diff}} \approx -0.05$ months^{-1}.

Equation 4 can be rewritten as

$$\tilde{\lambda} = \frac{\tilde{\lambda}^*_{\text{turb}}}{\rho c_p \tilde{H}} + \frac{\tilde{\lambda}^*_{\text{rad}}}{\rho c_p \tilde{H}} + \tilde{\lambda}_{\text{res}}, \tag{10}$$

where $\tilde{\lambda}^*_{\text{turb}}$ is the turbulent ($\tilde{\lambda}^*_{\text{SH}}$+$\tilde{\lambda}^*_{\text{LH}}$) heat flux feedback, $\tilde{\lambda}^*_{\text{rad}}$ is the radiative ($\tilde{\lambda}^*_{\text{SW}}$+$\tilde{\lambda}^*_{\text{LW}}$) heat flux feedback, and $\tilde{\lambda}_{\text{res}}$ is the residual feedback. $\tilde{\lambda}_{\text{res}}$ includes $\tilde{\lambda}_{\text{ent}}$, $\tilde{\lambda}_{\text{diff}}$, $\tilde{\lambda}_{\text{other}}$, and errors in estimating the air-sea feedbacks. From the estimations above, $\tilde{\lambda}_{\text{ent}}$+$\tilde{\lambda}_{\text{diff}} \approx -0.15$ months^{-1}, thus we expect $\tilde{\lambda}_{\text{res}}$ to have a similar value if there are not substantial errors in the calculation of the feedbacks and contributions from other unmodeled feedbacks. Because the large number of degrees of freedom in CESM2-LE (100 members) allows for robust statistical estimates of the atmospheric feedbacks, we expect $\tilde{\lambda}_{\text{res}}$ to primarily reflect damping by entrainment and diffusion. However, for observations/reanalysis, uncertainties in the heat flux, SST, and mixed layer depth data may compound to produce substantial errors in the calculated feedbacks and thus $\tilde{\lambda}_{\text{res}}$ may primarily reflect these errors rather than just damping from oceanic processes.

The change in the feedback can be expanded from equation 10 as

$$\Delta\tilde{\lambda} = \frac{\Delta\tilde{\lambda}^*_{\text{turb}}}{\rho c_p \tilde{H}_0} + \frac{\Delta\tilde{\lambda}^*_{\text{rad}}}{\rho c_p \tilde{H}_0} + \underbrace{\frac{-\tilde{\lambda}^*_{\text{turb},0} - \tilde{\lambda}^*_{\text{rad},0}}{\rho c_p \tilde{H}_0^2}\Delta\tilde{H}}_{\Delta\tilde{\lambda}_H} + \Delta\tilde{\lambda}_{\text{res}}, \tag{11}$$

where Δ indicates the change between the two time periods, a subscript 0 indicates that the value from the first time period is used and $\Delta\tilde{\lambda}_H$ is the change in the air-sea heat flux feedback due to the change in the mixed layer depth climatology.

2.4 Applicability of the Linear Stochastic-Deterministic Model

Equation 1 describes SSTs forced solely by the atmosphere: anomalous air-sea heat fluxes and anomalous Ekman advection of the mean SST gradient from stochastic weather processes and remote forcing from ENSO. Contributions to the variance from internal ocean dynamics (e.g., geostrophic advection, mixed layer depth variability, and entrainment) are neglected (Frankignoul & Reynolds, 1983). This simplification is inadequate to explain SST variance in the equatorial oceans, where coupled ocean-atmosphere dynamics in the Pacific give rise to ENSO; in western boundary currents, where ocean dynamics are important (Qiu, 2002; Reynolds, 1978; Schneider & Miller, 2001); and in the areas of the North Atlantic and Southern Ocean where the thermohaline circulation contributes to SST variability on long timescales (Delworth & Greatbatch, 2000; Zhang et al., 2019).

In previous studies, the applicability of a linear stochastic model to SST dynamics was tested by goodness of fit to a theoretical power spectrum (Frankignoul, 1985; Reynolds, 1978), by establishing a threshold of sea surface height variance over which oceanic processes were assumed to dominate (Hall & Manabe, 1997), or by comparing advection of SST anomalies with the estimated feedback term (Frankignoul et al., 2002).

We used an objective criterion based on the lagged covariance of SST anomalies T' and net surface heat flux anomalies Q', R_{TQ} (see Frankignoul and Kestenare, 2002; Frankignoul, 1985; Frankignoul and Reynolds, 1983). If SST anomalies are both damped and forced by Q', at negative lags (when the ocean leads), R_{TQ} should be negative, corresponding to damping of SST anomalies by Q'. At positive lags (when the atmosphere leads), R_{TQ} should be positive, corresponding to forcing of SST anomalies by Q'. Thus we considered that any grid point which had $R_{TQ} < 0$ at negative lags (averaged over lags -3 to -1 months and all ensemble members) and $R_{TQ} > 0$ at positive lags (averaged over lags 1 to 3 months and all ensemble members) to be well represented by a linear stochastic model forced by the atmosphere. The grid points that did not meet this criterion were excluded from our analysis and are shown as white hashed areas in the figures. As expected these grid points are in areas of high oceanic variability and strong air-sea coupling, such as the equatorial Pacific and Kuroshio-Oyashio Extension region. For observations, as with the calculation of the air-sea heat flux feedbacks, this criteria

was evaluated using data from January 1985 to December 2022. Figure S3 in the Supporting Information shows R_{TQ} at several representative locations.

2.5 Isolating SST Variance Contribution from Each Driver

Once $\tilde{\lambda}$, $\tilde{\beta}$, and ξ are determined, the SST variance due to changes in the corresponding drivers–the ocean memory, ENSO teleconnection, and noise forcing—can be isolated. We used two forward integrations, one isolating the SST anomalies forced only by the ENSO teleconnection T'_N and the other isolating SST anomalies forced only by noise T'_ξ:

$$T'_{N,k+1} = T'_{N,k} + \big(\tilde{\lambda}_k T'_{N,k} + \tilde{\beta}_k N_k\big)\Delta t, \tag{12}$$

$$T'_{\xi,k+1} = T'_{\xi,k} + \big(\tilde{\lambda}_k T'_{\xi,k} + \xi_k\big)\Delta t, \tag{13}$$

where k is the time index and Δt is the time step (one month). ξ_k was constructed using a shuffled fit residual (for each ensemble member): for each calendar month, the year was randomly shuffled, producing noise forcing that is temporally uncorrelated (i.e., white) but retains spatial correlations and seasonal variance modulation present in the fit residual. Our results differ little if the original fit residual (that contains both spatial correlations and a slight temporal autocorrelation) or a version in which the time dimension of the noise forcing is shuffled in a different random order at each grid point (and thus is white in both time and space; see Figure S4 in the Supporting Information).

We performed these integrations at each grid point and ensemble member for the following cases:

- $T'_{N,\mathrm{A}}$ using $\tilde{\lambda}$, $\tilde{\beta}$, and $N(t)$ at their 1960-2000 values
- $T'_{\xi,\mathrm{A}}$ using $\tilde{\lambda}$ and $\xi(t)$ at their 1960-2000 values
- $T'_{N,\mathrm{B}}$ using $\tilde{\lambda}$, $\tilde{\beta}$, and $N(t)$ at their 2060-2100 values
- $T'_{\xi,\mathrm{B}}$ using $\tilde{\lambda}$ and $\xi(t)$ at their 2060-2100 values
- $T'_{N,\mathrm{C}}$ using $\tilde{\lambda}$ at its 1960-2000 values, and $\tilde{\beta}$ and $N(t)$ at their 2060-2100 values
- $T'_{\xi,\mathrm{C}}$ using $\tilde{\lambda}$ at its 1960-2000 values and $\xi(t)$ at its 2060-2100 values

Each integration was initialized with the SST anomaly at the beginning of the specified time period (2060-2100 for case C). We calculated the change in variance due to the change

in each driver using the following expressions:

$$\Delta^{\lambda}\sigma^2(T') = \Big[\sigma^2\big(T'_{N,\mathrm{B}}\big) + \sigma^2\big(T'_{\xi,\mathrm{B}}\big)\Big] - \Big[\sigma^2\big(T'_{N,\mathrm{C}}\big) + \sigma^2\big(T'_{\xi,\mathrm{C}}\big)\Big], \tag{14}$$

$$\Delta^{N}\sigma^2(T') = \sigma^2\big(T'_{N,\mathrm{C}}\big) - \sigma^2\big(T'_{N,\mathrm{A}}\big), \tag{15}$$

$$\Delta^{\xi}\sigma^2(T') = \sigma^2\big(T'_{\xi,\mathrm{C}}\big) - \sigma^2\big(T'_{\xi,\mathrm{A}}\big), \tag{16}$$

where $\Delta^{x}\sigma^2(T')$ is the change in SST variance due to changes to the driver x, $\sigma^2(T'_{x,n})$ is the variance of the integrated SST time series corresponding to the case letter n (A, B, or C) above.

2.6 Statistical Significance Testing

All parameters shown in this report (e.g., $\sigma^2(T'_{x,n})$, $\tilde{\lambda}$, $\tilde{\beta}$) were calculated for each ensemble member, creating 100 independent samples. Welch's t-test was then used to assess the statistical significance of ensemble-mean changes of these parameters between 1960-2000 and 2060-2100 (Welch, 1947). Except in areas with minimal changes, the null hypothesis of no change between the two time periods is rejected at the 5% level.

3 Results & Discussion

3.1 Ocean Memory and Its Future Changes

The ocean memory varies considerably across the North Pacific, both in observations and CESM2. Over most of the North Pacific, the ocean memory diagnosed from the observations is between 2-6 months (Figure 2a). Equatorward of about 20°N, particularly toward the eastern side the basin, the ocean memory is substantially longer, typically around 9 months. The magnitude of the ocean memory is largely consistent with previous estimations (e.g., Frankignoul and Reynolds (1983) and Schneider and Cornuelle (2005)) and the autocorrelation timescale of large-scale modes such as the the Pacific Decadal Oscillation (Newman et al., 2016).

In the observations, the contribution of the different heat fluxes to the total feedback (Figure 3a-c) shows strong damping from turbulent heat fluxes (almost entirely the latent heat feedback) particularly in a band at 25°N in the western North Pacific. Over much of the North Pacific poleward of 20°N, the radiative heat flux feedback (almost entirely shortwave feedback) is positive, indicative of the low cloud-SST feedback, where negative SST anomalies are associated with increased atmospheric stability, leading to

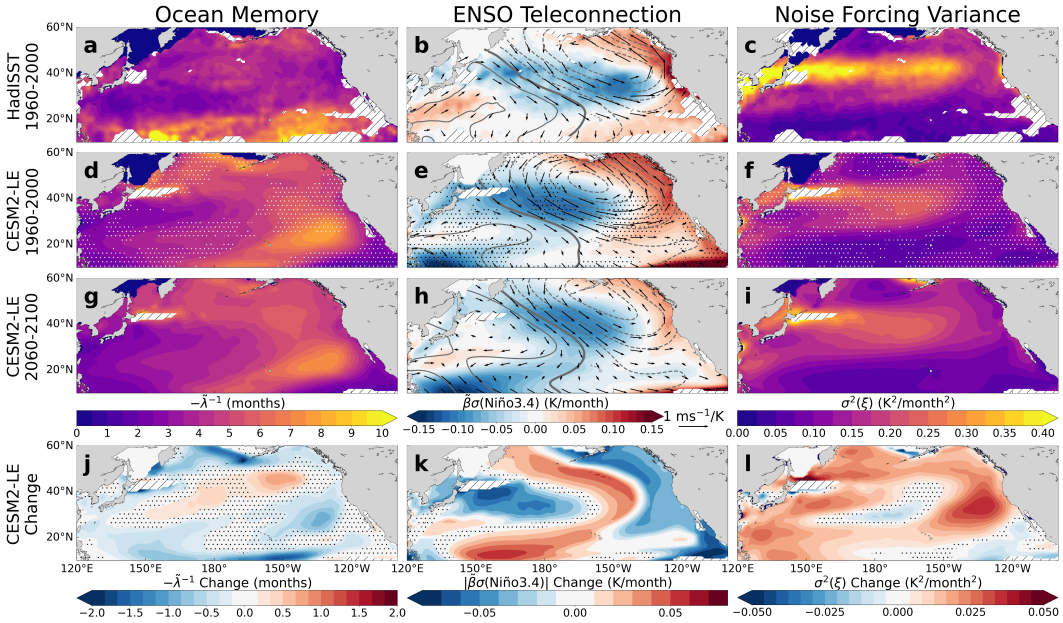

Figure 2. Equation 1 parameters fit to HadISST (a)-(c) and CESM2-LE (d)-(i) SST data in shaded contours, with CESM2-LE projected changes on the bottom row (j)-(l). (b), (e), (h) vectors and contours are the 850-hPa winds and sea level pressure regressed onto the Niño3.4 index, the latter with 0.25-hPa/K spacing (positive values are solid lines and negative lines are dashed, with a thicker line at the zero contour). Stippling in (d)-(f) indicates that the parameters derived from observations lie outside the 5$^{\text{th}}$-95$^{\text{th}}$ percentile range of those derived from the CESM2-LE ensemble members. Stippling in (j)-(l) indicates where the changes are not significant at the 5% level. The ocean memory and ENSO teleconnection panels show the mean over the seasonal cycle, and all CESM2-LE panels are the ensemble mean. Locations where the SST data is not well-described by a local linear stochastic model are shown as white hatched areas (see Section 2.4).

the formation of low clouds which reduce surface shortwave radiation and further cool the ocean (Clement et al., 2009; Norris & Leovy, 1994; Xie, 2023).

The ocean memory in CESM2-LE is similar in magnitude to observations, ranging between about 2 and 9 months, but has a distinct spatial pattern (Figure 2d, g). The ocean memory is shorter in the western North Pacific than in the east, which can mostly be attributed to strong damping by turbulent heat fluxes (Figure 3d). As in the observations, the turbulent and radiative feedbacks are dominated by the latent heat and shortwave feedbacks, respectively (see Figure S5 in the Supporting Information). A large area

of particularly long ocean memory is present between Hawai'i and North America, resulting from relatively weak turbulent heat flux damping and positive radiative feedback, likely from the low cloud-SST feedback.

Interestingly, the phases of $\tilde{\lambda}$ and $\tilde{H}$ differ: $\tilde{\lambda}$ is most strongly negative between August and December (depending on location) whereas $\tilde{H}$ is deepest between December and March (see Figure S1 in the Supporting Information). That implies that the seasonality of the air-sea heat flux feedbacks play a strong role in the seasonal modulation of $\tilde{\lambda}$ in addition to that of the mixed layer depth.

In observations, the residual feedback has considerable spatial structure (Figure 3c), with areas of negative and strongly positive feedbacks. In CESM2-LE, the residual feedback is negative everywhere except for coastal areas off China and Mexico. As related in Section 2.2, entrainment and horizontal eddy diffusion are expected to damp SST anomalies, with a combined feedback on the order of -0.15 months^{-1}, which corresponds well with the results from CESM2-LE. However, the strong positive feedbacks in observations could be the result of errors in the heat flux and mixed layer depth data. The magnitude of the feedbacks $\tilde{\lambda}_x^*$ for different heat flux components are similar between observations and CESM2-LE (see Figure S5 in the Supporting Information). However, the mixed layer depth is typically somewhat deeper in CESM2-LE than in the ORAS5 reanalysis, which would lead to the $\tilde{\lambda}_{\mathrm{rad}}$ and $\tilde{\lambda}_{\mathrm{turb}}$ being greater in magnitude in observations compared to CESM2-LE. Part of that discrepancy may be due to the different mixed layer definitions used: a density-based definition for ORAS5 (see Section 2.1) and a buoyancy-based definition for CESM2 (Large et al., 1997).

In the future climate in CESM2-LE, the ocean memory declines over most of the basin except for a zonally-elongated area in the central North Pacific where it increases (Figure 2j). The changes to the individual feedbacks are are spatially varied, but it appears that the change in ocean memory is primarily driven by changes to the radiative and residual feedbacks, suggesting that changes in clouds and ocean dynamics are most important for the change in ocean memory. In common with other climate models (e.g., Capotondi et al. (2012) and Shi et al. (2022)), the mixed layer depth in the North Pacific in CESM2-LE is shallower nearly everywhere in the future climate, leading to a reduced heat capacity and correspondingly shorter ocean memory (Figure 3g). However, the magnitude of the feedback change due to the shallower mixed layer is relatively mi-

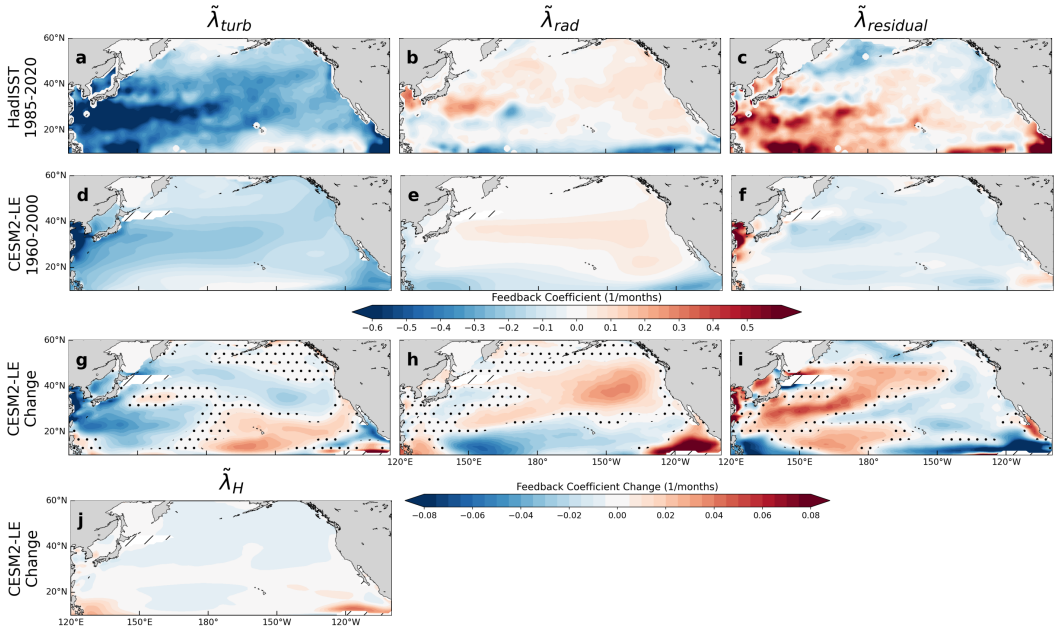

Figure 3. (a)-(f) Turbulent, radiative, and residual SST feedbacks in HadISST and CESM2-LE for 1960-2000. (g)-(i) Changes to those feedbacks in CESM2-LE between 1960-2000 and 2060-2100, with (j) showing the contribution of the mixed layer depth change. Stippling in (g)-(i) indicates where the changes are not significant at the 5% level. All panels show the feedbacks averaged over the seasonal cycle and the CESM2-LE panels showing the ensemble mean. Locations where the SST data does not meet the criterion described in Section 2.4 are shown as white hatched areas.

nor compared to the changes to the other feedbacks, in contrast with the findings of Shi et al. (2022), who attributed the projected decline in ocean memory in CMIP6 models primarily to mixed layer depth shallowing.

3.2 ENSO Teleconnection and Its Future Changes

The ENSO teleconnection, represented by $\tilde{\beta}$ multiplied by the standard deviation of Niño3.4, in both observations and CESM2-LE (Figure 2b, e, h) exhibits the well-known "atmospheric bridge" pattern: cooling (warming) of SSTs in the central North Pacific and warming (cooling) in the eastern North Pacific during El Niño (La Niña) (Alexander et al., 2002; Lau & Nath, 1996; Taschetto et al., 2020). This pattern is caused by anomalous tropical heating in the central Pacific during El Niño which excites atmospheric Rossby wave trains that propagate poleward and induce changes in atmospheric circulation and

surface heat fluxes. The Aleutian Low deepens during El Niño, resulting in anomalous cold and dry northwesterly winds over the central North Pacific that cool SSTs and anomalous warm and humid southeasterly winds over the eastern North Pacific that warm SSTs. These changes in wind, air temperature, and humidity modulate the air-sea heat fluxes, resulting in SST anomalies. These large-scale atmospheric patterns are evident in the sea level pressure and 850-hPa wind regressed onto the Niño3.4 index (line contours and vectors in Figure 2b, e, h).

The spatial pattern of the teleconnection in CESM2-LE for 1960-2000 is broadly similar to the observed pattern but is displaced slightly to the west and is somewhat stronger in magnitude. The westward displacement likely is due to the ENSO SST anomaly in CESM2 extending further west than in observations (Chen et al., 2021). However, in most of the North Pacific the observed teleconnection falls within two cross-ensemble standard deviations. At the center of action in the central North Pacific, the annually-averaged teleconnection coefficient $\tilde{\beta}$ is much stronger in observations than in CESM2-LE for either time period (see Figure S6 in the Supporting Information). However, the ensemble mean Niño3.4 standard deviation in CESM2-LE is about 50% greater than in observations: 1.30 K and 1.26 K for 1960-2000 and 2060-2100, respectively, compared to the observed value of 0.86 K for 1960-2000 in HadISST. Thus, the overall magnitude of forcing of the teleconnection on SST anomalies is comparable between the model and observations.

In CESM2-LE, the ENSO teleconnection pattern shifts to the northeast in the future climate. The teleconnection, both in its effect on atmospheric circulation and SSTs, weakens slightly. That shift likely is caused by the eastward shift of the location of maximum precipitation during ENSO due to the expansion of the western Pacific warm pool (see Power et al. (2013) and Yan et al. (2020)). Changes to the atmospheric waveguide may also contribute to the teleconnection shift.

3.3 Noise Forcing and Its Future Changes

The variance of the noise forcing ξ has a broad maximum at 40°N in both the observations and CESM2-LE, stretching from Japan to about 150°W (Figure 2c, f, i). This coincides with the subarctic SST front and the North Pacific storm track, thus high atmospheric and oceanic variability in this region is expected. The noise in observations

has considerably greater variance than in CESM2-LE even though the SST variance is similar. Because SST variance increases with increasing ocean memory (in an AR-1 process; see von Storch and Zwiers, 1999), the greater noise variance in observations is compensated by the somewhat shorter ocean memory to yield comparable overall SST variance to CESM2-LE.

The future change of the noise forcing variance is spatially heterogeneous in CESM2-LE. Although increasing in most areas, particularly in the eastern North Pacific between Hawai'i and North America, there are areas in the central and southeastern parts of the basin where noise variance decreases. The strong increase in variance north of Japan is potentially due to a poleward shift of the Kuroshio (Yang et al., 2016).

3.4 Drivers of future SST Variance Change

As described in Section 2.5 we used the fitted values of $\tilde{\lambda}$, $\tilde{\beta}$, and ξ to create several sets of reconstituted SST data forced either by ENSO or by the noise residual ξ. The variance of the ENSO-forced SSTs is appreciably smaller than the noise-forced SSTs (Figure 4b-c). However, the *change* in variance of the ENSO-forced SSTs due to the shift of the ENSO teleconnection is comparable in magnitude to the change in variance of the noise-forced SSTs (Figure 4e-f). The sum of the individual variance changes sums to close to the true variance change, supporting the validity of integrating the forcings separately (compare Figure 4a and g).

The pattern of variance change due to each of the three drivers closely resembles the changes to the corresponding parameters in Figure 2j-i. Increases in the ocean memory lead to increased SST variance and vice versa, as expected for an AR-1 process (see von Storch and Zwiers, 1999). Likewise, increases in the magnitude of the ENSO teleconnection and noise forcing lead to increases in SST variance, and vice versa. The change in the strength of the ENSO teleconnection is almost entirely a function of the change in $\tilde{\beta}$ as the change in the Niño3.4 variance is small between the two time periods in CESM2-LE.

Figure 4h shows the contribution of each driver to the overall variance change by assigning the change due to each driver to a color channel (red=$\Delta^{\xi}\sigma^2(T')$, green=$\Delta^{N}\sigma^2(T')$, blue=$\Delta^{\lambda}\sigma^2(T')$). At each grid point, a driver was only considered to contribute to the change in variance if its associated variance change was of the same sign as the total SST

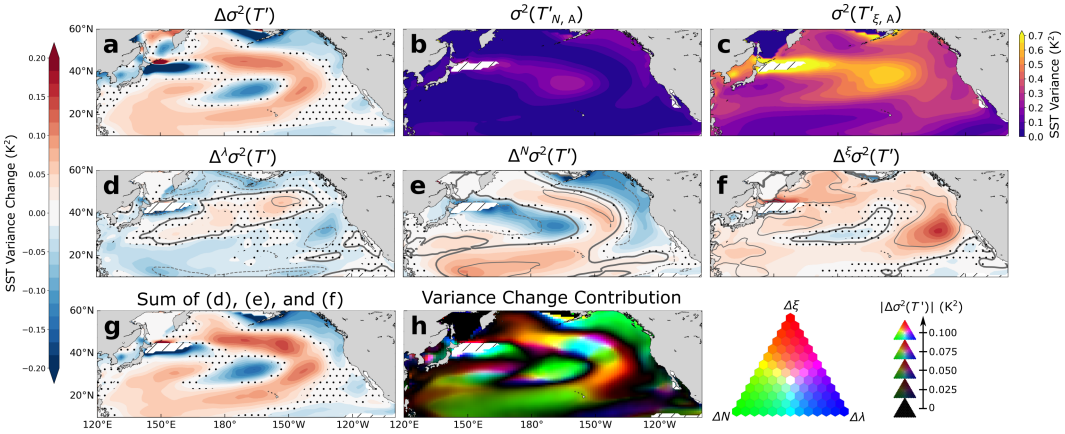

Figure 4. (a) The total SST variance change as in Figure 1c. (b) and (c) The SST variance associated with ENSO-only and noise-only forcing, respectively, for 1960-2000. (d)-(f) The SST variance changes associated with the change in ocean memory, the ENSO teleconnection, and stochastic noise. The grey contours represent the same changes as in Figure 2j-l: the change of the ocean memory $\tilde{\lambda}^{-1}$, ENSO teleconnection $\tilde{\beta}\sigma$(Niño3.4), and the noise variance $\sigma(\xi)$, respectively. The zero contour line is thicker, with contour intervals of 0.67 months, 0.04 K/month, and 0.02 K/month, respectively. (g) The total SST variance change computed by summing (d), (e), and (f). (h) The contribution of the change of each driver to the SST variance change. Hue indicates the relative contribution of each driver and brightness corresponds to the magnitude of the total SST variance change (see Figure S7 in the Supporting Information). Locations where the SST data does not meet the criterion described in Section 2.4 are shown as white hatched areas. Stippling indicates where the changes are not significant at the 5% level.

variance change (i.e., if at some grid point $\Delta\sigma^2(T') > 0$ and $\Delta^\lambda\sigma^2(T') < 0$, the change in $\tilde{\lambda}$ was considered to not contribute to the overall change in variance). Then the variance of the drivers that do contribute to the SST variance change is represented by a mix of colors, with the hue signifying the relative contribution of each driver, and the brightness being proportional to the magnitude of the total SST variance change. The construction of this visualization is detailed in Figure S7 in the Supporting Information.

As evidenced by the large areas of green in Figure 4h, the shift of the ENSO teleconnection dominates the SST variance change pattern. The arcuate pattern in the central North Pacific and the decrease in variance in the Gulf of Alaska are almost entirely due to the shift in the teleconnection. The change in the stochastic noise forcing contributes to a lesser extent, with its greatest influence being northeast of Hawai‘i. In most

of the North Pacific, decreased SST variance due to declining ocean memory is compensated for by increased variance due to increasing stochastic noise forcing. That memory is generally declining and noise increasing implies that the "damped-persistence" predictability of SST anomalies will decline in the future in most areas.

We also assessed the contribution of the change of each driver by using the pattern correlation, defined as the Pearson correlation coefficient between two arrays weighted by the cosine of the latitude. Areas of the arrays where the R_{TQ} criterion described in Section 2.4 are not met were removed. In the North Pacific (10°N-60°N, 120°E-100°W) the pattern correlations between the total variance change (as in Figure 4g) and the variance changes due to individual drivers are 0.15 for $\Delta^{\lambda}\sigma^2(T')$, 0.76 for $\Delta^{N}\sigma^2(T')$, and 0.47 for $\Delta^{\xi}\sigma^2(T')$. Those correlations support the above conclusion that the shift in the ENSO teleconnection is most important to the overall change in SST variance, followed by the change in the stochastic noise, with the change in ocean memory playing only a minor role.

4 Conclusions

In this work, we have demonstrated a conceptual model of SST variability that can explain the drivers behind future change of projected SST variance. By using this framework, we were able to quantify the SST variance change between 1960-2000 and 2060-2100 to three drivers:

- *Ocean Memory* – The ocean memory declines over most of the North Pacific with an elongated region in the center of the basin exhibiting longer memory in the future. We attribute this change primarily to changes in air-sea feedbacks and ocean damping, the latter presumably due to changes in horizontal diffusion and entrainment. The latent heat and shortwave feedbacks, the latter likely due to the low cloud-SST feedback, are the most important air-sea feedbacks. The shallowing mixed layer depth appears to play a secondary role. The change in ocean memory plays a minor role in the overall change in SST variance as its impact is largely compensated for by increases in stochastic noise forcing.
- *ENSO Teleconnections* – The "atmospheric bridge," which connects North Pacific SSTs to ENSO events via atmospheric Rossby waves, shifts to the northeast in the future climate. Although the extratropical SST variance associated with re-

mote ENSO forcing is much smaller than the variance driven by stochastic noise, the shift of the ENSO teleconnection pattern results in a large change in SST variance, dominating the overall change in SST variance.

- *Stochastic Noise Forcing* – The noise forcing, computed as a residual from a fit to an extended local linear stochastic-deterministic model (equation 1), increases in most of the North Pacific. Its impact on SST variance is somewhat attenuated by the change in the ocean memory.

These findings have implications for predictability – the generally lower ocean memory and higher noise forcing suggests that predictability of a simple "damped persistence" model will decline in skill in the future climate in most regions. ENSO is a major source of SST predictability on seasonal timescales, hence the shift of its teleconnections results in ENSO-associated changes in predictability in different regions. Our results highlight the importance of studies into future ENSO changes and its regional impacts.

Although this study was focused narrowly on the North Pacific and the CESM2-LE model, our framework should be equally applicable to other extratropical oceans and other climate models. Different large ensemble climate models show considerable diversity in their future ENSO dynamics (Maher et al., 2023), thus contribution of the various drivers of SST variability may differ greatly between models. This study also did not determine the physical mechanisms responsible for the change in ocean memory and stochastic noise forcing and how they relate to climate mean state changes. We aim to answer these questions in future work.

Data Availability Statement

The CESM2-LE data are available via the Earth System Grid (`https://www.earthsystemgrid.org`), the HadISST data are available from the Met Office (`https://www.metoffice.gov.uk/hadobs/hadisst/`), the ERA5 and ORAS5 data are available via the Climate Data Store (`https://cds.climate.copernicus.eu`), the OAFLUX data are available from WHOI (`https://oaflux.whoi.edu/`), and the CERES data are available from NASA (`https://ceres.larc.nasa.gov/`). The code and data required to reproduce the figures is available via Zenodo (`https://doi.org/10.5281/zenodo.10419764`).

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Acknowledgments

This study was supported by NOAA's Climate Program Office's Modeling, Analysis, Predictions, and Projections (MAPP) program under grant NA20OAR4310445 and NSF grant AGS-2141728. JLG acknowledges the support of the Uehiro Center for the Advancement of Oceanography. MFS participates in the MAPP Marine Ecosystem Task Force. The authors acknowledge helpful discussions with Fei-Fei Jin, Niklas Schneider, and Brian Powell. The CESM2-LE simulations were conducted on the Aleph supercomputer through a partnership between the Institute for Basic Sciences (IBS) Center for Climate Physics (ICCP) in South Korea and the CESM group at the National Center for Atmospheric Research (NCAR) in the U.S., representing a broad collaborative effort between scientists from both centers. Special thanks goes to Axel Timmermann, Keith Rodgers, Sun-Seon Lee, Nan Rosenbloom, and Jim Edwards from those institutions. This is IPRC publication X and SOEST contribution Y.

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