Long-term natural variability and 20th century climate change

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Global mean temperature at the Earth's surface responds both to externally imposed forcings, such as those arising from anthropogenic greenhouse gases, as well as to natural modes of variability internal to the climate system. Variability associated with these latter processes, generally referred to as natural long-term climate variability, arises primarily from changes in oceanic circulation. Here we present a technique that objectively identifies the component of inter-decadal global mean surface temperature attributable to natural long-term climate variability. Removal of that hidden variability from the actual observed global mean surface temperature record delineates the externally forced climate signal, which is monotonic, accelerating warming during the 20th century.

climate modeling | ocean variability

Delineating the relative role of anthropogenic forcing, natural forcing, and long-term natural variability in 20th century climate change presents a significant challenge to our understanding of the climate system (1–7). Observations suggest the warming of the 20th century global mean surface temperature has not been monotonic, even when smoothed by a 10–20 year low-pass filter. Temperatures reached a relative maximum around 1940, cooled until the mid 1970s, and have warmed from that point to the present. Radiative forcings due to solar variations, volcanoes, and aerosols have often been invoked as explanations for this non-monotonic variation (4). However, it is possible that long-term natural variability, rooted in changes in the ocean circulation, underlies much of this variability over multiple decades (8–12). Quantifying whether there is a large role for long-term natural variability in the climate system is important, as such variability could exacerbate or ameliorate the impact of climate change in the near future. Further, large magnitude variability may require revisiting the types and magnitudes of imposed forcings thought to be responsible for the observed 20th century climate trajectory (12). More ominously, a climate with large magnitude natural long-term variability in general is a climate very sensitive to imposed forcings, raising concerns about extreme impacts due to future climate change (13).

Due to its large heat capacity, the ocean is the likely source of natural long-term climate variability on interdecadal time scales. The oceans can impact global mean surface temperature in several ways; directly, through surface fluxes of heat, or indirectly, by altering the atmospheric circulation and impacting the distribution of clouds and water vapor. However, our understanding of how the ocean impacts the global mean surface temperature is strongly limited by available observations, which historically have consisted primarily of sea surface temperature (SST) measurements.

The desire to optimally use these SST observations suggests a two-stage approach to objectively quantify the role of internal variability in the 20th century climate trajectory. The first step requires linking SST anomalies to anomalies in the global mean surface temperature. Climate models provide a means to derive such a link, under the assumption that the current generation of climate models captures the essence of the signature of oceanic variability on the global mean temperature. To see that this is the case, we consider annual mean surface temperature fields extracted from 10 multicentury preindustrial control climate simulations, each derived from independently constructed models containing coupled ocean-atmosphere dynamics and advanced physical parameterizations. Such control simulations provide an ideal laboratory for testing ideas about internal variability in the climate because by definition all variability in these simulations is considered to be internal.

From these simulations, we consider the annual mean global mean temperatures and residual anomaly sea surface temperature (RASST) fields (9). Construction of the RASST fields involves first removing the climatology from a given point, as usual for the construction of anomaly fields, and then removing an appropriate global mean value as well. The rationale behind this is that there is no reason why natural long-term variability should be orthogonal to a global warming "mode" that inevitably dominates an empirical orthogonal function decomposition of 20th century fields. The global mean removed here is the mean SST averaged from 60°S to 60°N. Since RASST fields have zero global mean, they have no trivial link to the global mean temperature.

We apply a partition of 30° latitude by 60° longitude to these RASST fields, spanning the 60°S–60°N seasonally ice-free oceanic surface. The average RASST values within these partition elements are used as predictors in a multiple linear regression, with the global mean temperature as the predictand. This procedure is philosophically similar to that used to remove the interannual El Niño signal from observed global mean temperature trends (14), with the caveat that the observed time series are not sufficiently long to statistically identify the signature of inter-decadal internal climate variability on the global mean temperature, necessitating the use of long time-period climate model integrations.

The multiple linear regression provides a series of weights linking the RASSTs within the partition elements to the global mean surface temperature. These weights allow for an objective, statistical prediction of global mean temperature fluctuations arising solely from SST-associated internal variability within a given model. Testing these weights in both preindustrial control and retrospective climate change situations suggests they can successfully identify internal variability (see *SI Text* and Table S1).

Significantly, the models appear to be consistent in their predicted global mean surface temperature response to RASST anomalies. Fig. 1*A* shows the various models' weights applied to the observed residual anomaly SSTs derived from the extended reconstruction of global SST based upon COADS data (15). The global mean temperature response to observed RASST anom-

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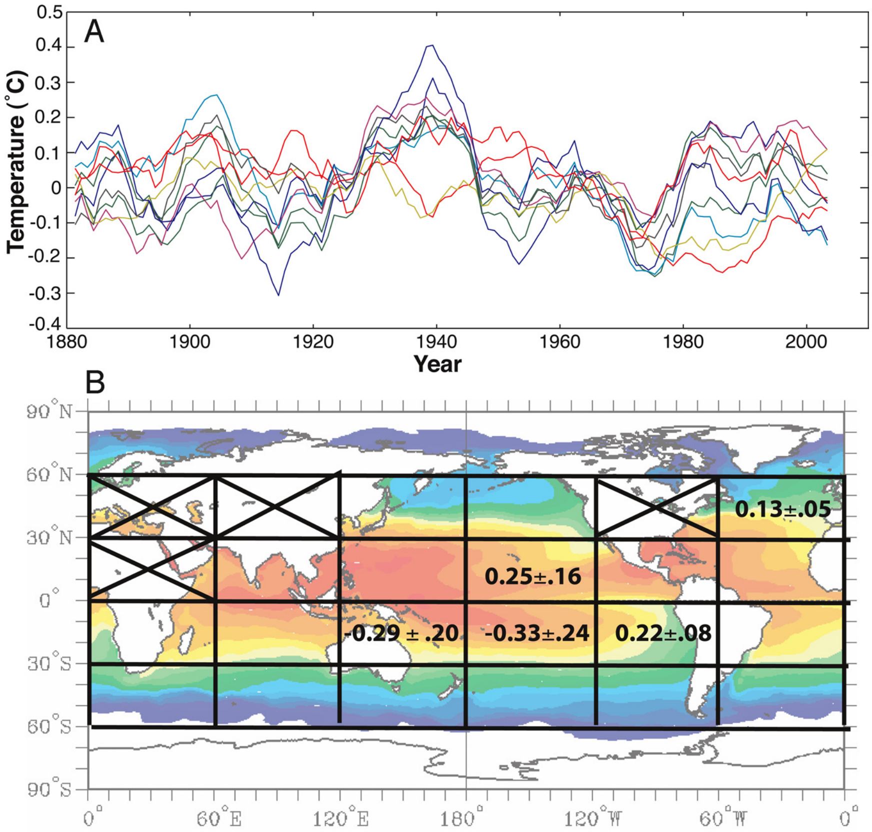

Fig. 1. Regression weights derived from preindustrial control climate model simulations allow for estimation of the observed signature of internal variability in the observed 20th century global mean temperature. (*A*) The global mean temperature anomalies resulting from the various models' weights applied to the observed residual anomaly SSTs derived from the extended reconstruction of global SST based upon COADS data (14). The two outlying cold trajectories during the 1940s belong to the GISS-ER and MIROC-MEDRES models. (*B*) The robust weights derived from the preindustrial control simulations. Partition elements where the weights are not significantly different from zero at the $P = 0.1$ level (indicated by the plus/minus) are left blank. Units are °C global mean surface temperature for °C change in SST within the partition element.

alies consistently highlights a cooling from 1900–1915; a warming from 1915–1940; a cooling from 1940 to the late 1970s, and a return to neutral after that point. The exceptions to this behavior are the GISS Model E-R (4.0° × 5.0°) and MIROC 3–2-MEDRES (2.8° × 2.8°), both of which have been documented as having difficulties with air-sea interaction due to limitations in their resolution (16). All other higher resolution models appear to be converging on a common response to observed residual SST anomalies.

Relatively few SST partition elements actively participate in the generation of the global mean temperature fluctuations. Fig. 1*B* shows that over the eight active models, the regression weights differ significantly from zero only in the tropical Pacific and the North Atlantic. Within this context, the spread of the model predicted global mean surface temperatures in Fig. 1a reflects the uncertainty of this technique (90% confidence interval 0.08 °C). Note that this result is not directly a test of model fidelity, but rather of linearity; what is converging here is the model's representations of air-sea interaction leading to global mean surface temperature anomalies, not whether the models have the ability to capture the magnitude or even the spatial patterns of observed RASST variability.

Some caution is necessary in implicating the tropical Pacific and North Atlantic as the primary sources of oceanic-forced variability in the global mean temperature. In particular, multidecadal time-scale variability in the tropical Pacific has global connections (9). As such, variability in the north Pacific, such as the Pacific Decadal Oscillation, that influences the tropical Pacific might well be the ultimate cause of a fraction of observed variability in the global mean temperature. Such concerns, however, are tangential to the global mean temperature signature of oceanic natural variability, which is robust and independent of spatial correlations that might obscure the identification of the precise geographical source of such variability.

While the convergence of the model response to SST variability is encouraging, any technique used to identify internal variability must not be confounded by forced patterns of climate variability. Volcanism, solar forcing, and sulfate aerosols all have a unique "fingerprint" of climate variability, and a useful technique must not confuse such fingerprints with internal variability. Linear discriminant analysis, an exploratory data analysis pattern recognition technique, provides a way to distinguish forced from internal RASST variability when applied in an identical fashion to modeled and observed RASST fields (17). This analysis lifts components of slow interdecadal SST variations from faster intradecadal variations, effectively peeling back layers of longer-time scale variability. These linear discriminants, which consist of an RASST anomaly field and a time series that describes the projection of that anomaly in the annual mean RASST field, maximize the ratio of inter-decadal to inter-annual variability, in keeping with our desire to understand the decadal-to-century scale variability in the global mean surface temperatures (see *SI Text* and Figs. S3 and S4).

Prior results suggest the leading linear discriminant RASST contains the bulk of the anthropogenic forced climate signal (a mixture of greenhouse gas and aerosols) (17). If our technique

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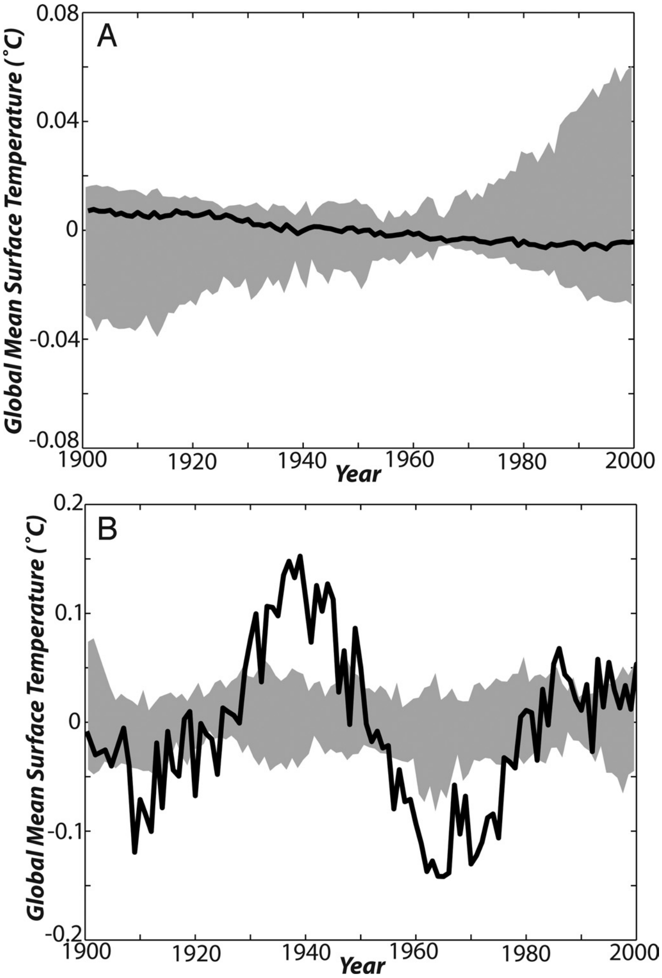

Fig. 2. Global mean surface temperature calculated by applying the weights of Fig. 1*B* to the linear discriminants that maximize the ratio interdecadal-to-interannual variability in the residual anomaly SST. The shaded area denotes the 10–90% confidence intervals from the CMIP3 20th century retrospective model ensemble, and the heavy solid curve denotes the global mean temperature signature derived from the discriminant RASST fields. (*A*) Global mean surface temperature associated with the leading discriminant, which contains the forced climate change signal (''footprint''), showing that the weights of Fig. 1*B* are not confounded by this forced pattern in either models or observations. (*B*) Global mean surface temperature associated with higher order oscillatory discriminants. The model mean is indistinguishable from zero throughout the 20th century, suggesting that the observed higher SST discriminants describe internal variability. The underestimation of modeled versus observed interdecadal variability is apparent.

is confounded by this signal, there should be a substantial trend in the inferred global mean temperature over the 20th century in both the models and observations, matching the trend in this signal. The shaded area in Fig. 2*A* shows the 10–90% confidence intervals for the global temperature signal associated with the leading linear discriminant in an ensemble of 32 20th century retrospective simulations (20c3m) taken from the CMIP3 archive. No significant trends are found, as the model mean is indistinguishable from zero, with contamination providing at most a warming of 0.1 °C (−0.04 °C to 0.06 °C) over the 20th century. This is not only significantly smaller than the observed 20th century temperature increase of 0.7 °C, but does not have the oscillatory pattern of the temperature anomalies in Fig. 1*A*. Hence, the weights used to define internal variability appear more-or-less blind to this leading pattern of forced RASST variability. The solid curve in Fig. 2*A* shows that the same is true

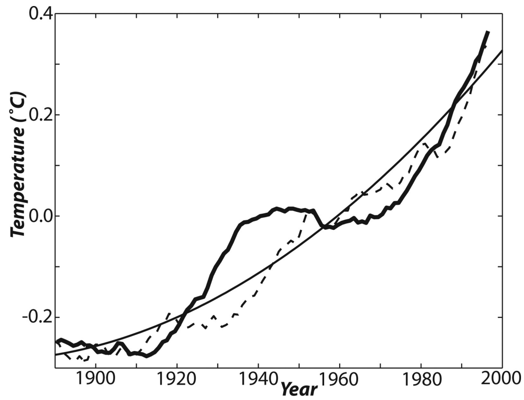

Fig. 3. Observed GISS 21-year running mean global mean surface temperature (heavy solid), along with that temperature cleaned of the internal signal, which is the mean over the eight active models of Fig. 1*A* (dashed). The cleaned global mean temperature warms monotonically, and closely resembles a quadratic fit to the observed 20th century global mean temperature (thin solid). The standard deviation of the cleaned temperature from the quadratic fit is 0.03 °C compared with 0.06 °C for the observed.

for the leading linear discriminant of observed RASST. Global temperature excursions inferred from this discriminant using the weights of Fig. 1*B* are indistinguishable from zero.

It is possible that oscillatory interdecadal patterns of RASST might be forced as well, perhaps representing some lagged feedback process in the models and in observations. If our technique is confounded by a lagged feedback of some sort, there should be substantial departures of the mean model inferred global temperature from zero, indicating the presence of a forced signal. The shaded area in Fig. 2*B* shows the 10–90% confidence intervals for the global temperature signal associated with higher order, oscillatory discriminants taken from the same ensemble of climate simulations as above. The model mean is indistinguishable from zero for the entire 20th century. Hence, at least in the models, these higher order discriminants describe internal RASST variability.

The lack of a forced SST-associated oscillatory signal in models suggests global temperature anomalies inferred from higher order observed RASST discriminants should signify internal variability. The heavy line in Fig. 2*B* shows the global temperature anomaly associated with these observed oscillatory discriminants consists of an interdecadal global mean temperature fluctuation effectively identical to that in Fig. 1*A*. This oscillatory signal is inconsistent with the model-estimated envelope, as models appear to underestimate inter-decadal variability by a factor of roughly three compared to the observations. This suggests that the current generation of models has difficulty reproducing important aspects of the observed spatiotemporal character of inter-decadal variability (18).

The lack of an oscillatory model signal suggests that the interdecadal global mean surface temperature signal derived from the observations and shown in Figs. 1*A* and 2*B* is indeed the signature of natural long-term climate variability. Removing this internal signature from the observed global mean temperature record should clean up the individual and unique realization of nature, isolating the forced climate signal. Fig. 3 shows that the resulting cleaned signal presents a nearly monotonic warming of the global mean surface temperature throughout the 20th century, and closely resembles a quadratic fit to the actual 20th century global mean temperature. Interdecadal 20th century temperature deviations, such as the accelerated observed 1910–1940 warming that has been attributed to an unverifiable increase in solar irradiance (4, 7, 19, 20), appear to instead be due to natural variability. The same is true for the observed mid-40s to mid-70s cooling, previously attributed to enhanced sulfate aerosol activity (4, 6, 7, 12). Finally, a fraction of the post-1970s warming also appears to be attributable to natural variability. The monotonic increase of the cleaned global temperature throughout the 20th century suggests increasing greenhouse gas forcing more-or-less consistently dominating sulfate aerosol forcing, although our technique cannot exclude other mechanisms not contained in the current generation of model forcing (22).

This result is another link in a growing chain of evidence that internal climate variability played leading order role in the trajectory of 20th century global mean surface temperature. Freely evolving general circulation model trajectories have been shown to have large global mean surface temperature excursions similar to that observed in the early 20th century (8). These excursions appear to be consistent with fluctuations in the Atlantic thermohaline circulation (THC), which significantly impacts the northern hemisphere temperature (10, 11, 23). The apparent internal variability of the THC has been shown to have a different relation of the SST to subsurface ocean temperatures from that expected for forced variability in the North Atlantic (24), consistent with the THC at least playing a partial role in the internal variability identified here.

A vigorous spectrum of interdecadal internal variability presents numerous challenges to our current understanding of the climate. First, it suggests that climate models in general still have difficulty reproducing the magnitude and spatiotemporal patterns of internal variability necessary to capture the observed character of the 20th century climate trajectory. Presumably, this is due primarily to deficiencies in ocean dynamics. Moving toward higher resolution, eddy resolving oceanic models should help reduce this deficiency. Second, theoretical arguments suggest that a more variable climate is a more sensitive climate to imposed forcings (13). Viewed in this light, the lack of modeled compared to observed interdecadal variability (Fig. 2*B*) may indicate that current models underestimate climate sensitivity. Finally, the presence of vigorous climate variability presents significant challenges to near-term climate prediction (25, 26), leaving open the possibility of steady or even declining global mean surface temperatures over the next several decades that could present a significant empirical obstacle to the implementation of policies directed at reducing greenhouse gas emissions (27). However, global warming could likewise suddenly and without any ostensive cause accelerate due to internal variability. To paraphrase C. S. Lewis, the climate system appears wild, and may continue to hold many surprises if pressed.

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