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Atlantic Multidecadal Variability since 1850 is largely externally forced

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Abstract. Whether observed Atlantic Multidecadal variability (AMV) is truly an intrinsic internal mode of climate variability or an externally forced response remains contentious, with conflicting literature that North Atlantic SST variability arises from internal dynamics or external forcing. The availability of several single model initial-condition large ensembles (SMILEs) and new insights into potential biases in sea surface temperature (SST) variations offer a fresh opportunity to reassess this question. We show that SMILE ensembles provide strong evidence that AMV-like variability is largely externally forced. New insights into potential SST biases also raise questions about apparent early 20th Century oscillatory behaviour. SMILE models with stronger multidecadal variability show weaker agreement with observed AMV phasing, even in the best performing individual ensemble members, suggesting that large internal model variability may obscure the forced signal. We conclude that future variations in North Atlantic SST will very likely be driven primarily by future anthropogenic activities.

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1 Introduction

AMV manifests as alternating warm and cold sea surface temperature (SST) anomalies centred on the North Atlantic basin with a nominal cycle of 60 to 90 years (Delworth and Mann, 2000). Such variations in North Atlantic SST (NASST) have been linked to regional hydroclimate and surface temperature fluctuations over Europe and North America (Sutton and Dong, 2012; Sutton and Hodson, 2005), and its influence extends globally through teleconnections (Kravtsov et al., 2018). Despite its wide-ranging relevance, the physical origin of AMV remains contested. There is ongoing debate whether the observed NASST anomalies reflect a persistent internally generated mode of climate variability, or a transient feature shaped by external forcing (Bellomo et al., 2018; Booth et al., 2012; Clement et al., 2015; Klavans et al., 2022; Knudsen et al., 2011; Murphy et al., 2017; Otterå et al., 2010).

One school of thought regards the AMV as an expression of naturally occurring internal variability, typically associated with changes in the Atlantic Meridional Overturning Circulation (AMOC) (Ba et al., 2014; Wang and Zhang, 2013; Wills et al., 2019; Zhang et al., 2019) or stochastic atmospheric processes (Clement et al., 2015). From this perspective, AMV phases are governed by natural dynamics and may be expected to continue with a quasi-predictable pattern. In contrast, others argue that much of the directly observed AMV signal is a coincidence that is preliminarily the response to external drivers, particularly from anthropogenic GHGs and aerosol emissions (Bellomo et al., 2018; Booth et al., 2012; Murphy et al., 2017) and volcanic activities (Booth et al., 2012; Otterå et al., 2010). This distinction is critical: if the AMV is primarily a natural oscillation, a transition to a cooling phase could be expected in the coming decades; if externally forced, its future trajectory will largely follow the evolution of external drivers, principally anthropogenic GHGs and aerosol emissions.

Resolving this debate is complex. First, the shortness and uncertainties of the observational record potentially hinder robust detection of multidecadal oscillations (Buckley and Marshall, 2016; Mann et al., 2020, 2021). Although reconstructions using proxy data have identified multi-decadal variability in NASST extending back hundreds or thousands of years (Gray et al., 2004; Knudsen et al., 2011), it is unclear whether this is consistent with direct observations, and the interpretation of paleoclimate data is challenged by proxy limitations and by difficulties in calibrating against a modern,

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anthropogenically influenced climate (Mann et al., 2021). Second, the representation of multidecadal variability in climate models is highly sensitive to model physics and atmosphere-ocean coupling (Kravtsov et al., 2018; Wang and Zhang, 2013; Zhang et al., 2019).

Internal variability is the natural fluctuations of the climate system that occur independently of external factors. These variations stem from the inherent nonlinear and chaotic nature of the atmosphere-ocean-ice-land system and are sensitive to small differences in initial conditions (Lehner and Deser, 2023; Lorenz, 1963). In climate modelling, internal variability is quantified by running multiple simulations with identical external forcing but slightly different starting states. The divergence among these simulations represents the range of plausible unforced climate outcomes.

Recent modelling innovations provide new tools for assessing the uncertainty associated with internal variability. Single-model initial-condition large ensemble simulations (SMILEs) have emerged as a powerful means of separating internal variability from externally forced signals (Deser et al., 2020a, b). SMILE experiments consist of multiple realisations from the same climate model, each with identical external forcing but slightly perturbed initial conditions. This allows the model's internal variability to emerge as the spread across ensemble members, while the ensemble mean isolates the modelled forced response. Studies using SMILEs have shown that ensemble means often evolve in phase with observed AMV signals, lending support to the argument that AMV signals may be externally forced (Bellomo et al., 2018; Booth et al., 2012; Murphy et al., 2017). However, others highlight the persistence of internally generated variability, particularly in the latter half of the 20th century (Kim et al., 2018). High-resolution climate models offer another way to study the internal atmospheric and oceanic dynamics, and have also successfully replicated AMV-like patterns (Hao et al., 2025).

This study is focused on an ensemble-based separation of AMV signals by incorporating seven SMILEs and a 52-member ensemble of historical runs from CMIP6 models to quantify the forced components and the internal variability envelope of North Atlantic multidecadal SST variability over the period 1850-2014.

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2 Data and Method

2.1 Observational datasets and model simulations

Three SST observations are used: DCENT (Chan et al., 2024), HadSST4 (Kennedy et al., 2019) and ERSST5 (Huang et al., 2026). Historical simulations come from seven SMILEs produced by six modelling centres (Supplementary Table 1), each SMILE run within the same model with small perturbations introduced to either their initial atmospheric or ocean conditions; some models perturb both. Alongside, a multimodel ensemble is formed by using the first realisation (r1i1p1f1) from the 52 CMIP6 models that were available through the UK Science and Technology Facilities Council (STFC) Centre for Environmental Data analysis (CEDA) Archive at the time of analysis (Supplementary Table 2). The historical forcing followed a prescribed CMIP5 forcing (Taylor et al., 2012) for MPI-GE and CESM1-LENS, and a CMIP6 forcing (Eyring et al., 2016) for the remaining LEs. Most simulations span 1850 to 2014, however, shorter coverage SMILEs such as MPI-GE, CESM1-LENS and CANARI are retained in the analysis to broaden model physics sampling and strengthen ensemble-based conclusions.

2.2 AMV indices

The computation of AMV indices follows a consistent methodology applied to both observational and simulation data, following (Barghorn et al., 2025; Robson et al., 2023). Monthly SST anomalies were rebased to a common 1961-1990 climatology, then averaged into annual means. All grid cell data were bilinearly interpolated to regrid onto a 5×5 resolution consistent with the HadSST4 grid. Due to the consistent data availability across the North Atlantic domain during the study period, masking to match HadSST4 or DCENT spatiotemporal coverage was deemed unnecessary. Annual anomalies for the North Atlantic region (0-60° N, 0-80° W) were extracted and aggregated into an area-weighted mean timeseries. A best-fit linear trend over the entire timeseries for each large ensemble was removed to eliminate the long-term warming trend. Last, the series were smoothed with a centred 10-year rolling average.

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Methodological choices used to remove long-term warming trends have a direct influence on the inferred AMV index (Frankcombe et al., 2018; Peings et al., 2016; Robson et al., 2023; Si and Hu, 2017a). To assess sensitivity, AMV indices were recalculated using detrending methods: linear detrending of NASST timeseries, as in the main text; and a second-order polynomial fit detrending of NASST times series. Only the detrending methods vary, the other procedures follow the same exact steps.

For each large ensemble (LE), the mean across the ensemble members is taken as the forced response, since averaging cancels random internally generated variability while preserving the common response to external forcing.

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3 Results

3.1 Sea surface temperature uncertainties

Differences between historical SST estimates can complicate AMV diagnosis. A critical example of SST observation uncertainty is a possible early twentieth-century cold bias (Sippel et al., 2024), which has been recently reevaluated and adjusted in the Dynamically Consistent ENsemble of Temperature (DCENT) dataset (Chan et al., 2024). Between 1900-1920, DCENT exhibits systematically higher NASST anomalies compared to the two most widely used records, HadSST4 and NOAA ERSST5, substantially modifying apparent multidecadal variability (Fig. 1). Given these inter-dataset differences, the subsequent analysis adopts two SST datasets: HadSST4, which reflects the conventional records; and DCENT which reflects the new insights into early 20th Century NASSTs. Using both datasets enables a more comprehensive assessment of model-observation comparisons and reduces the risk of over-reliance on a single, potentially biased observational estimate.

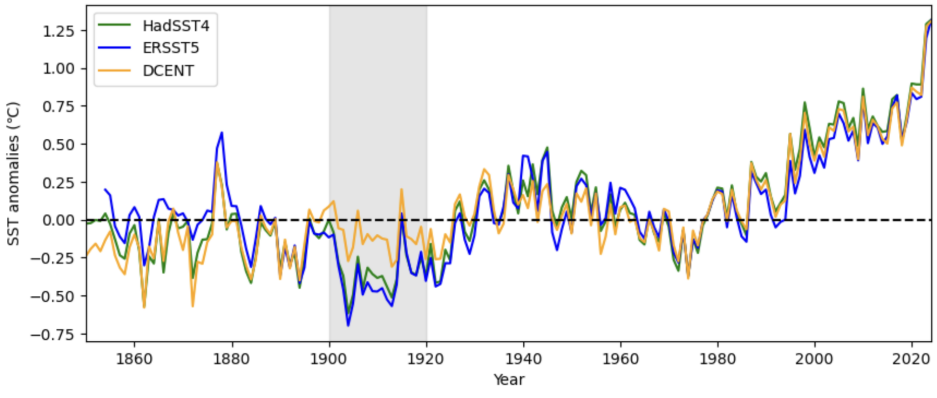

Figure 1 Observed annual SST anomalies over the North Atlantic domain (0-60°N, 0-80°W), relative to the 1961-1990 average, HadSST4 (green), ERSST5 (blue) and DCENT (orange). The grey-shaded area represents the period of maximum divergence between the three SST estimates.

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3.2 Ensemble means track AMV phase

The SMILE ensemble results fall into two distinct categories. Several SMILE models exhibit limited multidecadal variability in their ensembles whereas others exhibit substantial multidecadal variability. In CESM2-LENS2, taken as an example of the first family which exhibit limited multidecadal variability, the ensemble mean closely tracks the observed AMV evolution (R^2=0.84 with HadSST4, R^2=0.93 with DCENT), and the individual ensemble members display similar phase transitions (the average member-observation-correlation is 0.73 with HadSST4 and 0.81 with DCENT) (Fig. 2a), including early twentieth-century cooling, a 1930-1950 warm phase, the mid-century cooling and post-1970 warming. The ensemble mean falls within the range defined by the two observational datasets, except during the 1930-50 warming, which appears to be damped in the model. This close alignment between the ensemble mean, individual members and observations suggests that in CESM2-LENS2, the AMV-like oscillations are primarily externally forced. This externally forced AMV-like behaviour is not exclusive to CESM2-LENS2, similar consistency with observations is found in several other SMILEs that exhibit intrinsically limited multidecadal ensemble variability (CESM1-LENS, CanESM5-LE, MIROC-LE and CANARI-LE; Supplementary Fig. 1-4). If the AMV were an expression of internal variability, such coherent multidecadal features would not be visible: the ensemble members would evolve more independently, and by averaging across the ensemble members, the internal variability would cancel on averaging, yielding a comparatively flat ensemble mean.

By contrast, FGOALS-LE which in its SMILE ensemble has large multidecadal variability, exhibits a relatively flat ensemble mean, and a wide spread amongst ensemble members (Fig. 2b). The overall agreement with observations (R^2=0.79 with HadSST4, R^2=0.65 with DCENT) is considerably lower than in CESM2-LENS2 , the average member-observation-correlation (grey dashed line) is also systematically lower than the ensemble-mean-observations correlation (blue dashed line). The presence of substantial decadal variability means that FGOALS-LE struggles to replicate observed behaviour. A comparable behaviour is evident in the other SMILE with large multidecadal internal variability (MPI-GE, Supplementary Fig. 5).

The ensemble members within each SMILE that maximised correlation with each observational series were identified. Again, CESM2-LENS2 ensemble members show

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a greater similarity with observations compared to those from FGOALS-LE (Figure 2). This behaviour holds across other models as well; models with lower intrinsic multidecadal variability consistently perform better in replicating observed AMV behaviour (Supplementary Fig. 1-5). If AMV were internally generated then it would be expected that while on average a model which captured the relevant physics might not capture the observed signal well, when run enough times in a SMILE context it would, by chance, have a member that was in phase and better reproduced the observed behaviour. This is not the case for either FGOALS-LE or MPI-GE. Their best ensemble member is less well correlated than that for the models with small intrinsic multidecadal NASST variability.

In CESM2-LENS2 (Fig. 2a), no individual ensemble member reproduces the pronounced cooling around 1910 as seen in HadSST4. Previous studies have interpreted such mismatches as model limitations in reproducing the multidecadal variability, especially for the twentieth century(Kravtsov et al., 2018). However, after applying their bias correction to early twentieth-century SST records, the DCENT dataset shows a greater agreement with the CESM2 ensemble mean during 1910-1930 (RMSE=0.05℃) than HadSST4 (RMSE=0.16℃). This suggests that a large part of the apparent discrepancy could arise from observational biases rather than model errors. This would also add credence to recent findings(Sippel et al., 2024) suggesting that DCENT may more faithfully reflect the physically consistent evolution of NASST anomalies over this interval.

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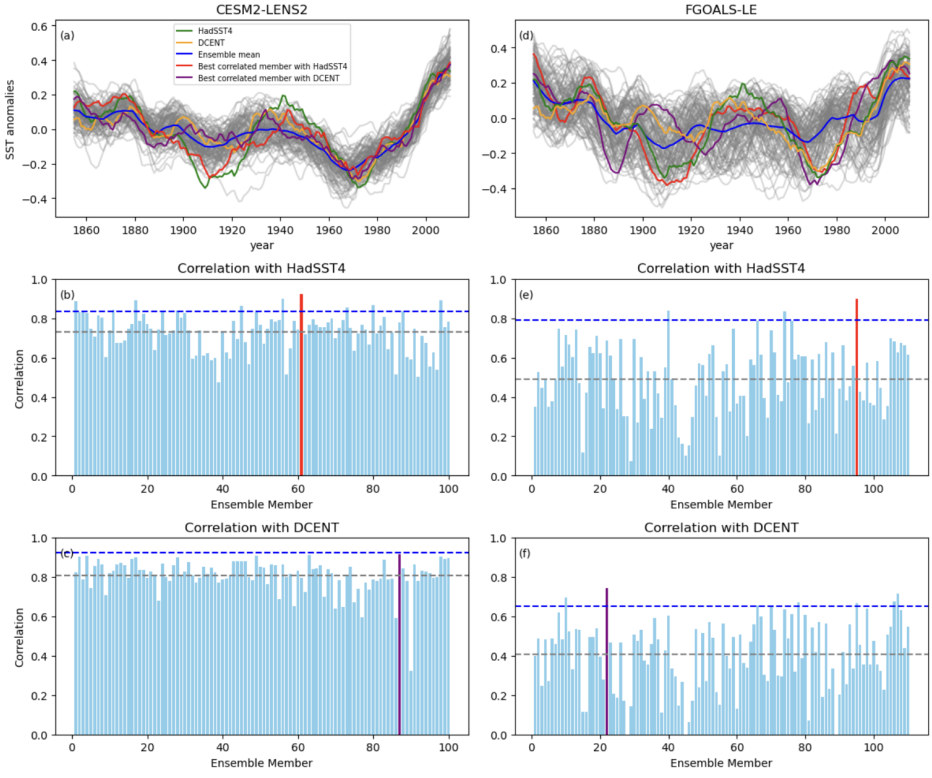

Figure 2 AMV indices and correlation statistics from CESM2-LENS2 (left) and FGOALS-LE (right) over 1855-2010. a, AMV indices from CESM2-LENS2, calculated by linear detrending the annual average NASST and smoothed with a 10-year rolling mean. The forced signal is represented by an ensemble mean (blue). Comparison is made with observed AMV derived from HadSST4 (green) and DCENT (orange). The ensemble member that is best correlated with the HadSST4 (red) and DCENT (purple) is also highlighted. **b**, correlation coefficient between each CESM2-LENS2 member and HadSST4. The ensemble mean correlation is shown with a blue dashed line, the average correlation across members is shown with a grey dashed line. **c**, Same as **b**, but for correlation with DCENT. **d-f**, same as **a-c**, respectively, but for FGOALS-LE.

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Given the contrasting AMV-like behaviour in different SMILEs, we further examine the model-dependent AMV-pattern by including the first historical simulation (r1i1p1f1) from those models participating in CMIP6 that were available via the UK STFC node and treating them collectively as a pseudo-SMILE. Unlike SMILEs, which isolate internal variability within a single model structure, this multi-model approach introduces structural model uncertainty, encompassing different physical parameterisations and ocean-atmosphere coupling schemes.

The spread in SST anomalies across the CMIP6 ensemble is considerably larger than in any single-model large ensemble, reflecting the combination of model uncertainty and internal variability (Fig. 3). Despite this, the CMIP6 multi-model mean captures the phasing of key multidecadal features evident in the observational records, though, the 1930-1950 warming phase remains damped, as in the SMILEs. The best observations-matched members closely follow the observations, as in CESM2-LENS2 (Fig. 2a-c).

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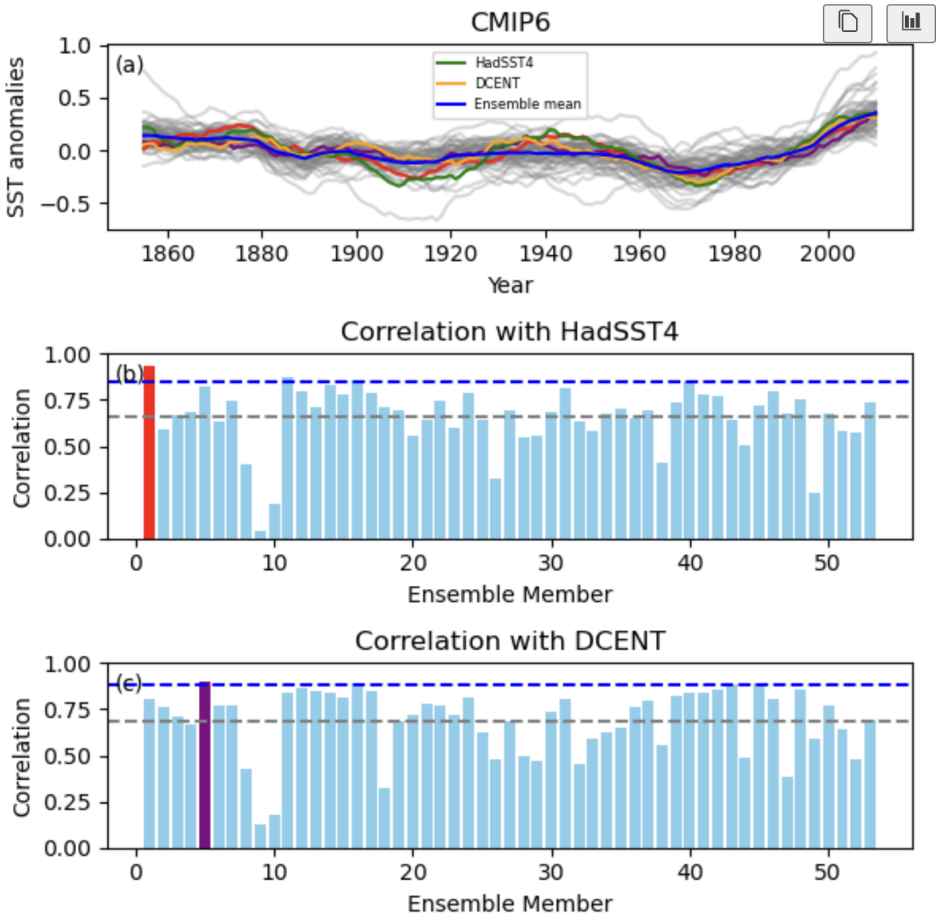

Figure 3 AMV indices from the first simulation of 52 models in CMIP6. The multi-model ensemble mean is shown in blue. Observational datasets include HadSST4 (green) and DCENT (orange). Same as Fig. 2, but for CMIP6 models.

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Overall, the ensemble means from seven SMILEs and the CMIP6 ensemble broadly tracked the observed AMV behaviour (Fig. 4a). Several robust inferences can be drawn. First, the phasing of AMV is highly consistent across models and observations, with most ensemble means capturing the major multidecadal transitions. Second, the amplitude of these swings is systematically weaker in most ensemble means relative to HadSST4 and to a much lesser extent DCENT, especially the nearly flat 1930-1950 warm phase, a feature that recurs across many SMILEs and in the CMIP6 mean. This might be associated with a potential warm bias during World War II (Chan and Huybers, 2021) which remains unresolved. Third, none of the ensemble means reproduces the ~1910 cooling evident in HadSST4, instead, the ensemble means cluster more closely around DCENT during this interval. Taken together, the alignment in timing of AMV phase transitions across these structurally diverse models, despite differences in internal variability, robustly implies the presence of a common forced signal governing NASST variability over the entire observational record and heavily discounts the potential that it arises from internal multidecadal variability. The better agreement with DCENT also highlights the likelihood of residual biases in both HadSST4 and ERSSTv5 in the early 20th Century, at least in the North Atlantic basin.

3.3 Sensitivity analysis to detrending method

The two detrending approaches captured the principal AMV features from the observational records (Fig. 4), with the timing of the phase transitions largely unchanged, but the amplitude varies substantially. Linear detrending yields a stronger magnitude, particularly exaggerating the mid-20 century warming in HadSST4. The ensemble mean from linear and quadratic detrending, yields similar inferred variability. Consistent with previous findings (Si and Hu, 2017b), the phase transitions are robust to methodological choices, whereas amplitude is more sensitive.

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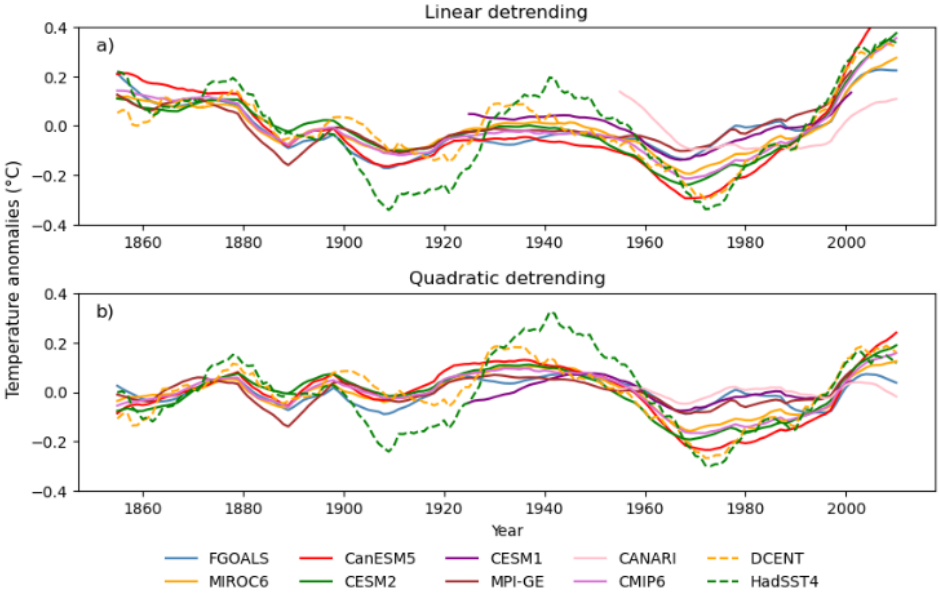

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237 Figure 4 Sensitivity of AMV index to detrending methods. a, AMV indices derived
238 from linear detrending of NASST, compared with HadSST4 (green dashed line) and
239 DCENT (orange dashed line). b, same as a, using quadratic detrending.

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4 Summary and Discussion

The physical causes of AMV remain disputed (Robson et al., 2023). Ensemble means from SMILE simulations reproduce the observed AMV temporal evolution under prescribed external forcing, particularly for those models with limited intrinsic multidecadal variability, indicating that AMV-like variability is predominantly a forced response. Our analysis thus supports the growing evidence that external forcing, such as by anthropogenic emissions and volcanic effects, exerts a dominant influence on multidecadal NASST variability (Bellomo et al., 2018; Booth et al., 2012; Klavans et al., 2022; Murphy et al., 2017). Thus, the future trajectory of NASST and the nearby continents' climate will largely evolve as a result of future emission choices.

A counterintuitive result emerges when comparing SMILEs. Models with stronger multidecadal variability, such as FGOALS-LE (Fig. 2d) and MPI-GE (Supplementary Fig. 5), perform less well in replicating the observed AMV evolution. While such models might be expected to better capture observed variability through their internal dynamics representation, correlation analysis reveals that even the best-correlated ensemble members in these models deviate more from the observed AMV than those from models with weaker multidecadal variability, such as CESM2-LENS2 (Fig. 2a) or MIROC6-LE (Supplementary Fig. 2). This raises a critical question: could strong multidecadal internal variability be actively unhelpful for capturing observed AMV features? One possibility is that in models where internal variability dominates, ensemble members evolve too independently, masking the externally forced signal that governs observed phase transitions. Conversely, in models where internal variability is more subdued, the forced signal is more distinct.

Discrepancies between observations and projections can be traced to several factors. First, internal variability explains part of the residual, as observed trajectories often lie within the ensemble spread. Second, anthropogenic aerosols can modulate the ocean dynamics by strengthening AMOC, they enhance northward heat transport and partially offsets the initial cooling (Robson et al., 2022). In the context of AMV, the magnitude of externally forced SST variation may be muted by AMOC variability. Third, observational uncertainty can introduce systematic errors in estimating variability amplitude. From the possible cold biases in the early 20th century (Sippel et al., 2024), to the unresolved World War II warm anomaly (Chan and Huybers, 2021),

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the reliability of SST records is often overlooked and too quickly attributed to internal variability, and thus warrants more attention (Folland et al., 2018; Osborn and Kennedy, 2024). Fourth, model design limitations, particularly the inability to reproduce the magnitude and spatiotemporal structure of observed multidecadal variability (Kravtsov et al., 2018; Zhang et al., 2019), together with initialization choices contribute to systematic biases. Recent work shows that simulations initialised from 1750 improved representation of earlier 20th century cooling (Ballinger et al., 2026). Last, the prescribed volcanic forcing may itself be underestimated, numerous studies indicate that CMIP5 and CMIP6 forcing datasets have overlooked the volcanic forcing in both the future and historical periods (Bethke et al., 2017; Chim et al., 2025).

Interpretation of AMV-like variability is sensitive to AMV index calculation. The common approach to isolate global-scale warming is linear detrending of NASST (Bellomo et al., 2018; Huang et al., 2021; Si and Hu, 2017a), however, it often overestimates the AMV amplitude (Robson et al., 2023). Regression-based approaches using global mean SST can remove part of the genuine AMV variability, leading to underestimation (Peings et al., 2016). Several studies have concluded that the inferred external responses are highly dependent on the methodological choices, as well as the time periods considered (Christiansen et al., 2025; Robson et al., 2023). Despite these differences, the essential phase transitions and low-frequency variability remain robust (Si and Hu, 2017a). A comparison of the sensitivity of our principal findings to different detrending methods is provided and shown unaffected by such choices.

Future work could extend the attribution of forced responses by separating individual anthropogenic drivers, an approach that is becoming increasingly feasible with the growing availability of single forcing simulations. Recent applications of single forcing large ensemble have demonstrated their potential for attributing AMV (Huang et al., 2021) and the updated CESM2 single forcing large ensemble (Simpson et al., 2023) provides longer simulations and improved model design, offering new opportunities for more robust attribution analyses.

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Data availability

The observational sea surface temperature DCENT (Chan et al., 2024) is available at https://climatedataguide.ucar.edu/climate-data/dcent; HadSST4 (Kennedy et al., 2019) is available at https://climatedataguide.ucar.edu/climate-data/sst-data-hadsst4; and ERSST5(NOAA Extended Reconstructed Sea Surface Temperature (ERSST), Version 5, 2026) is available at https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html.

The modelling outputs of MPI-GE (Maher et al., 2019) is available at https://esgf-metagrid.cloud.dkrz.de/datacart/add_all/1/4779/?back=/search_reload/; CESM1-LENS1 (Kay et al., 2015) https://www.cesm.ucar.edu/community-projects/lens/data-sets; CESM2-LENS2 (Rodgers et al., 2021) https://gdex.ucar.edu/datasets/d651056/; FGOALS super LE (Zhao, 2023) https://www.scidb.cn/en/detail?dataSetId=f75af1c5d2cf484faa354437dc85acfc. CANARI-LE (Williams et al., 2018), MIROC6-LE(Shiogama et al., 2023) and CanESM5-LE (Swart et al., 2019), CMIP6 multi-model ensemble is achieved at the UK Science and Technology Facilities Council Centre for Environmental Data Analysis (CEDA).

Code availability

Analysis scripts used for this study are available at https://github.com/YongyaoLiang/AMV_LE_simulations

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Competing interests

The authors declare no competing interests.