Defining the Internal Component of Atlantic Multidecadal Variability in a Changing Climate

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Submitted to Geophys. Res. Lett. 17 April 2021

Revised version submitted 27 June 2021

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Key points

1. A common index of Atlantic Multidecadal Internal Variability is low-pass filtered sea surface temperatures averaged over the North Atlantic minus the global mean.

2. The global pattern of sea surface temperature anomalies associated with this index is corrupted by the structure of forced climate change in the future.

3. An alternative index based on removing the pattern of sea surface temperature anomalies linked to global-mean temperature is generally robust to climate change.
Plain Language Summary

As anthropogenic climate change escalates, conventional methods aimed at isolating modes of natural climate variability from forced changes may be inadequate. This study considers the “Atlantic Multidecadal Oscillation” (also known as “Atlantic Multidecadal Variability”), a well-known phenomenon canonically defined from the timeseries of sea surface temperatures averaged over the North Atlantic basin. A simple and widely-used approach for removing the anthropogenic signal from this index and its associated spatial pattern is to subtract the global-mean temperature at each location and time. However, this method aliases the pattern of forced climate change onto the pattern of natural Atlantic Multidecadal Variability. A simple alternative approach based on subtracting the pattern of anthropogenic climate change associated with global-mean temperature is much more successful at isolating the natural component of Atlantic Multidecadal Variability within a background changing climate. The conclusions are based on evidence from 9 different state-of-the-art coupled climate model “large ensembles”, which serve as methodological testbeds by providing robust estimates of the true structure of the models’ natural modes of variability under human-induced climate change. The results have general implications for how modes of natural variability are defined in a future warming world.

Abstract

The canonical index of “Atlantic Multidecadal Variability” (AMV) is the low-pass filtered timeseries of sea surface temperature anomalies (SSTA) averaged over the North Atlantic. This index and its associated SSTA spatial pattern confound externally-forced climate change and internally-generated climate variability. The internal component of AMV is commonly isolated
by either subtracting the global-mean SSTA or removing the pattern of SSTA associated with the global-mean. This study evaluates the skill of each method with regard to the spatial pattern of internal AMV, using 9 coupled model Large Ensembles over the period 1940-2100 as a testbed in which the true internal AMV is known \textit{a priori}. The first method aliases the structure of forced climate change onto internal AMV, while the second method is generally robust to climate change. The models simulate realistic patterns of internal AMV, although such an assessment is hampered by the brevity of the observational record.

1. Introduction

The “Atlantic Multidecadal Oscillation” (also known as “Atlantic Multidecadal Variability”; AMV) is a prominent mode of low-frequency variability of the coupled ocean-atmosphere system, with climate impacts in many regions worldwide (see the recent review by Zhang et al. 2019: hereafter Z19). Originating within the Atlantic basin, this mode is thought to be initiated by low-frequency interactions between the oceanic thermohaline circulation (the Atlantic Meridional Overturning Circulation: AMOC) and the large-scale atmospheric circulation (the North Atlantic Oscillation: NAO) (e.g., Delworth et al., 2017; Kim et al., 2018; Wills et al. 2019), with additional contributions from coupled atmosphere-ocean mixed layer interactions (e.g., Clement et al. 2015). At the sea surface, AMV is expressed as a basin-wide pattern of temperature anomalies generally of one sign throughout the North Atlantic (NA) and of opposite sign in the tropical South Atlantic (Z19). While many processes contribute to the formation of AMV sea surface temperature anomalies (SSTA) within the NA, ocean dynamics are a key driver in the subpolar region while
atmospheric influences predominate at lower latitudes (e.g., Kim et al. 2020; Wills et al. 2019; Buckley et al. 2014).

AMV is commonly characterized with a simple SSTA index, namely the area-averaged monthly SSTA over the NA (0°-60°N, 80°W-0°; Enfield et al., 2001). To emphasize the multidecadal nature of AMV, this index is typically low-pass filtered and the secular trend removed. Some studies remove a linear trend (e.g. Enfield et al., 2001 and Bellomo et al., 2018), but this procedure has been shown to alias the non-linear component of global warming (Trenberth and Shea, 2006: hereafter, T&S; Simpson et al. 2018; Z19). An alternative approach introduced by T&S is to subtract the global-mean SSTA from the NA SSTA to derive an index of the unforced (e.g., internal) component of AMV; this method is in wide use due to its simplicity. However, by design, this approach does not account for any spatial structure in the pattern of SSTA associated with anthropogenic climate change. The degree to which such structure corrupts the spatial pattern of AMV remains an open question. Indeed, there is active debate regarding the relative contributions of external radiative forcing due to changes in anthropogenic aerosols and greenhouse gases vs. internal processes to the observed characteristics of AMV over the historical record (e.g., Booth et al., 2012; Murphy et al., 2017; Bellomo et al., 2018; Yan et al. 2019; Qin et al. 2020). It is likely that some combination of internal and external influences are present in the instrumental record of AMV (e.g., Qin et al., 2020). Paleoclimate proxy data also support the existence of internally-generated AMV over at least the last millennium (Z19), although this has been questioned by Mann et al. (2021). Additionally, some state-of-the-art fully coupled climate models are able to simulate realistic AMV characteristics due to internal mechanisms alone (Z19).
In this study, we focus on the component of AMV that is internally-generated (hereafter termed iAMV), and address the following questions: 1) Does the T&S method successfully isolate iAMV in a changing climate?; 2) If not, why not and when does the method start to fail?; and 3) Is there a simple, alternative approach that is robust to climate change, in particular the method of removing the SSTA pattern associated with global-mean temperature (Ting et al. 2009; Z19)? To answer these questions, we employ the framework of coupled model “initial-condition Large Ensembles” (LEs) for which a good estimate of the true iAMV is known a priori. We analyze 9 different model LEs over the period 1940-2100 under historical and projected radiative forcing. Our focus is on simple SSTA-based definitions of iAMV; other, more complex statistical approaches such as those of Ting et al. (2009), Frankignoul et al. (2017) and Wills et al. (2019) are beyond our scope.

The rest of this study is organized as follows. Section 2 describes the model and observational data sets, and methodologies. Section 3 presents an assessment of two simple methods for defining the global spatial pattern of SSTA associated with iAMV under a changing climate in 9 model LEs, along with an evaluation of model fidelity that takes into account sampling uncertainty in the observational record. Section 4 provides a summary and discussion.

2. Data and methods

We make use of two gridded observational SST products updated to 2020: NOAA Extended
Reconstruction Sea Surface Temperature version 5 (ERSSTv5; Huang et al. 2017) and the Hadley Center Sea Ice and Sea Surface Temperature version 1 (HadISST1; Rayner et al., 2003). We analyze available Coupled Model Intercomparison Phase 5 (CMIP5) and Phase 6 (CMIP6) model LEs (see Deser et al. 2020) that contain a minimum of 30 ensemble members and simulate both the historical and future periods (the latter using either the RCP8.5, SSP5-85 or SSP3-70 radiative forcing scenario): see Table S1 for details. All 9 model LEs use a similar experimental design, but vary in their start dates and initial-condition perturbation methods (Table S1). Where possible, we discard the first 10 years of simulation to avoid potential effects of initial-condition memory, and analyze the period 1940-2100, which is generally common to all of the model LEs. All model and observational data have been bi-linearly interpolated to the Community Earth System Model version 1 (CESM1) grid for ease of comparison. All data are annual averages smoothed with a 20-year Butterworth low-pass filter (similar results are obtained using a 10-year Butterworth filter; not shown). Note that in the models, SSTA values in areas of sea ice denote the surface temperature of the ice.

True iAMV in model LEs

With an initial-condition LE of sufficient size, it is straightforward to separate the forced component of SSTA (estimated by the ensemble-mean) from the internal component of SSTA (estimated as the residual from the ensemble-mean; iSSTA) in each member at each grid box and time step. For each member, we compute a “true iAMV” Index based on iSSTA averaged over the NA minus the global (60°S-60°N) mean (G), and obtain the “true iAMV” spatial pattern by
regressing iSSTA (minus G) at each location onto the true iAMV Index. These regression maps
are unitless (°C per °C iAMV).

Estimated iAMV in model LEs and observations

Without the benefit of an initial-condition LE, the forced component of a given quantity must be
estimated. Here, we use two methods to estimate and remove the forced component of SSTA: 1) subtract G (SSTA averaged over 60°S-60°N) from SSTA at each grid box and time step (T&S method); 2) subtract the pattern of SSTA associated with G (obtained by regressing SSTA at each location onto G, scaled by the value of G at each time step) from SSTA at each grid box and time step ( “Residual” method: Ting et al. 2009). We apply the same procedures to the observed SSTA, noting that the instrumental record is analogous to one of many possible “ensemble members” that could have occurred in the real world (see Deser et al. 2020 for more discussion on this point).

To assess the performance of the T&S and Residual methods, we compute pattern correlation coefficients and rms differences between the estimated and true iAMV regression maps using area-weighted values for the domain 60°S-60°N. Statistical significance of the iAMV regression maps is assessed using a 2-sided Student-t test at the 90% confidence level, taking into account temporal autocorrelation in the low-pass filtered data.

3. Results
a. Spatial patterns of estimated and true iAMV

The estimated and true iAMV regression maps for the 100-member MPI LE during 1950-2020 and 1950-2090 are shown in Fig. 1 (results for the 8 other model LEs are shown in Figs. S1-8). Note that the estimated (true) iAMV regression map is the average of the 100 individual estimated (true) iAMV regression maps. In general, regression coefficients > 0.4 in absolute value are statistically significant, except for portions of the Southern Ocean (Fig. S9). The true iAMV pattern, similar for the two time periods, exhibits positive anomalies throughout the NA with the largest values in the central subpolar region and along the sea ice edge, and weaker anomalies extending into the tropics; negative anomalies are found to the south of the equator in the Atlantic sector (Figs. 1c and d). A coherent pattern of anomalies is also evident over the Pacific sector, with positive values in the western and central North Pacific, and negative values in the eastern North Pacific extending southwestward into the tropics, with a strong resemblance to the negative phase of Pacific Decadal Variability (PDV; Newman et al., 2016). The true iAMV patterns in the other models are similar to that in MPI with one exception (mainly over the Pacific sector: Fig. S1).

How well can the true pattern of iAMV be estimated with the T&S and Residual methods applied to each ensemble member individually? For MPI, both methods show high fidelity during the period 1950-2020, with pattern correlations (r) of 0.99 and 1.00 against the truth (Figs. 1a and e). Over the longer period 1950-2090, the Residual method remains highly skillful (r = 0.98; Fig. 1f) while the T&S method is much less successful (r = 0.59) and also strongly overestimates the amplitude over the subpolar NA (Fig. 1b). The degradation of the T&S method for the longer period is due to aliasing of the forced climate change pattern onto the estimated iAMV. This can
be seen by the resemblance between the T&S regression map and the (oppositely-signed) forced trend pattern \((r = -0.72; \text{Fig. S1h})\). The climate change pattern effect is less of an issue for the historical period 1950-2020 when forced SST trends are considerably weaker and more spatially homogeneous \((r = 0.19; \text{Fig. S1g})\). Unlike T&S, the Residual method explicitly accounts for the forced pattern effect; however, it too may be vulnerable if the pattern of forced climate change evolves substantially over the period of analysis (see further discussion in Section 4). The skill of the T&S and Residual methods in estimating the structure and amplitude of true iAMV (and the role of the forced SST pattern effect) in the other models is considered in Section 3b.

\(b. \ \text{Time-evolution of true and estimated iAMV patterns and amplitudes}\)

In the previous subsection, we established that the T&S method gives an accurate estimate of true iAMV during 1950-2020 in the MPI LE, but deteriorates considerably when the analysis period is extended to 2090. When does this degradation occur? To address this question, we repeat our analysis for all end dates between 2020-2090: that is, we add one year at a time to the end of our analysis period \((1950-2020, 1950-2021, \ldots 1950-2089, 1950-2090)\) to examine the progression of the degree of resemblance between the estimated and true iAMV patterns. These “cumulative” pattern correlations between the true iAMV and the T&S estimate decline from a maximum value of 0.99 in the 2020s (years refers to the ending date of the analysis period) to a minimum value of 0.59 in the 2080s (Fig. 2a, blue curve). This decline in pattern correlation is accompanied by an increase in spatial rms error \((\text{rmse})\) from 0.1 in the 2020s to 1.2 in the 2080s (Fig. 3a, blue curve), where \(\text{rmse}\) is defined as the spatial rms of the difference between the estimated and true iAMV patterns, divided by the spatial rms of the true iAMV pattern. [For the rmse calculations, the
regression maps are computed using normalized iAMV indices and then scaled by the standard deviation (°C) of the iAMV index for a proper comparison of pattern amplitudes. In contrast to the T&S method, the Residual method remains skillful for all end dates, with pattern correlations > 0.97 (Fig. 2a, red curve) and rmse values < 0.2 (Fig. 3a, red curve).

The decline of \( r(T&S, \text{True}) \) and rise of \( \text{rmse}(T&S, \text{True}) \) over the 21st century is associated with an increasing (inverse) resemblance between the patterns of T&S iAMV and the forced trend (Fig. 2a, cyan curve). That is, \( r(T&S, \text{forced trend}) \) drops from 0.2 in the 2020s to -0.72 in the 2080s, in tandem with the behavior of \( r(T&S, \text{true}) \). This result supports the notion that as the forced trend pattern becomes more pronounced, it becomes progressively aliased onto the T&S estimate of iAMV. It should be noted that the true iAMV pattern has little projection on the forced trend regardless of the time period analyzed (Fig. 2a, green curve).

As mentioned earlier, the 9 model LEs used in our study have different ensemble sizes, ranging from 30 – 100 members (Table S1). Before turning to the results for the other models, we briefly investigate the sensitivity of the cumulative pattern correlations to ensemble size using the MPI LE as a testbed. Repeating our analysis on three 30-member subsets (ensemble members 1-30, 31-60 and 61-90), we find qualitatively consistent results among the three, alleviating any major concerns regarding the effect of ensemble size discrepancy for our multi-model LE inter-comparison (Fig. S14); similar conclusions hold for the other cumulative metrics (not shown).
Cumulative pattern correlation and rmse metrics for all 9 model LEs are compared in Figs. 2 and 3, respectively. In all models and for both metrics, the Residual method nearly always outperforms the T&S method (compare red and blue curves). The skill of the Residual method is evidenced by its high pattern correlation against the true iAMV ($r > 0.8$) for all end dates in all models, and rmse values generally ranging from 0.2-1.0 (with somewhat higher values in two of the models after about 2050: Figs. 3h and i). In comparison, rmse values for the T&S method are generally 2-5 times higher than those for the Residual method, especially for the later end dates.

There is considerable model dependence to the character of the cumulative $r$(T&S, true) curves, with some models exhibiting an evolution similar to the MPI, albeit with different magnitude and timing of the reduction relative to present-day, while others show more uniform values throughout the 21st century (Fig. 2, blue curves). In addition, the pattern correlations between T&S iAMV and the forced trend vary widely across models, with some showing values close to +1 and others close to -1, depending on time period (Fig. 2, cyan curves). The disparate behavior can be traced to the relative magnitudes of the forced trends in NA vs. G: those models for which the forced trend in G exceeds that in NA exhibit a negative $r$(T&S iAMV, forced trend) and vice versa (not shown), due to how the T&S iAMV index is constructed (e.g., NA – G). Regardless, the spatial pattern of the forced trend is aliased onto the T&S estimate of iAMV, whether via NA or via -G. Finally, all models show generally modest pattern correlations ($< 0.3$ in absolute value) between the true iAMV and the forced trend, except for CanESM5 which shows values around 0.6 regardless of time period (Fig. 2, green curves).
The results discussed above pertain to the full global (60°S-60°N) domain. The reader is referred to Figs. S10-13 for the corresponding cumulative metrics calculated over just the NA, and over the global domain exclusive of the NA.

c. Assessing the realism of models’ iAMV patterns

How realistic are models’ iAMV patterns? Figure 4 shows the observed (ERSSTv5) iAMV regression patterns estimated with the T&S and Residual methods over the period 1950-2020 (panels a and c, respectively). The results are similar for the two approaches, with some differences in amplitude over the North Pacific and northern NA. To evaluate the realism of the simulated iAMV patterns in each model LE, we compute the spatial correlation coefficient between the observed iAMV regression map estimated with the Residual method, and the model’s true iAMV regression map obtained by averaging the true iAMV regression maps in each member to reduce the influence of sampling variability. We then compare these “r(obs_resid, model_true)” values to the distribution of “r(model_resid, model_true)” values obtained by computing the pattern correlation between the Residual estimate in each member with the ensemble-average of the model’s true iAMV based on the period 1950-2020, analogous to our procedure for observations. The r(obs_resid, model_true) values based on ERSSTv5 and HadISST1 lie within the 5th-95th percentile range of the distribution of r(model_resid, model_true) values in each LE, with the exception of ERSSTv5 in one model, which lies at the upper tail (95th - 99th percentile) of the distribution (Fig. 4b). Repeating our procedure using rmse in place of pattern correlations, we find that the observed values lie within (but never outside) the upper tail of each model distribution (above the 95% percentile in two-thirds of the models), and generally exceed the median value of
each LE by a factor of 2-3 (Fig. 4d). These results indicate that the models very likely underestimate the amplitude of observed iAMV pattern (estimated with the Residual method), although the possibility that the observations represent an extreme sample of the model distributions cannot be ruled out.

By these measures, all of the models simulate realistic patterns of observed iAMV (determined from the Residual method during 1950-2020), but underestimate its amplitude. However, it is important to note the large (5th-to-95th percentile) range of each model distribution (typically 0.2 – 0.7 for pattern correlations and a factor of 3 for rmse), underscoring that: 1) a single ensemble member from a given model LE is not sufficient to assess model fidelity of the global iAMV pattern, even with 70 years of data; and 2) the observed estimate of iAMV pattern may also be subject to large sampling fluctuations (e.g., the “true” iAMV pattern in the real world, obtained from a hypothetically infinite timeseries, might differ from the pattern estimated from the past 70 years of instrumental data). In this regard, we note that the observed iAMV regression map based on an independent period of record (1880-1950) exhibits some differences with the one based on 1950-2020, especially over data-sparse areas of the tropical Indo-Pacific and Southern Ocean (not shown).

4. Summary and discussion

The canonical index of AMV is the low-pass filtered timeseries of SSTA averaged over the North Atlantic (e.g., Enfield et al., 2001; Z19). This index confounds externally-forced climate change and internally-generated climate variability. To isolate the contribution from internal variability,
various methods have been employed, including linear detrending (Enfield et al. 2001), subtracting
the global-mean SSTA (T&S) or subtracting the pattern of SSTA associated with global-mean
temperature (the so-called “Residual” method: Ting et al., 2009; Z19); more sophisticated
approaches such as optimal fingerprinting (Ting et al, 2009), optimal linear inverse modeling
(Frankignoul et al., 2017) and low-frequency pattern recognition (Wills et al., 2019) have also been
used. Here, we have evaluated the skill of the T&S and Residual methods in isolating the internal
component of the global SSTA pattern of AMV, using a multi-model archive of LEs as a testbed
in which the true internal AMV pattern in each model is known a priori (via subtraction of the
ensemble-mean). Our analysis examines the skill of each method under evolving anthropogenic
climate change during the period 1940-2100.

We find that the T&S method aliases the structure of forced climate change onto the pattern and
amplitude of internal AMV (iAMV) in all 9 model LEs examined, especially by the mid-21st
century. In contrast, the Residual method generally provides a skillful assessment of the spatial
characteristics of iAMV in all models throughout the analysis period. The simulated patterns of
iAMV during 1950-2020 are found to be realistic in all the LEs, but their amplitudes are biased
low. However, there is considerable sampling uncertainty across the individual members of each
LE, underscoring the challenge of evaluating low-frequency modes such as iAMV against a
relatively short observational record.

Despite its excellent performance overall, the Residual method does not accommodate changes in
the forced pattern of SSTA (i.e., the SSTA pattern associated with the global-mean SSTA
timeseries) that occur within the analysis period. Such changes may happen as a result of evolving
sources of anthropogenic radiative forcing (for example, regional aerosol emissions), or as a result
of feedbacks within the climate system that operate on different time scales, thereby modulating
the regional pattern of response (e.g., Armour, 2017). This complexity underscores the need for
more sophisticated approaches to determining the evolving pattern of the forced response (e.g.
Frankignoul et al. 2017; Wills et al., 2019).

While it is beyond the scope of the present study to investigate the dynamical mechanisms
governing the global SSTA pattern of iAMV in nature and in models, the definition of iAMV
should ultimately be based on physical considerations. These physical considerations include
stochastic atmospheric forcing of the ocean mixed layer and wind-driven ocean circulation, the
role of AMOC in inducing subpolar SSTA, subsequent air-sea interactions that extend the SSTA
into the tropical Atlantic, and atmospheric teleconnections that transmit the signal to other basins
and trigger coupled interactions within the Pacific and beyond.

Acknowledgements

We thank the members of NCAR’s Climate Analysis Section for valuable discussions during the
course of this work, and the two anonymous Reviewers for their constructive comments. This
material is based upon work supported by the National Center for Atmospheric Research, which
is a major facility sponsored by the National Science Foundation under cooperative agreement
1852977. The authors acknowledge high-performance computing support from Cheyenne
(https://doi.org/10.5065/D6RX99HX) provided by NCAR’s Computational and Information
Systems Laboratory, sponsored by the National Science Foundation.
Data Availability Statement

All model simulations and observational datasets used in this study are publicly available. ERSSTv5 data is available from NOAA-NCEI at https://www.ncdc.noaa.gov/dataaccess/marineocean-data/extended-reconstructed-sea-surface-temperature-ersst-v5. HadiSST1 data is available from the UK Met Office Hadley Centre at https://www.metoffice.gov.uk/hadobs/hadisst/index.html. All CMIP5-class model data is available from the Multi-Model Large Ensemble Archive at https://www.cesm.ucar.edu/projects/community-projects/MMLEA/. All CMIP6 model data is available from the Earth System Grid Federation’s Lawrence Livermore National Laboratory’s data portal at https://esgf-node.llnl.gov/search/cmip6/. Analysis code is posted at https://github.com/NCAR/CVDP-LE.

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[https://doi.org/10.1029/2019RG000644](https://doi.org/10.1029/2019RG000644).
**Figure Captions**

**Figure 1.** SST regression maps of internal AMV (iAMV) in the 100-member MPI Large Ensemble during (left) 1950-2020 and (right) 1950-2090 estimated with the T&S (a,b) and Residual (e,f) methods; True patterns are shown in (c,d). Numbers in the upper right indicate the pattern correlation with the Truth for the domain 60°S-60°N (marked by dashed gray lines). The color bar is unitless (°C per °C of the iAMV index). Panels g,h show the forced (ensemble-mean) SST trends minus the global-mean forced trend (°C per 70 years and °C per 140 years, respectively); numbers in the upper right denote the pattern correlation with the T&S regression map.

**Figure 2.** Cumulative pattern correlations between iAMV SST regression maps for 9 different model Large Ensembles: T&S vs. Truth (blue curves); Residual vs. Truth (red curves); Forced trend vs. T&S (cyan curves); Forced trend vs. Truth (green curves). The cumulative analysis periods begin in 1950 and end in the year labeled along the x-axis. Panel titles indicate the model name and number of ensemble members (see Table S1).

**Figure 3.** As in Fig. 2 but for cumulative spatial rms differences relative to the spatial rms of the true iAMV (“rmse”) for each model Large Ensemble: T&S vs. Truth (blue); Residual vs. Truth (red).
Figure 4. (Left) Observed (ERSSTv5) iAMV SST regression map for 1950-2020 estimated with the (a) T&S and (c) Residual methods (°C per °C of the iAMV index). (Right) Distribution of (b) pattern correlations and (d) spatial rmse for each model between true and estimated (Residual method) iAMV in each member based on 1950-2020 (gray dots); box-and-whisker plots show the 5th-95th percentile range (whiskers), 25th-75th percentile range (box outlines) and the 50th percentile value (horizontal bar inside the box). Black circles show the pattern correlation and spatial rmse between observed (Residual method) iAMV (filled circles for ERSSTv5 and open circles for HadISST1) and the models’ true iAMV.
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