Constraining Decadal Variability Yields Skillful Projections of Near-Term Climate Change

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Abstract Targeted adaptation to near-term climate change requires accurate, reliable, and actionable climate information for the next few decades. Climate projections simulate the response to radiative forcing, but are subject to substantial uncertainties due to internal variability. Decadal climate predictions aim to reduce this uncertainty by initializing the simulations using observations, but are typically limited to the next 10 years. Here, we use decadal predictions to constrain climate projections beyond the next decade and demonstrate that accounting for climate variability improves regional projections of 20-year average temperatures. Applying this constraint to climate projections of the near future until 2035, summer temperatures over land regions in Asia and Africa tend to show stronger changes within the warming range simulated by the larger, unconstrained, ensemble—consistent with a warm phase in North Atlantic variability. This improved regional climate information can enable tailored adaptation to climate changes in the coming decades.

Plain Language Summary We present a novel approach to reduce the uncertainty from internal climate variability, which can limit the capability to develop suitable adaptation strategies, in climate projections of the near future. This approach combines information from decadal climate predictions and climate projections to constrain decadal climate variability. We demonstrate that this constraint improves the skill of temperature projections for the next 20 years after starting the prediction. Applying this method to predict the near-term future until 2035, we find an increased probability of stronger warming during summer in several land regions, consistent with a warm phase in North Atlantic variability. Such improved estimates of near-term climate change are a promising basis for developing better adaptation strategies and avoiding mal-adaptation.

1. Introduction

Climate is unequivocally warming as a consequence of human activities (IPCC, 2014), and new climate states are emerging (King et al., 2015). In this context of ongoing climate change, policy and investment decisions on climate change adaptation require accurate, reliable, and actionable climate information for the decades to come. Information about the future climate evolution is typically obtained from climate projections (Eyring et al., 2016; Taylor et al., 2012) that simulate transient climate evolutions over the 21st century according to different socioeconomic, political, and technological pathways (O’Neill et al., 2014; Riahi et al., 2017).

During the first decades of the climate projections at regional scales the dominant source of uncertainty is internal variability of the climate system followed by model and scenario uncertainties (Hawkins & Sutton, 2009, 2011; Lehner et al., 2020). Decadal predictions, where the initialization of the climate models phases in the simulated and observed climate variability, aim to reduce this uncertainty by constraining the internal variability (Doblas-Reyes et al., 2013; Keenlyside et al., 2008; Kushnir et al., 2019; Meehl et al., 2009; Smith et al., 2007). Recent studies have shown that decadal climate predictions initialized from observed climate states are highly skillful in many regions and improve the information compared to uninitialized projections, in particular in the North Atlantic region (Smith et al., 2019, 2020). However, the current decadal prediction systems provide data for only up to 10 years after initialization, as running initialized predictions is computationally very expensive (Boer et al., 2016). For example, running annually initialized decadal predictions requires 10 times the computing resources needed to perform transient historical simulations and projections with the same ensemble size.

As climate change estimates typically consider long-term averages over 20 or 30 years (Brunner et al., 2019; IPCC, 2014), the decadal predictions hence leave a gap for users requiring near-term climate change information beyond the next 10 years. Recent work has demonstrated the potential to improve near-term climate projection...
information by constraining projection ensembles according to their agreement with observed variability (Hegerl et al., 2021). In particular, combining information from decadal predictions and climate projections has the potential to provide skillful predictions of the Atlantic subpolar gyre beyond 10 years (Befort et al., 2020). Here, we build on this initial demonstration of longer-term predictive information and explore whether and to what extent combining information from initialized decadal predictions and uninitialized climate projections can provide improved near-term climate change estimates for regions of direct interest to society.

We present a novel approach to constrain large ensemble climate projections based on their agreement with initialized decadal predictions over the common period. Similar to initialized predictions, this approach aims to phase in the climate variability of the projections with the observed climate. This constraint can additionally help to improve the representation of forced responses that depend on the background climate conditions, like the ocean circulation response to major volcanic eruptions (Swingedouw et al., 2015, 2017). As the projections provide data beyond 10 years, this approach offers a way to provide climate change information with reduced uncertainty from internal variability for multiple decades.

2. Materials and Methods

2.1. Model and Observational Data Sets

We use large ensembles of climate projections (Kay et al., 2015) and retrospective decadal predictions (Yeager et al., 2018) performed with the Community Earth System Model (Hurrell et al., 2013) with both ensembles consisting of 40 members. The climate projections ensemble (referred here as UNINIT40) provides transient long-term historical and future model simulations (1920–2100). The future simulations (2006 and onwards) use radiative forcings from the representative concentration pathway 8.5 (RCP8.5). All members of UNINIT40 use the same historical forcings and differ only in small atmospheric perturbations at the start implying that the ensemble spread is mainly generated by the internal climate variability (Kay et al., 2015). The second large ensemble is the initialized decadal prediction large ensemble (referred here as DPLE) (Yeager et al., 2018). The DPLE provides decadal predictions initialized toward the observed state for a total of 62 start dates (from 1954 to 2015), each prediction integrated for 122 months after initializing on 1 November of each start year. DPLE uses historical CMIP5 external radiative forcings until 2005, and radiative forcings from RCP8.5 for 2006 and onwards. The ocean and sea ice initial conditions in DPLE come from an ocean/sea-ice reconstruction forced by observations-based atmospheric fields from the Coordinated Ocean-Ice Reference Experiment forcing data set, and the atmospheric initial conditions are taken from the ensemble of climate projections.

The observed sea surface temperature (SST) data from the Met Office Hadley Center’s sea ice and sea surface temperature (HadiSST1.1; Rayner et al., 2003) is used for evaluating large-scale SST indices including global mean SST (GMSST), Atlantic Multidecadal Variability (AMV), and Interdecadal Pacific Oscillations (IPO). The IPO index is calculated following the IPO Tripole Index (Henley et al., 2015) and the AMV index is based on area-weighted averages of North Atlantic SSTs (0°–60°N and 80°W-0) with global mean SST (60°S–60°N) removed (Trenberth & Shea, 2006). In addition, we used HadCRUT4.6 which is a blended product of CRUTEM surface air temperature over land and HadSST over the ocean (Morice et al., 2012) for evaluating the simulated global surface air temperatures. All the results discussed in this study are based on anomaly fields calculated by removing the forecast-time dependent climatology (García-Serrano & Doblas-Reyes, 2012) (using the start dates 1954–1998).

2.2. Constraining Protocol

We apply a constraining procedure to select those UNINIT40 ensemble members better aligned with the variability of the initialized predictions. This procedure involves comparing the spatial distribution of SST anomalies between the predicted DPLE ensemble mean and the individual ensemble members of UNINIT40 using pattern correlations. For each start year, we select a subsample of UNINIT40 according to the pattern correlations with DPLE (see Figure S1 in Supporting Information S1). We select 10 ensemble members with highest pattern correlations (Best10), but to test the sensitivity to the ensemble size we also selected the 20 members with highest pattern correlations, which led to mostly similar results (not shown). Each start year uses a different selected ensemble based on the agreement with the initialized DPLE anomalies. The selection of 10 different members every year corresponds to the standard procedure to run decadal hindcasts (Boer et al., 2016). The Best10 ensemble thus
represents a climate prediction system with 10 members per start date and a forecast range as long as the length of the climate projections. In this study, we focus on near-term climate change estimates for the first 20 years after initialization, but also longer time horizons are theoretically possible without requiring new simulations to be run. The time horizon depends on the ability of the decadal predictions to efficiently constrain the uninitialized projections, as the efficacy of the constraint typically reduces for longer forecast times (Befort et al., 2020). The choice of 20-year windows for the constrained estimates is a compromise that matches the time spans used by the Intergovernmental Panel on Climate Change (IPCC) to analyze projected climate changes (Collins et al., 2013). To test the effectiveness of this constraint, we also select the 10 members with the lowest pattern correlations (Worst10).

To verify the quality of the constrained and unconstrained projection ensembles, a time series of 20-year mean ensembles (also referred to as hindcasts) is developed using start dates from 1954 to 1998 inclusive, i.e., we evaluate the temperatures of the consecutive 20-year windows 1955–1974 to 1999–2018. The last hindcast that can be evaluated against observations corresponds to the start date of 1998 (which predicts the 1999–2018 data), while the last initialization of the decadal prediction (i.e., 2015) provides a prediction for the 2016–2035 period for the analysis of near-term climate change, which cannot be compared to the corresponding observations. We analyze anomaly correlation (ACC), root mean square skill score (RMSSS), and spread-over-error ratio (SOE) to verify the forecast quality of the projections, and residual correlations to analyze added value of the constraints (see Supporting Information S1 for details).

There are a number of choices related to the constraint criteria, the most important being (a) the region over which the SST anomalies are compared and (b) the forecast range considered from the initialized predictions for the selection. We explored several of these sensitivities in detail (see e.g., Figures S2 and S3 in Supporting Information S1 and the Supporting Information S1). The optimal choices depend on the specific region of interest. We used five selection domains and 11 forecast periods (from the first 5 months to 10 years after initialization of DPLE) to understand the sensitivities when constraining the uninitialized projections. The specific spatial domains considered are: global ocean (Global), global ocean without polar regions (NoPolar), Atlantic and Pacific (Atl + Pac), Pacific (Pac), and North Atlantic (NAtl) (see Table S1 in Supporting Information S1 for domain definitions). The results discussed in the main text of the paper are based on pattern agreement calculated using the average of the first nine forecast years of the decadal predictions, based on the indication that constraints based on longer forecast times led to significant skill in larger areas of the globe (Figures S4 in Supporting Information S1).

3. Results

3.1. Skillful Near-Term Projections of Ocean Temperature Indices

A preliminary analysis of the skill of the decadal predictions for forecasting the GMSST and the two most important internal climate variability modes at decadal scales (i.e., AMV and IPO) is performed (green markers in Figure S8 in Supporting Information S1) to highlight where the constraints are expected to be more efficient. Both the ACC and RMSSS metrics show high and significant skill for the first 10 forecast years of GMSST and AMV, which translate in significant skill for the same indices in the first 10 years of the constrained projections (red markers in Figure S8 in Supporting Information S1). No skill in the decadal predictions is found for the IPO, which is consistent with the lack of skill for this index in the constrained Best10 predictions.

The skill of the 20-year Best10 predictions for GMSST, AMV, and IPO is shown in Figure 1. All ensemble predictions exhibit very high correlations (ACC > 0.9) in predicting GMSST variability (Figure 1a), mostly arising from the external forcing as evident from the high skill in UNINIT40. The Best10 ensemble obtained according to the different regional constraints leads to small differences in ACC compared to the UNINIT40 ensemble. For the global selections (both with and without the polar regions) the Best10 ensemble shows slightly higher ACC than UNINIT40. The effectiveness of the constraint is also seen when selecting the 10 ensemble members of the uninitialized projections with the lowest pattern agreement with the decadal predictions (“Worst10”), which for most regional SST selections shows consistently lower ACC than both UNINIT40 and Best10. Also, to test whether the Best10 ensemble is significantly different from randomly selecting 10 members, the ACC of the Best10 and Worst10 is compared with a distribution of values from 40,000 random selections of 10-member ensembles from UNINIT40 (referred to as “Random10”; see also Supporting Information S1). This shows that the Best10 ACC values obtained by constraining global SST patterns are above the 95th percentile of the
Random10 distribution, illustrating the effectiveness of the constraint. Because of the strong contribution of the trends to the GMSST skill that saturates measures like the ACC, Smith et al. (2019) suggested to calculate residual correlations to more robustly demonstrate the added value of initialization. These residual correlations are found to be significant and positive ($R > 0.6$) for the Best10 selections based on global SSTs (Figure S9 in Supporting Information S1) and negative ($R < -0.8$) for the Worst10 selections, which confirms the efficacy of our variability-based constraint to improve global mean temperature projections for the following 20 years. The RMSSS and also the SOE (Figures 1d and 1g) do not indicate clear improvements in the amplitude of the predicted GMSST signal or the reliability from the constraint in Best10 over UNINIT40 and lead to slightly reduced skill for these measures for this index.

While the North Atlantic is the region showing most added skill from initialization in decadal predictions (Doblas-Reyes et al., 2013; Yeager et al., 2018), selecting Best10 only based on North Atlantic SSTs does not show a strong effect on GMSST 20-year mean constrained projections. This regional constraint, however, outperforms the global one in predicting the AMV index (Figure 1b) with ACC larger than 0.77 (significant at 95% confidence level) and both ACC and RMSSS values above the 95th percentile of Random10 (Figure 1e). This indicates that using regional constraints might be useful to optimize the approach for improving regional climate projections. There are only marginal effects of the constraints on the reliability of the ensembles (Figure 1h). Over the Pacific Ocean both the constrained and unconstrained projections show very poor skill in capturing the IPO index evolution (Figures 1c, 1f, and 1i). The poor skill of Best10 in predicting IPO is as expected since the decadal predictions are not skillful in this region (Figure S8 in Supporting Information S1).

For the remainder of this paper, we focus on the Best10 constrained projections based on global SST pattern agreement, as this selection leads to a larger total area with improvements in the quality measures (Figures S5 and S7 in Supporting Information S1) compared to those based on regional constraints. Note, however, that regional
constraints like the North Atlantic can lead to regionally increased skill of the 20-year information (e.g., in the North Atlantic in Figures S4, S6, and S10 in Supporting Information S1).

### 3.2. Regionally Improved Temperature Projections

We next evaluate regional characteristics of the different skill scores for predicting the 20 years annual mean surface air temperature anomalies (Figure 2). Due to the presence of strong warming trends in observations and model simulations, the ACC is high for most regions globally (Figure 2a). A similarly high ACC is obtained for the UNINIT40 ensemble mean (not shown). Given the very high correlations, we again use residual correlations (Smith et al., 2019) to identify skill improvements in Best10 over UNINIT40. Apart from the Atlantic subpolar gyre region, where decadal predictions typically show added value from initialization (Doblas-Reyes et al., 2013; Smith et al., 2020), we also find significant positive residual correlations in some areas of the tropical Indian Ocean, and tropical and North Atlantic Ocean, including some land regions, e.g., in northern Africa, and Southern and Southeast Asia (Figure 2d), indicating added value of the global pattern constraint.

We find significant positive skill for the Best10 ensemble also in terms of RMSSS in most nonpolar regions, which are significant at the 95% confidence level when compared with the random10 distribution in the North Atlantic, parts of the Pacific and Indian Oceans, Europe, and East Asia (Figure 2b). The RMSSS of Best10 shows added value compared to UNINIT40 (Figure 2e) over some areas also highlighted with positive residual correlations, such as the North Atlantic and the tropical Atlantic and Indian Oceans, and also over eastern Asia, western and central Europe, and parts of Africa. In some other areas, however, such as the tropical Pacific and Southern Ocean, the UNINIT40 skill is higher (Figure 2e). The SOE values larger than 1 indicate that the Best10 ensemble is underconfident over North America and large parts of Europe while they are overconfident over east Asia, Africa, parts of south America, the North Atlantic, tropical central Pacific and the Southern Ocean (Figure 2e). To identify regions where the Best10 ensemble is more reliable than UNINIT40, regardless of being overconfident or underconfident, Figure 2f indicates if the SOE distance to the ideal value of 1 is reduced (for negative values) or increased (for positive values) in Best10 with respect to UNINIT40, and by how much. We note that, in general terms, the UNINIT40 ensemble shows largely similar spatial patterns of SOE compared to Best10, i.e., both are overconfident or underconfident in the same regions. The comparison of SOE values indicates that Best10 is less
underconfident than UNINIT40 over northern and eastern Europe and eastern North America. Best10 indicates also improved reliability compared to UNINIT40 in large areas of the eastern North Atlantic, tropical eastern Indian Ocean, and some land regions in Asia, northern Africa, and eastern parts of South America (Figure 2f). When analyzing the skill for decadal averages instead of 20-year forecast periods (Figures S11 and S12 in Supporting Information S1 for forecast years 1–10 and 11–20, respectively), the added value of the constrained projections reduces in the second decade as compared to the first, indicating reduced effect of initialization at longer forecast lead times. However, several regions including the Subpolar North Atlantic, the Tropical Atlantic, and the Indian Ocean retain significant added value of the Best10 over UNINIT40, while regions like the Tropical Pacific or the Southern Ocean show poorer skill in Best10 than in UNINIT40.

3.3. Providing Improved Climate Estimates of the Near Future

We next demonstrate the application of the globally constrained Best10 ensemble to provide improved near-term projections of summer (June-July-August) temperatures over the subpolar North Atlantic region and three land regions as used in previous IPCC assessments (IPCC, 2014; Seneviratne et al., 2012) (see Figure S13 in Supporting Information S1 for region definitions). We argue that the constrained Best10 near-term projections are improved in comparison to the unconstrained UNINIT40 large ensemble of projections when (a) the skill measures calculated for the 20-year hindcasts indicate improved skill in Best10 compared to UNINIT40 and (b) the projected changes for the next 20 years differ between Best10 and UNINIT40, the latter criterion indicating that the constraint actually leads to modified estimates of near-term climate change (Figure 3).

For the subpolar North Atlantic region, e.g., we find improved skill for the Best10 ensemble with a residual correlation of 0.79, increased RMSSS, and improved reliability for 20-year mean hindcasts (Figure 3). In the near-term projections for 2016–2035, the constraint excludes those UNINIT40 members exhibiting a weaker warming, resulting in an increased probability of larger warming magnitudes including a larger ensemble mean increase. Near-term climate change projections of summer temperatures for the 20-year period 2016–2035 indicate continued warming trends into the future, where the constraint removes the ensemble members with smaller warming (the minimum change is +0.37 K in Best10 compared to −0.05 K in UNINIT40, while the maximum of the range remains unchanged at +0.81 K). This results in a larger ensemble mean warming signal in Best10 (+0.56 K) compared to UNINIT40 (+0.47 K). These results suggest that, when aligning the climate variability phases in the projections with the decadal predictions, the climate change projections up to 2035 indicate enhanced warming compared to projections that are not constrained by the predictions. This is due to the reduced probability of small summer temperature increases.

Best10 also shows improved skill over UNINIT40 for 20-year summer temperature hindcasts over land regions such as the Sahara, West Asia, and Southern Asia (Figure 3). The improved skill compared to the unconstrained ensemble is apparent from positive residual correlations (up to 0.85 for SAS) and increased RMSSS values, indicating on average smaller forecast errors in Best10 compared to UNINIT40. Also, for these regions, the Best10 summer temperature projections for the next 20 years exhibit a reduced uncertainty range compared to UNINIT40, where constraining the decadal variability systematically excludes those projection members with the smallest temperature increases. Summer climate in these regions has been shown to be related to the state of the North Atlantic Ocean (Hoerling et al., 2006; Hurrell, 1995; Krishnamurthy & Krishnamurthy, 2016; Qasmi et al., 2021; Zhang & Delworth, 2006), and the favoring of warmer summer temperatures is consistent with the preference of the constrained projections for a warm Subpolar North Atlantic.

4. Discussion and Conclusions

We present an approach to provide near-term climate change information of increased accuracy, by combining initialized decadal predictions with longer-term projections. Subselecting members from a large ensemble of climate projections that closely resemble the decadal prediction, uses only those projections that best align with the climate variability phases. We demonstrate that this approach enables skillful retrospective 20-year predictions of increased accuracy compared to the large (unconstrained) ensemble, for hindcasts of large-scale SST indices such as AMV, and surface air temperatures in several regions. We also show that projections constrained by climate predictions can provide different climate change estimates for the next two decades compared to the large, unconstrained, ensemble. In particular, this approach reduces the uncertainty of the near-term climate change.
Figure 3. Cumulative distribution functions of 20-year average (i.e., 2016–2035) projections of summer (June-July-August) surface air temperature anomalies (relative to 1961–1999) over the Subpolar North Atlantic (SPNA, 45°–60°N; 50°–20°W) and three IPCC SREX regions (over land areas) including Sahara (SAH), West Asia (WAS), and South Asia (SAS). Best10 results shown in red and UNINIT40 in blue. Results for Best10 are based on the values of the ensemble selected with the decadal prediction initialized in 2015. Selections are based on 9-years mean global SST anomaly patterns. The horizontal bars at the bottom of each panel show the range (minimum to maximum) of the 20-year average projections. The inset table summarizes the different skill measures of hindcasts of 20-year average values from 1955–1974 to 1999–2018. For the Best10 skill measures (except for spread-over-error ratio (SOE)), a single (double) star indicates that the skill is better than the 90th (95th) percentile of the corresponding skill of the Random10 distribution. For the SOE, a single (double) star indicates that the abs(1 − SOE) of Best10 ensemble is lower than the 10th (fifth) percentile of abs(1 − SOE) distribution of Random10. The amount of overall observed variability explained by residuals for SPNA, SAH, WAS, and SAS is 47.6%, 25.3%, 10.4%, and 74.3%, respectively.
projections by removing a specific part of the spread from the large ensemble of projections. In our examples, for summer temperatures in the Sahara, West Asia, and Southern Asia, constraining the climate variability reduces the probability of small temperature increases compared to the large ensemble, and thereby suggests a stronger summer warming in these regions until 2035—consistent with a warm state of the North Atlantic Ocean.

Constraining future climate projections using so-called “emergent constraints” that relate some measures of model performance (evaluated against observations) with the magnitude of future projected changes have recently become common practice in the analysis of longer-term climate projections (Brunner et al., 2020; Cox et al., 2013; Hall et al., 2019). The approach presented here is different to such established constraints, as it does not consider model performance as such but instead the ability to predict spatial anomalies and is therefore also applicable to large single-model ensembles. An advantage of our approach for near-term projections is that its efficacy can be proven by evaluation against observations using standard techniques of forecast quality assessment though the limited length of the time series puts limits on the significance of skill assessment. In a multimodel context, future developments could combine both constraining approaches, considering both prediction ability and measures of model performance. This may help to also reduce the uncertainty related to the climate response, in addition to climate variability, and further narrow down the uncertainty of near-term climate change estimates.

We expect large potential to further improve near-term climate change projections by using much larger ensembles than in this first demonstration of the approach. Ensembles consisting of hundreds of members, for example, from CMIP6 multimodel simulations (Eyring et al., 2016) or combining multiple large ensembles of projections that are increasingly becoming available (Deser et al., 2020), can potentially also improve near-term projections of noisier climate variables such as atmospheric circulation or precipitation (Smith et al., 2020), as well as of climate extremes. Subselecting from substantially larger ensembles may also unlock improved near-term projections for longer time horizons beyond 20 years. For these much larger ensembles other constraining criteria could be useful, e.g., taking the magnitude of anomalies into account, in particular when combining projections from multiple models.

This approach to constrain projections based on the states of future climate variability may also inform the choice of global climate model simulations for future downscaling activities (Gutowski et al., 2016) to produce more accurate near-term climate information at high spatial resolution. While this study provides a proof-of-concept for the constraining method in which the last initialization is already in 2015, decadal predictions are now produced quasi-operationally on an annual basis (https://hadleyserver.metoffice.gov.uk/wmolc/), which enables the development of more recently initialized multimodel forecast products.

Data Availability Statement
NCAR CESM LENS data available at: https://www.cesm.ucar.edu/projects/community-projects/LENS/data-sets.html, DPLE at: https://www.earthsystemgrid.org/dataset/ucar.cgd.csm4.CESM1-CAM5-D.html, UKMO HadISST1.1 available at: https://www.metoffice.gov.uk/hadobs/hadisst/data/download.html, and HadCRUT4 at: https://crudata.uea.ac.uk/cru/data/temperature/#datdow.

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