

1 Multi-decadal initialized climate predictions using the EC-Earth3

2 global climate model

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9 **Abstract.** Initialized climate predictions are routinely carried out at many global institutions that predict the climate up to
10 next ten years. In this study we present 30 year long initialized climate predictions and hindcasts consisting of 10 ensemble
11 members. We assess the skill of the predictions of surface air temperature on decadal and multidecadal timescales. For the
12 10 year average hindcasts, we find that there is limited added value from initialization beyond the first decade over a few
13 regions, but no added value from initialization was found for the third decade (i.e. forecast years 21-29). The ensemble
14 spread in the initialized predictions grows larger with the forecast time. However, the initialized predictions do not
15 necessarily converge towards the uninitialized climate projections within a few years and even decades after initialization.
16 There is in particular a long-term weakening of the Atlantic Meridional Overturning Circulation (AMOC) after initialization
17 that does not recover within the 30 years of the simulations, remaining substantially lower compared to the AMOC in the
18 uninitialized historical simulations. The lower AMOC mean conditions also result in different surface temperature anomalies
19 over northern and southern high latitude regions with cooler temperature in the northern hemisphere and warmer in the
20 southern hemisphere in the later forecast years as compared to the first forecast year. The temperature differences are due to
21 less transport of heat to the northern hemisphere in the later forecast years. These multi-decadal predictions therefore
22 highlight important issues with current prediction systems, resulting in long-term drift into climate states inconsistent with
23 the climate simulated by the historical simulations.

24 1 Introduction

25 Global and regional climate is changing due to anthropogenic emissions of greenhouse gases, atmospheric aerosols and
26 internal climate variability (Chung and Soden, 2017; Bonfils et al., 2020; Chiang et al., 2021; IPCC, 2023). The ongoing
27 increase in global temperature is causing devastating effects on life, ecosystems and important infrastructures requiring
28 appropriate adaptation strategies to minimize the potential future effects (Gampe et al., 2021; Naumann et al., 2021; Brullo

et al., 2024). Accurate and reliable information about the near-term (10 to 30 years) future climate could underpin such adaptation efforts, obtained either from historical and projection climate simulations (hereafter also referred to as “uninitialized projections”, as these simulations are not started from observational climate states) or from initialized decadal climate predictions. The long-term uninitialized projection simulations experience various types of uncertainties including the modeled forced response, assumptions about expected future conditions, and internal climate variability (e.g. Lehner et al., 2020). In particular for the near-term regional climate projections, internal climate variability can be the largest source of uncertainty (Hawkins and Sutton, 2009; Lehner et al., 2020) since these model simulations are started from different climate states during the preindustrial time.

The initialized decadal climate predictions are aimed at aligning the phase and amplitude of variability between numerical simulations and observations (e.g. Meehl et al., 2021), and initialization has been shown to correct forced model responses, by starting the simulations from observationally-constrained climatic states (Smith et al., 2007; Keenlyside et al., 2008; Doblas-Reyes et al., 2013). For the most recent version of the Coupled Model Intercomparison Project phase 6 (CMIP6), such model simulations were typically initialized every year and forecasts were made up to 10 years after initialization (Boer et al., 2016). On multi-annual and decadal timescales, the initialized climate predictions have shown skill in predicting climate over global regions (Smith et al., 2019, 2020; Delgado-Torres et al., 2022). In particular for near-surface air temperature predictions, the initialized predictions have also shown added value from initialization over the uninitialized projection simulations on multi-annual timescales in some regions (e.g. Smith et al., 2019; Delgado-Torres et al., 2022).

Initialized climate predictions are computationally expensive to run and therefore most prediction systems only forecast up to 10 years after initialization (Boer et al., 2016). Some recent studies have suggested that there is enhanced skill beyond 10 years from internal climate variability. This has been found, for example, by combining information from decadal predictions and longer-term uninitialized projections (Befort et al. 2022) and constraining patterns of sea surface temperature anomalies in large ensembles of the uninitialized projection simulations (Mahmood et al., 2021, 2022; Donat et al., 2024). Mahmood et al. (2022) demonstrated added skill over forcing alone for 20-year constrained projections. Similarly, Donat et al. (2024) found enhanced climate predictability up to 20 years when constraining climate variability in large multi-model ensembles from CMIP6, basing the constraints on either observations or decadal predictions. While initialized predictions beyond 20 years were considered during the Coupled Model Intercomparison Project phase 5 (CMIP5), these simulations were restricted to only three start dates (Meehl and Tang, 2012), which did not allow for robust estimates of skill over such longer forecast horizons. Düsterhus and Brune (2023) recently produced initialized predictions out to 20 years with the MPI-ESM model, and concluded that the information from initialization may not necessarily be lost even up to 20 years after initialization, resulting in skillful predictions of surface air temperature beyond 10 forecast years over a few regions. Recent work by Deser et al. (2025) with idealised experiments further suggests that initialized internal variability can constrain

62 surface climate variability for multiple decades, highlighting the potential for extended predictability when key modes of
63 variability are properly captured.

64

65 Motivated by the prospect of multi-decadal predictability from model initialization and with the aim to understand the model
66 dependence in a previous study (Düsterhus and Brune, 2023), in this study we performed a set of initialized climate
67 predictions with the EC-Earth3 model with a forecast horizon of 30 years. These predictions build on and extend decadal
68 predictions produced with the same model (Bilbao et al. 2021). These experiments allow us to further study climate
69 predictability on multi-decadal time scales, and more generally to assess initialized climate predictions and uninitialized
70 projections as complementary sources of climate information for near-term climate change estimates beyond the next
71 decade.

72

73 The primary goal of the current study is to introduce the initialized 30-year long predictions, which were performed with a
74 state-of-the art forecast system and involve a large number of hindcasts, considering together the forecast range, number of
75 initialization years and number of members per forecast. Additionally, we address several specific research questions related
76 to the scientific relevance of the multi-decadal predictions, from whether the initialized predictions can be skillful in
77 predicting surface temperature beyond 10 years after initialization, whether and when the spread in initialized predictions
78 and the uninitialized projection simulations converge and if the drift in Atlantic Meridional Overturning Circulation
79 (AMOC) continues after the first decade of forecasts which was discussed in Bilbao et al. (2021).

80 **2 Data and Methods**

81 We performed a new set of multidecadal climate predictions with the Barcelona Supercomputing Center (BSC)’s decadal
82 prediction system (Bilbao et al., 2021), which uses the CMIP6 version of the EC-Earth3 climate model (Döscher et al.,
83 2022). This hindcast consists of a 10-member ensemble of 30-year predictions initialized on the first of November of every
84 5th year starting from 1960 to 2020 (i.e a total of 13 start dates predicting 30 years). Since the simulations start from
85 November, the final forecast year (i.e. the 30th prediction year) finishes in October and therefore only 29 full years are
86 available for analysis.

87

88 This new hindcast uses the initial conditions from the current operational BSC decadal prediction system, which have been
89 updated with respect to those from Bilbao et al. (2021). The new system uses interpolated initial conditions from the ERA5
90 atmospheric reanalysis (Hersbach et al., 2020; Soci et al., 2024) , and ocean and sea ice initial conditions from a 5-member
91 NEMO3.6-LIM3 simulation forced with historical ERA5 surface fluxes that assimilates ORA-S5 (Zuo et al., 2019) ocean
92 temperature and salinity at the surface using a standard surface nudging approach with restoring coefficients of $-200 \text{ W m}^{-2} \text{ K}^{-1}$
93 and -750 mmd^{-1} , respectively. Below the mixed layer, a Newtonian relaxation term is also applied to assimilate three-

94 dimensional EN4 (Good et al., 2013) temperature and salinity fields. For this, a relaxation timescale that increases
95 monotonically with depth is used, which takes approximate values of 30 days at the subsurface, 700 at 1000m and 3300 at
96 5000m. The spread in the 10-member ensemble was generated by adding a small (i.e. on the order of 10^{-5} K) perturbation to
97 the 3-dimensional atmospheric air temperature, combined with the five ocean and sea ice initial conditions.

98

99 While decadal predictions using EC-Earth3 have been provided with annual initializations as a contribution to CMIP6 and to
100 the WMO Lead Centre for Annual to Decadal Prediction (Hermanson et al., 2022), the new multi-decadal predictions
101 presented in this study are initialized at reduced frequency (every fifth year) primarily for computational cost reasons. Given
102 the high auto-correlation of the time series when predicting decadal to multi-decadal averages, this somewhat reduced
103 initialization frequency does not affect the degrees of freedom for skill evaluation. Initializing only every five years, as
104 opposed to every year, may however lead to missing potential windows of opportunity when the predictability is enhanced in
105 relation to specific initial climate states (e.g. Liu et al. 2023) and to a certain level of aliasing (García-Serrano and Doblas-
106 Reyes, 2012).

107

108 For reference and to evaluate added value (and possibly deteriorating effects) from initialization, we also use in this study a
109 10 member ensemble of CMIP6 historical and scenario simulations performed using the EC-Earth3 model. Both the transient
110 climate simulations and initialized predictions use observed historical forcings up to the year 2014 and afterwards the
111 estimates of forcings based on the SSP2-45 (“middle of the road”) emissions scenario (O’Neill et al, 2016).

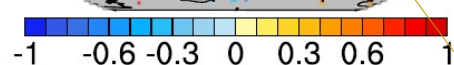
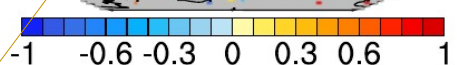
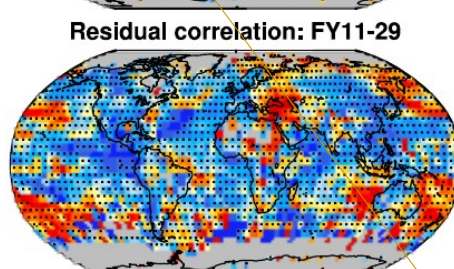
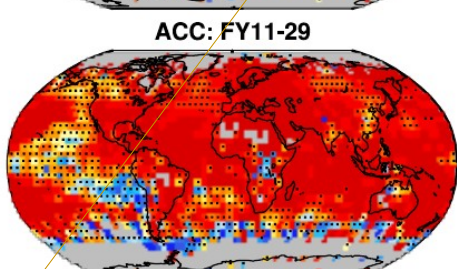
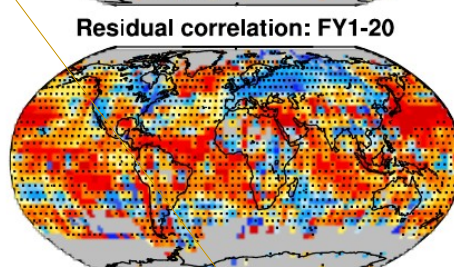
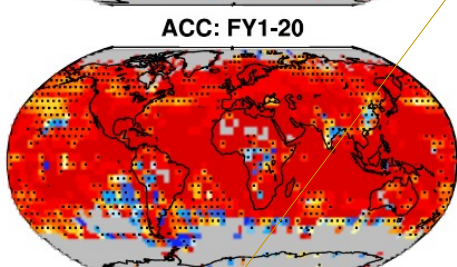
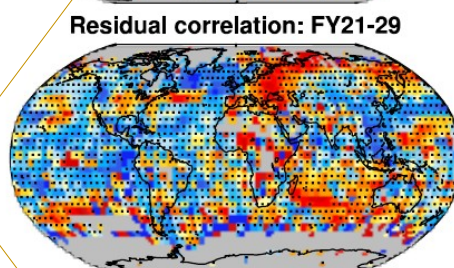
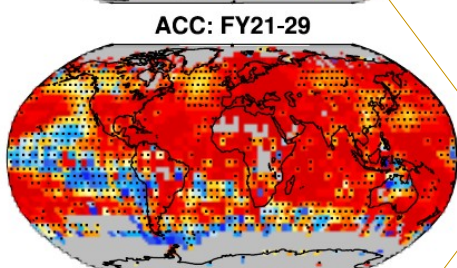
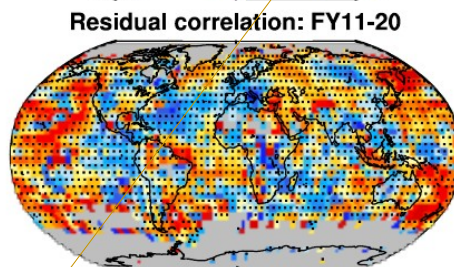
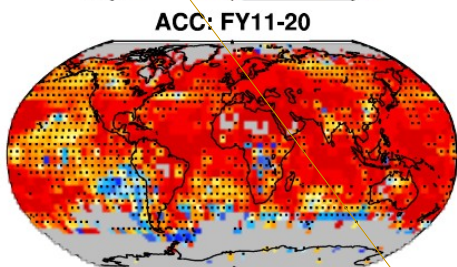
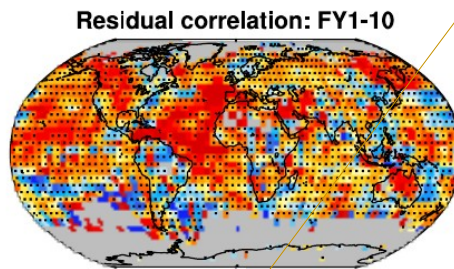
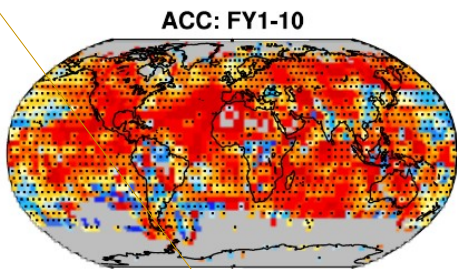
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113 For skill evaluation, all model simulations were converted to a uniform five-degree grid in order to minimize effects from
114 small-scale noise in the identification of large-scale predictable signals, recommended practice for evaluating the initialized
115 climate predictions (e.g. Goddard et al., 2013). The skill of the predictions is evaluated based on anomaly correlation
116 coefficient (ACC) and the residual correlations following Smith et al. (2019). The ACC assesses the common variability
117 (both from internal and forced origin) between the observations and the simulations. The residual correlations indicate added
118 value from initialization and are computed by correlating the residuals obtained after removing an estimate of the forced
119 signal from predictions and observation using the ensemble mean of the historical simulations (Smith et al., 2019). We
120 evaluate here the skill of the mean predictions for 10, 20 and 29 years after initialization. Specifically, we focus on averages
121 of forecast years 1 to 10 (FY1-10), 11 to 20 (FY11-20), 21-29 (FY-21-29), 1 to 20 (FY1-20) and 11 to 29 (FY11-29). The
122 observed surface temperature data used for evaluating the skill is from HadCRUT4.6 (Morice et al. 2012). The sea surface
123 temperature observations used were obtained from the Met Office Hadley Center’s sea ice and sea surface temperature data
124 (HadISST1.1; Rayner et al., 2003)

125

126 Evaluation of the initialized predictions is performed in anomaly space, with anomalies calculated based on forecast-time
127 dependent climatologies to minimize the impacts related to the climate drift inherent in these systems (Meehl et al., 2014).

128 We note that anomalies computed for initialized predictions with a reduced number of start dates (as it is the case in the
129 current study) are subject to uncertainties given the small sample used for computing the climatologies. Here we compute
130 anomalies for each forecast month based on their respective climatologies from the seven start dates (every fifth start date
131 from 1960 to 1990). The observed and historical simulation climatologies are computed for the same temporal period used to
132 define the hindcast climatology. The statistical significance of the correlations and temperature differences is estimated by
133 using a two tailed student's t-test. We apply the false detection rate (FDR) procedure to test for multiple testing (Wilks,
134 2016) using $\alpha_{\text{CDR}}=0.1$.
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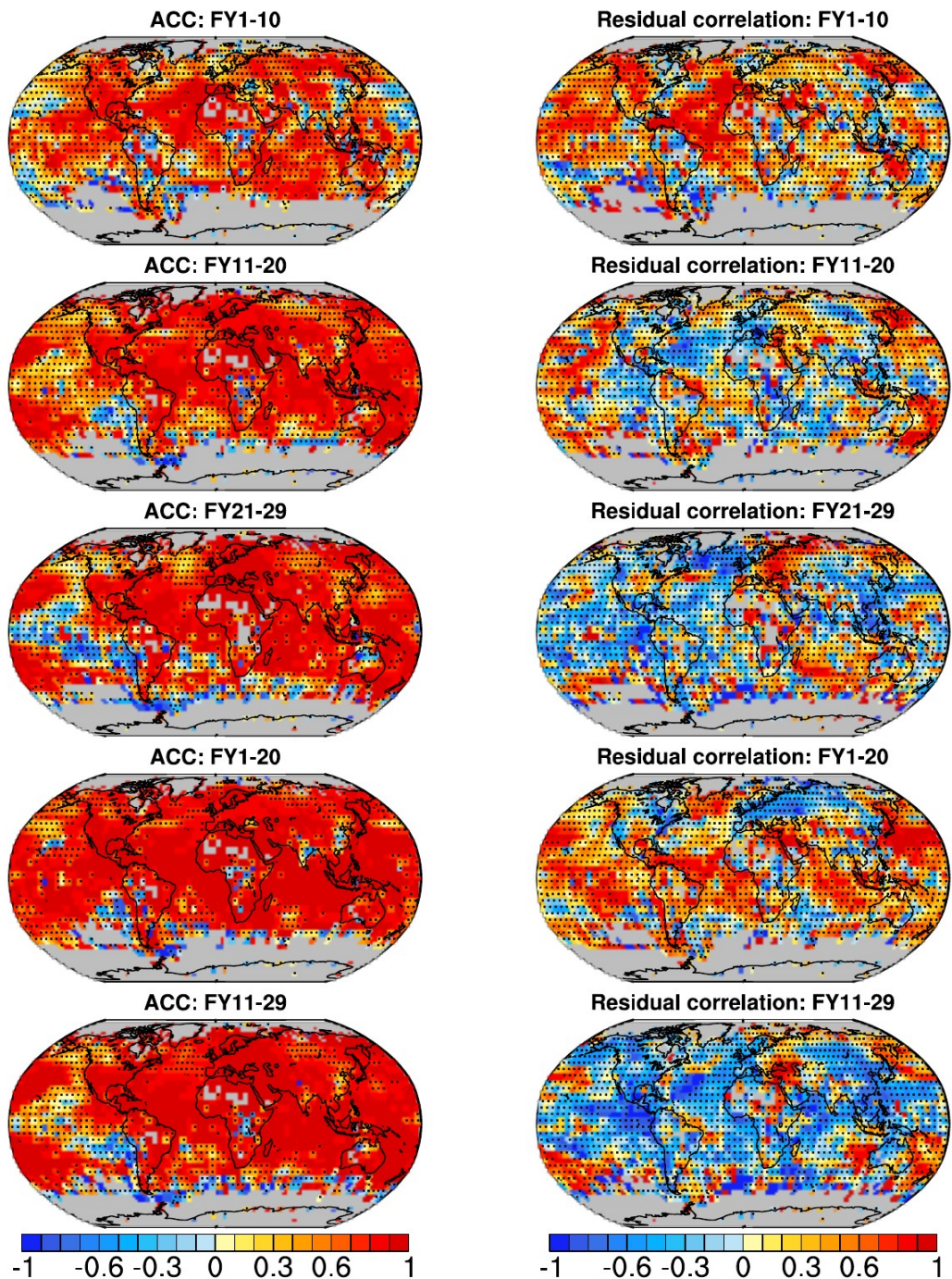


Figure 1. ACC (left column) and residual correlation (right column) of the near-surface air temperature hindcasts for different forecast horizons. The first three rows show ACC and residual correlations for 10 year mean hindcasts while the last two rows are for 20 year mean hindcasts. Stippling indicate regions where ACC and residual correlations are not statistically significant at 95% confidence level.

142 3 Results

143 3.1 Evaluating the skill of the initialized predictions

144 We first evaluate the skill of the initialized multi-decadal prediction system in predicting surface air temperature anomalies
145 for different forecast periods (Fig. 1). The initialized predictions are generally skillful in simulating observed surface air
146 temperature anomalies over most regions globally. For the first decade (i.e. FY1-10), the ACC over the Atlantic, Indian and
147 parts of the Pacific ocean and many land areas is positive and statistically significant suggesting overall good
148 correspondence with observations. These results are generally consistent with the ACC values computed from an updated
149 version of the previous decadal hindcast system (Bilbao et al., 2021) that was initialized every year (Figure S1a and S1b), in
150 supplementary material) and using every 5th start-date (Figure S1c and S1d). When subsampling the system to use every 5th
151 start-date (Figure S1c and S1d) the ACC loses significance in several regions in which also the new 30 year prediction
152 system has no significant ACC. These results suggest that while overall patterns of skill remain similar in reduced
153 initializations compared to annual initializations, however, there may be sampling uncertainties induced by the reduced
154 number of initializations. For the second and the third decades (i.e. FY11-20 and FY21-29) the correlations between
155 predictions and observations are generally higher than 0.7 over most regions of the globe. Over the eastern Pacific, however,
156 the skill of the initialized predictions degrades after the first decade. We note that some of the differences in ACC between
157 the three decadal forecasts are related to the fact that their evaluation periods are different (i.e. 1961-2000 for FY1-10, 1971-
158 2010 for FY11-20 and 1981-2019 for FY21-29). Using the common analysis period (i.e. 1981-2020) for the three decadal
159 mean predictions show ACC skill over similar regions in all three forecast periods with relatively more significant regions in
160 the Atlantic ocean for the first decade (Fig. S2, in supplementary material). We note here that using the common analysis
161 period for skill assessment also introduces uncertainties since different initializations are used for different forecasts. The
162 multi-decadal forecast times (i.e. FY1-20 and FY11-29) show high correlations with the observations over the globe
163 especially for FY1-20.

164
165 Since the ACC for temperature is strongly influenced by the model response to forcings such as e.g. the increase in GHG
166 forcings, we use residual correlations following Smith et al. (2019) to evaluate the added value from initialization. We find
167 here that the added value from initialization is largest in the first ten-year average hindcasts (i.e. FY1-10), but a few regions
168 show added value for the second forecast decade (i.e. FY11-20). For the FY1-10 we find significant added value over the
169 Atlantic ocean and parts of the Pacific and over land regions including northwest Canada, central USA, the Middle East and
170 northern Australia. For the second decade, the added value from initialization is found only over a few regions in the Pacific
171 ocean. The residual correlations are generally not statistically significant over global land areas for FY11-20. For the third
172 forecast decade (i.e. FY21-29), almost no added value from initialization is found in any of the three main ocean basins,
173 suggesting that the information from initialization is lost over time especially after the first decade of the forecasts. When
174 using a common analysis period (i.e. 1981-2020), the added value even for the first decade (i.e. FY1-10) is also limited to

175 parts of the Atlantic ocean, Eastern USA and southern Indian ocean (Fig. S2) indicating sampling uncertainties due to using
176 different forecast analysis periods. The multi-decadal forecast times show added value from initialization for FY1-20 while a
177 widespread detrimental value is found for FY11-29. For FY1-20 most of the added value is in similar regions as the added
178 value for the first decade although parts of tropical regions in the Pacific and Indian oceans seem to show significant added
179 value only in 20-year mean predictions.

180

181 3.2 Time series analysis of the initialized predictions and the uninitialized projection simulations

182 To understand how the 30-year predictions compare with the corresponding (uninitialized) historical/scenario simulations,
183 we evaluate here the time evolution of their regionally averaged sea surface temperature (SST). For this we focus on two
184 regions of well-known multidecadal variability such as the Subpolar North Atlantic (SPNA: 45°N-60°N, 50°W-20°W) and
185 the northeast Pacific (NEP: 40°N-55°N, 140°W-122°W). Previous studies have shown that the decadal predictions can be
186 highly skillful in forecasting temperature over SPNA region (e.g. Yeager et al., 2018; Delgado et al., 2022). This is also a
187 region strongly influenced by forecast drifts associated with the Atlantic Meridional Overturning Circulation (AMOC) in
188 initialized predictions. initialized decadal prediction systems have also shown skill in predicting climate over NEP region
189 (e.g. Kataoka et al., 2020; Choi and Son, 2022).

190

191 As expected from small differences in the initial conditions, the spread in the initialized predictions is small at the beginning
192 and grows over the course of the simulations (Fig. 2). In the SPNA region, the SSTs tend to drift towards a lower (i.e. cooler)
193 mean state a few years after initialization resulting in larger biases (Fig. 2). Interestingly, while the mean SSTs for both the
194 initialized predictions and uninitialized projections are close to each other at the beginning of the predictions, however, the
195 drift in initialized predictions leads to a different mean state after ~10-15 years which is completely outside the ensemble
196 spread of the uninitialized projection simulations. We also note that the spread tends to be narrower at the end of the
197 forecasts than for the uninitialized projection ensemble, in particular for the earlier start dates (i.e. 1960 to 1995). For the
198 NEP region, the mean SSTs in the initialized predictions follow the observations closely at all forecast years while the
199 uninitialized projection simulations tend to be biased high (i.e. warmer than observations and predictions) (Fig. 3). The
200 ensemble spread in the predictions is generally similar to the spread in uninitialized projections for this region (Fig. 3).
201 Compared to the SPNA region, the predictions do not show a strong drift after initialization for the NEP region.

202

203 The SST anomalies show that the initialized and uninitialized ensemble spreads overlap (Fig. S3 and S4). The corresponding
204 plots also nicely illustrate that the ensemble spread for the SPNA region is generally smaller in the initialized predictions
205 compared to the uninitialized projections while similar for the NEP region (Fig. S3 and S4). Due to the non-stationary drift
206 in individual prediction simulations (i.e., the different start dates in Fig. 2), the temperature anomalies for the SPNA region
207 tend to be higher than the projection ensemble in the most recent initializations (cf Figs. 2 and S3). For the NEP region,

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208 which is not strongly affected by the drift, the temperature anomalies remain similar for all start dates (Fig. S4). All these
209 results suggest that the climate information from different experiments (i.e. initialized predictions and the uninitialized
210 projections) of the same model may not converge even after several years of predictions, depending on the region.

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SPNA (tos): runavg:36mon

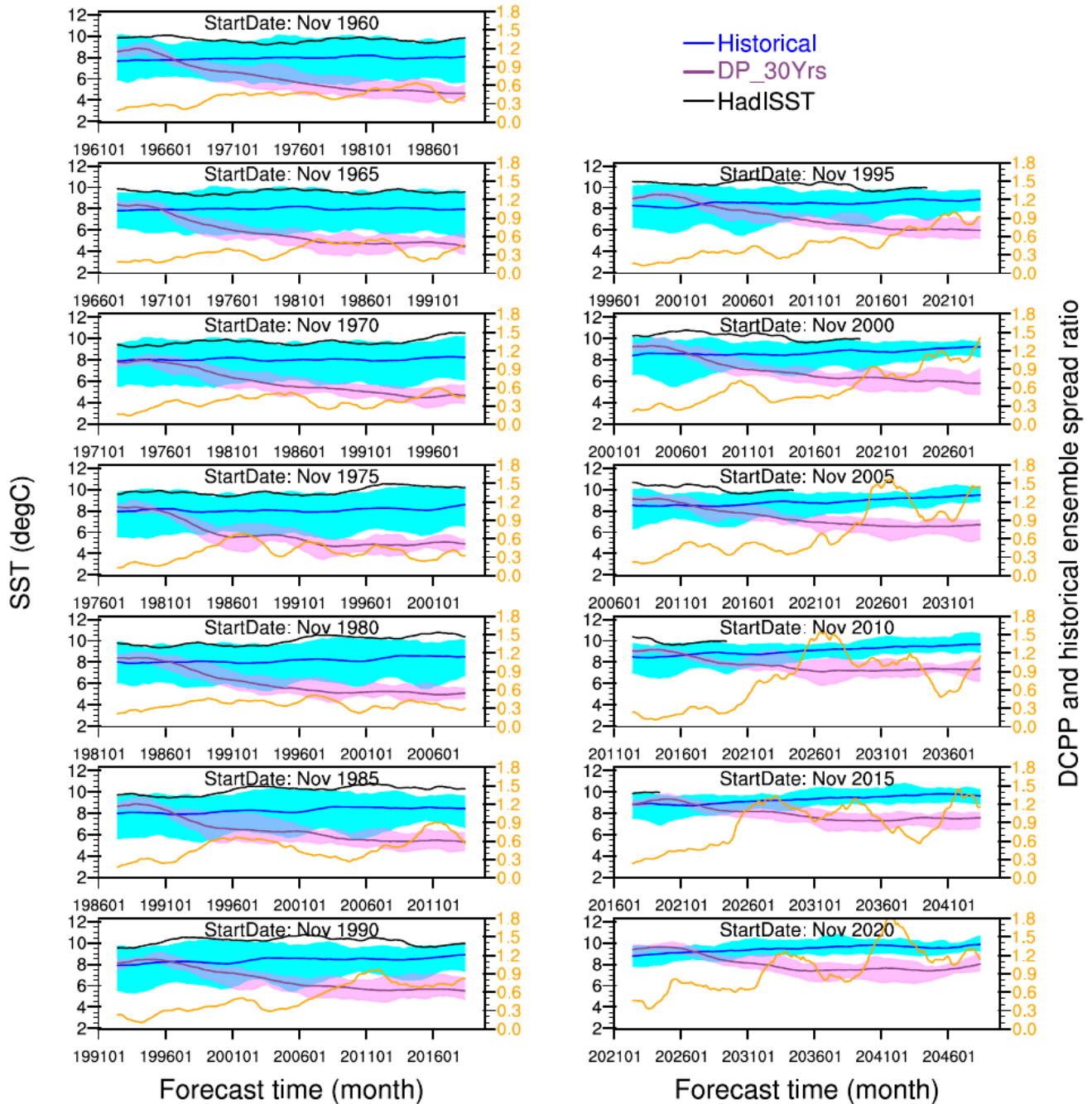
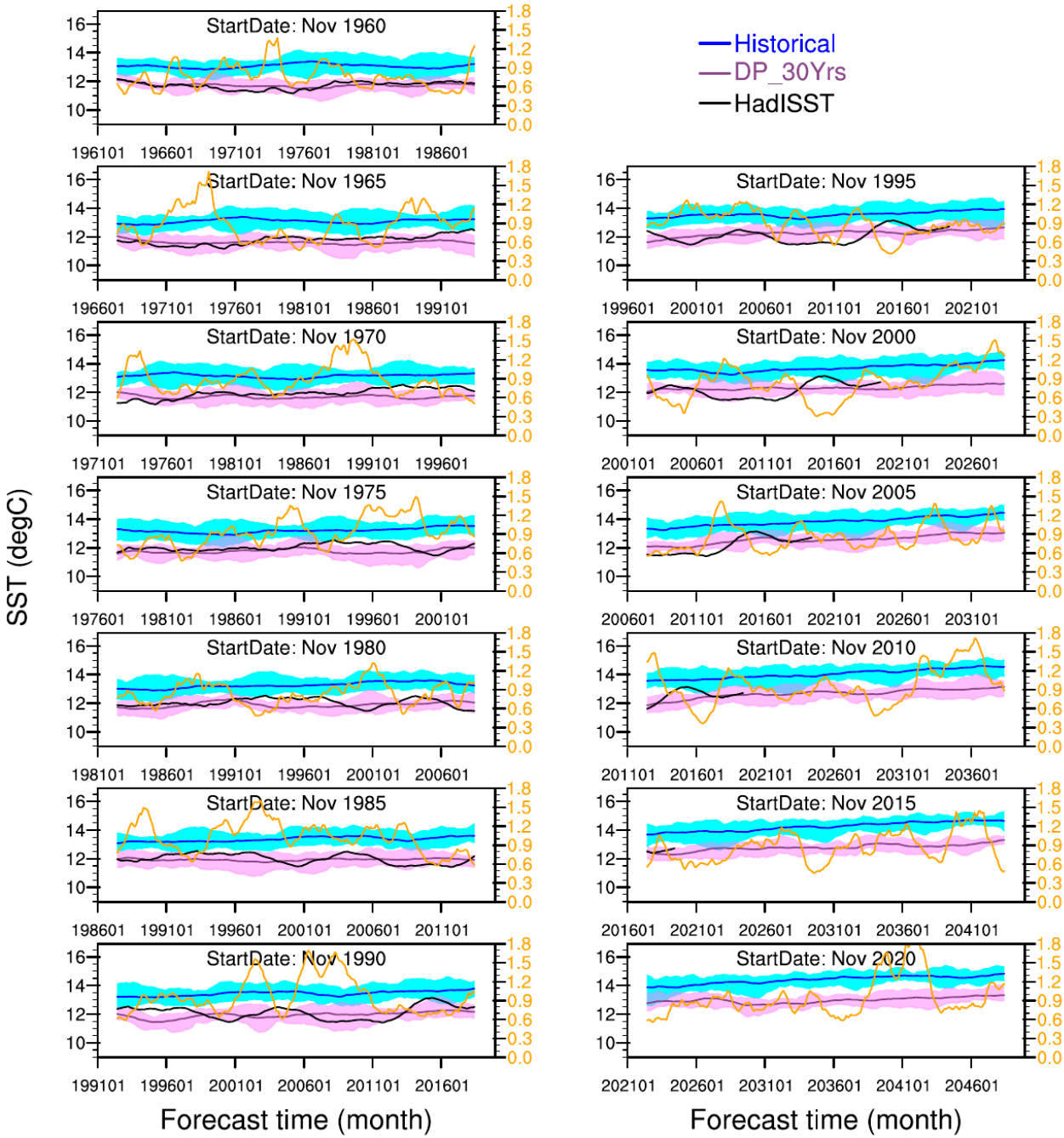


Figure 2. Comparison of mean SST time series in SPNA in initialized predictions (in pink) and the uninitialized projections (in blue). The colored polygons show spread in 10 ensemble members (i.e. based on minimum and maximum values of the 10 members). Observations are shown by the black lines. The monthly mean time series were smoothed using a 36 months running average. The yellow lines (right y-axis) represent spread ratios between initialized and uninitialized ensembles.

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NEP (tos): runavg:36mon



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224 **Figure 3. Same as Figure 2 but for the northeast Pacific (NEP) region.**

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229 **3.3 AMOC**

230 The AMOC is one of the main drivers of decadal-to-centennial variability in the Atlantic Ocean and it is thought to be
231 strongly predictable due to its slowly evolving modulations (e.g. Zhang et al., 2019). Previous studies have shown that, even
232 though decadal prediction systems exhibit various AMOC errors associated with initialization shocks and model drift
233 (Polkova et al., 2023), the effects of initialization on the AMOC can persist for longer than the length of the predictions,
234 which are typically of 10 years (e.g., Bilbao et al., 2021).

235

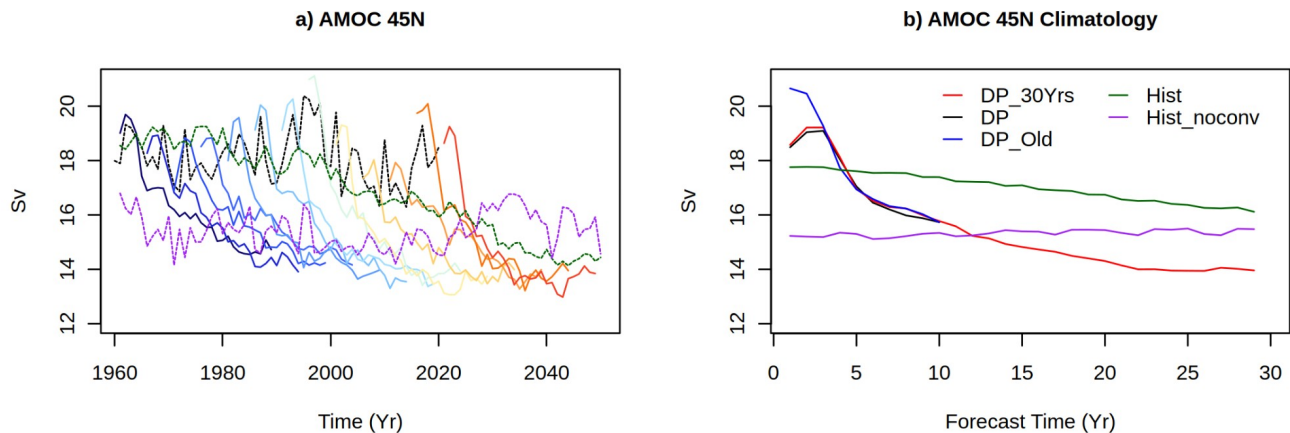
236 We analyse the AMOC at 45°N, defined here as the overturning streamfunction value at 45°N and at 1000 m depth. The EC-
237 Earth3 model produces a shutdown in Labrador Sea convection (and associated AMOC slowdown) also in some of the
238 historical runs (Bilbao et al., 2021). We compare the predictions to the EC-Earth3 historical simulations run by BSC as part
239 of CMIP6 simulations (a total of 15 members) for which we define two ensembles formed by members with (12 out of 15)
240 and without (3 out of 15) deep ocean convection in the Labrador Sea region. These differences in historical simulations
241 originate from the AMOC multi-centennial variability in the EC-Earth3 pre-industrial simulations (Meccia et al., 2023), from
242 which the initial states are taken to initialize these runs.

243

244 Figure 4a shows that the 30-year predictions start from the reconstruction and then follow a similar evolution of the AMOC
245 at 45°N (AMOC45) across all start-dates. This evolution is characterized by an initial strengthening in the first 2-3 years,
246 followed by a rapid weakening, stabilizing at around 14 Sv within the first 25 forecast years, as shown by the climatological
247 values (Fig. 4b). Comparing AMOC45 in the 30-year predictions with the current decadal prediction system shows that the
248 climatology is well constrained, despite the different sampling of initial states. By contrast, the comparison with the previous
249 forecast system shows differences in the AMOC45 during the first few years, since the reconstruction used in that system
250 produces a stronger AMOC. Another difference is that the drift in the current system is rather consistent across start dates,
251 which did not occur in the previous system (see Figure 6c in Bilbao et al., 2021), for which there was a different behavior pre
252 and post-2000 . Despite the updated initial conditions, the current system also suffers from the same initialization problem of
253 the previous system (described in detail in Bilbao et al., 2021) where the model drift causes a progressive increase in
254 Labrador Sea density stratification that ends up suppressing the mixed layer depth and weakening the AMOC. This effect
255 persists beyond the first decade in these new predictions with updated initial conditions, and the AMOC does not recover

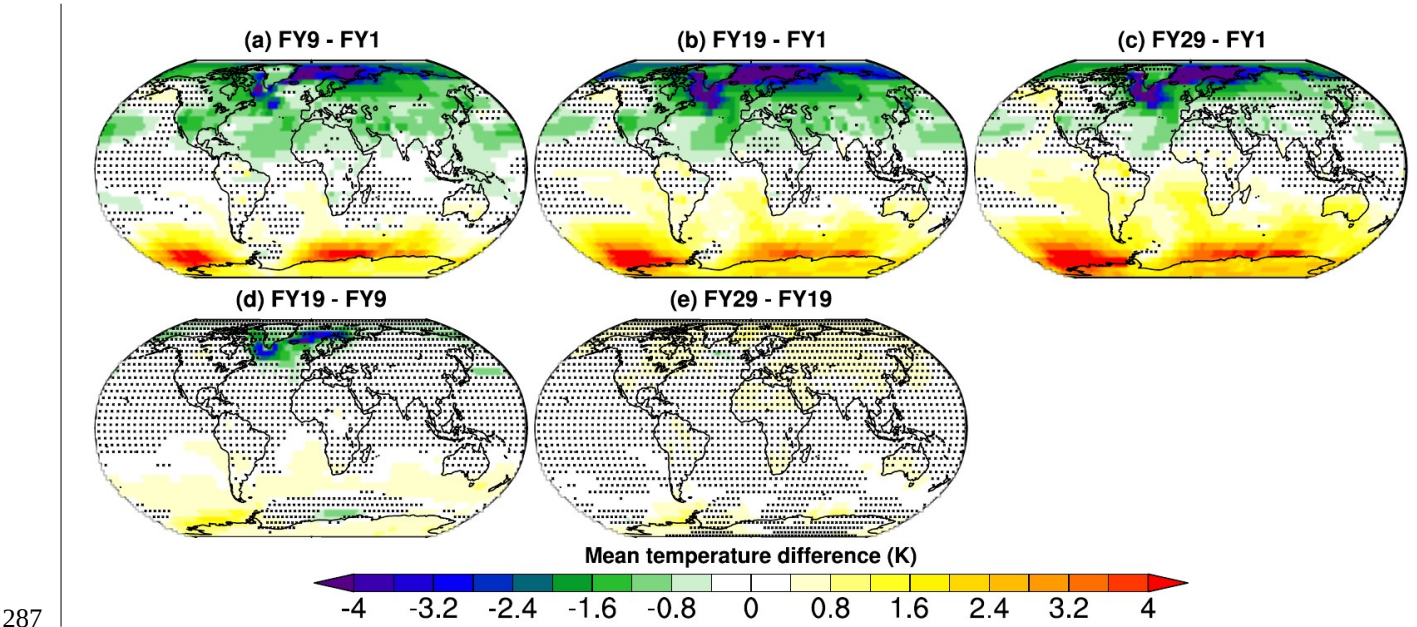
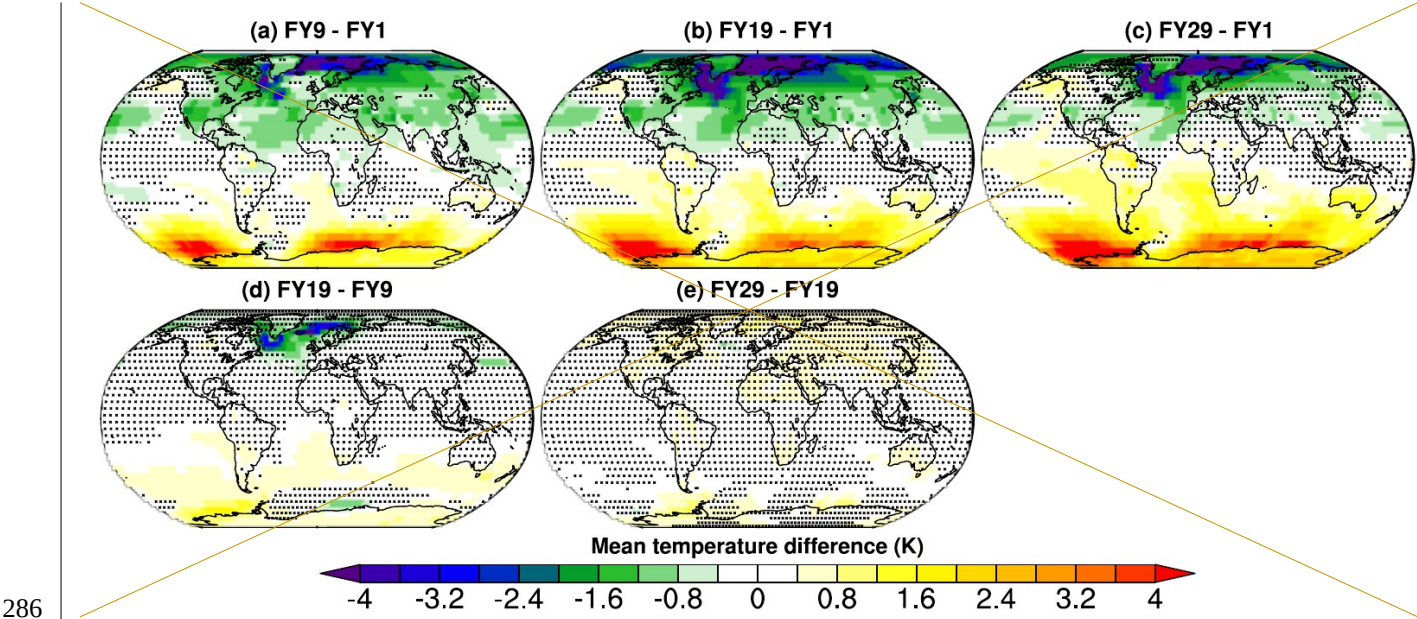
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256 within the 30 forecast years to the historical mean state. We note that this systematic shutdown of convection in the forecasts
 257 is an artefact from initialization, as observational records in the Labrador Sea show instead intermittent deep-convection
 258 events, closely tied to interannual-to-decadal variability in the North Atlantic Oscillation, whose positive phase enhances
 259 winter mixed-layer deepening (Yashayaev & Loder, 2016).
 260
 261 Consistent with Bilbao et al. (2021), the predictions tend to drift towards a state closer to the historical simulations with
 262 suppressed convection in the Labrador Sea (purple), in contrast with those members that exhibit convection (green).
 263 However, the longer predictions also reveal that the decadal forecasts stabilize at an even weaker AMOC state (i.e. ~ 14 Sv)
 264 which is lower than the historical mean AMOC (and lower even than the mean of those historical runs with suppressed
 265 Labrador sea convection). Therefore, in contrast to previous expectations (i.e. based on 10 year predictions), we find here
 266 that the AMOC45 does not converge to the state in the historical simulations. This conclusion supports the previous findings
 267 of Düsterhus and Brune (2023) in their 20-year predictions in which the AMOC in initialized predictions tends to drift
 268 towards much lower values than the historical simulations albeit using a different climate model.
 269



270
 271 **Figure 4. (a) Evolution of the AMOC at 45N in the 30 year prediction ensemble mean (blue to red every five start dates), the**
 272 **historical+projection ensembles with and without Labrador sea convection (green and purple, respectively) and the ocean**
 273 **reconstruction used to generate the initial conditions (black). (b) The climatological values as a function of forecast time. DP and**
 274 **DP_30yrs in b represent decadal and the muliti-decadal (i.e. 30 year long) prediction systems respectively, both both of which use**
 275 **the same updated initial conditions. DP_Old represents the previous decadal prediction system from Bilbao et al. (2021)**
 276
 277 We find that surface temperature responses during the course of the simulations are strongly influenced by the prominent
 278 drift in the AMOC. The climatological mean surface air temperature differences between the later forecast years compared to
 279 the first forecast year (Fig. 5a-d) are negative in the northern hemisphere while positive in the southern hemisphere, a pattern

280 that is consistent with the reduced northward heat transport that follows an AMOC weakening. These bipolar temperature
 281 differences persist until decades after initialization and are consistent with the AMOC drift towards lower mean state. The
 282 temperature differences between forecast year 29 and 19 (Fig. 5e) are relatively small and symmetrical in both hemispheres,
 283 consistent with the stabilization of AMOC after the first two decades of initialization. The interhemispheric asymmetrical
 284 responses of surface air temperature due to AMOC decline has been found in previous studies (e.g. Orihuela-Pinto et al.,
 285 2022).



288 | **Figure 5. Differences in mean near-surface air temperature between different forecast years of the initialized predictions. Stippling**
289 **indicates regions where the differences are not statistically significant at 95% confidence level.**

290 4 Summary and discussion

291 The initialized climate predictions are designed to synchronize the model variability with that of observations and thus can
292 provide potentially more skillful climate information for the next few decades than the forced-only climate projections. Most
293 of the current initialized climate prediction systems generally forecast up to ten years after initialization (e.g. Boer et al.,
294 2016). Here we performed a new set of multidecadal climate predictions with the BSC's decadal prediction system using
295 updated initial conditions. Ten-member ensembles of 30-year long hindcasts and predictions were performed using the EC-
296 Earth3 model by initializing every fifth year starting from 1960 to 2020.

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298 The evaluation of the multidecadal predictions suggest that the predictions are skillful for the different forecast periods
299 considered (up to 30 years), however the added value from initialization was primarily found for the first 10 year average
300 forecasts after which very limited added value from initialization is found. In particular for the third decade (i.e. FY21-29)
301 we did not find added value from initialization over the uninitialized projection simulations, and identify even some
302 detrimental effects associated with long-term model drift after initialization. Similar issues pointing to long-term drift in
303 AMOC were found in a previous study which presented 20-year initialized hindcasts with a different decadal prediction
304 system based on the MPI-ESM climate model (Düsterhus and Brune, 2023). While the skill evaluations are subject to large
305 uncertainties related to the limited sample size relative to the forecast times, an important result of this 30-year prediction
306 experiment is the indication of long-term model drift into a different climate state characterised by weakened AMOC, that
307 does not recover within the 30 years of the simulations.

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309 As a consequence of this long-term drift the initialized predictions and the uninitialized projections may not necessarily
310 provide consistent information for near-term climate change estimates. Also the ensemble spreads for the two types of
311 simulations are non-stationary (especially for the SPNA region, Figure 2) and generally smaller in initialized predictions
312 than the uninitialized projections. Besides the inconsistent near-term climate estimates from the initialized and uninitialized
313 simulations, these results also imply that caution must be taken when combining climate information from these two types of
314 model simulations. For example, these inconsistencies will challenge approaches to concatenate data from decadal
315 predictions and climate projections (Befort et al., 2022).

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317 Similar to the findings by Bilbao et al. (2021), we find that the climate predictions do not converge to the model attractor
318 characterized by the historical ensemble, a deviation that is particularly evident for the AMOC. Indeed, the AMOC drifts in
319 the first ~22 forecast years and then tends to stabilize at ~14 Sv which is lower than the mean AMOC state in non-initialized
320 simulations. A similarly lower AMOC mean state in initialized predictions compared to historical simulations was also

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found by Düsterhus and Brune (2023) using a different climate model. This suggests that both models can experience different stable AMOC states, with initialization from observations playing a pivotal role to move from one state to the other.

The progression in the AMOC drift is found to have a strong influence on the predicted global surface air temperature anomaly pattern. The climatological mean temperatures in later forecast years compared to the first forecast year, tend to be cooler in the northern hemisphere and warmer in the southern hemisphere, as expected in response to an AMOC weakening, in line with results in idealized experiments enforcing an AMOC shutdown (Orihuela-Pinto et al. 2022).

One side effect of long prediction time horizons and using multiple ensemble members is the need for large amounts of computational resources for running simulations, post-processing data and the storage space requirement. Due to these reasons, the current prediction system was only initialized every fifth year which makes it challenging for computing anomalies and also evaluating the skill of the predictions. Alternative approaches for providing climate information on 10 to 20 year mean timescales have been developed which require a fraction of computational costs as compared to the state-of-the-art initialized climate predictions. These alternative approaches make use of existing climate simulations and constrain them according to the similarity of their SST variability patterns with observations at a given initialization time. The climate predictions based on these variability-constrained projections (e.g. Mahmood et al., 2022; Donat et al., 2024) even show higher and more widespread added skill, compared to the initialized predictions presented in this study, for both 10 and 20 year mean predictions. The skill in these constrained projections suggests that the decadal and multi-decadal predictability of climate might be higher than what is achieved with the new initialised prediction using EC-Earth3. This warrants further in-depth comparison of the different modelling and the constraining approaches in predicting climate over multidecadal timescales, ideally in a multi-model context.

While our results show very limited added predictive skill from initialization beyond the first decade, they highlight important issues often affecting initialized prediction systems. The model drift following an initialization shock can cause the model to adjust into a different climate state compared to uninitialized simulations for an extended time period. Our results show that even after 30 years there is no sign of convergence between the initialized and uninitialized climate simulations. This highlights important challenges in the use of initialized predictions for estimates of near-term climate changes, that should be taken into account in the further development of both the climate models and the initialization approaches.

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Data availability

The data from these simulations are freely available at the ESGF archive.

Author contributions

MD, FDR and RM designed the study. RM performed the climate model simulations. RM and RB analysed the results. RM, MD, RB and PO discussed the results for presentation in the study. RM and MD wrote the initial manuscript draft with contributions from all co-authors. VL, RB, and ET generated initial conditions and also developed capability to perform initialised predictions with the EC-Earth3 model.

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